Fama French factors and US stock return predictability

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Abstract

This paper investigates whether the HML, the SMB along with the short-term reversal, the long-term reversal and the momentum factors exhibit both in-sample and out-of-sample forecasting ability for the US stock returns. Our findings suggest that these factors contain significantly more information for future stock market returns than the typically employed financial variables. We also go one step further and test whether these variables can proxy for the aforementioned factors. Our results suggest that the default spread and to a lesser extent the term spread contain important information for the evolution of the factors examined.

JEL Classification: C53; G12.

Keywords: ICAPM; Fama French factors; Out-of-sample forecasts; Stock return predictability;

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1 Introduction

A series of papers by Fama and French (1993, 1995, 1996, FF henceforth) indicate that the Capital Asset Pricing Model (CAPM) fails to capture the cross-sectional variation of average stock returns. In this respect, the authors propose a three-factor model, according to which the expected return on a portfolio in excess of the risk-free rate is explained by three factors; namely, the excess return on the market portfolio, the return on a portfolio long in small stocks and short in big stocks (SMB), and the return on a portfolio long in high-book-to-market stocks and short in low-book-to-market stocks (HML). SMB is often referred to as the size premium, while HML as the value premium. FF (1993) show that this model performs well on portfolios formed on size and book-to-market equity, and that size and book-to-market can proxy for the sensitivity of stock returns to common risk factors. In FF (1995), the authors provide evidence that size and book-to-market are related to profitability. They also argue that their results are consistent with those of Merton's (1973) Intertemporal Capital Asset-Pricing Model (ICAPM), in which size and book-to-market proxy for the sensitivity to risk factors in returns. In a subsequent paper, FF (1996) show that their model captures priced default risk, and, as a result, can explain equity returns. In an effort to identify the factors that capture the systematic return covariation in stock returns, Chan, Karceski, and Lakonishok (1998) conclude that with the exception of the FF factors, only the default premium and the term premium can explain return covariation.

More recently, Liew and Vassalou (2000) investigate the extent to which the profitability of the HML and SMB factors can be linked to future economic growth (GDP), and conclude that, indeed, the hypothesis of FF (1993, 1995, 1996) is supported across various markets. Going one step beyond, Vassalou (2003) provides an economic interpretation and concludes that the HML and SMB factors include information related to news about future GDP growth. Petkova (2006) shows that the same factors proxy for the term spread and default spread, respectively, thus establishing a link between a set of variables associated with time-series return predictability and a set of variables associated with cross-sectional return predictability. Similarly, Hahn and Lee (2006) find that changes in the default spread and the term spread capture the cross-sectional pattern of stock returns in size and book-to-market. The degree to which these factors are linked to the state variables over various time scales is examined by In and Kim (2007), who conclude that both SMB and HML play a limited role in the short run, but the opposite takes place in the long run. On the contrary, Gharghori, Chan, and Faff (2007) using data from the Australian equities market prove that neither SMB nor HML proxies for the default spread, but they suggest that the FF three factor model is vastly superior to the CAPM in explaining returns.

In this paper, we investigate whether the value premium (HML) and the size premium (SMB), along with the long-term reversal, the short-term reversal and the momentum factors exhibit both in-sample and out-of-sample forecasting ability for the US stock returns. Our set of predictors is enriched with four financial variables that are typically employed in the literature; namely, the 3-month T-bill, the 1-month T-bill, the term spread, and the default spread. We also examine whether any of the financial variables considered can proxy for the factors at hand. These issues are addressed for a variety of horizons ranging from the short-run (1 month) to the long-run (3 years).

We assess the forecasting ability of the various factors for the US returns by means of an Autoregressive Distributed Lag (ARDL) model (see Rapach and Weber, 2004). The in-sample forecasting ability is assessed by the typical Wald test, while the out-of-sample one is assessed via the statistics for forecast encompassing developed by Harvey et al. (1998) and Clark and McCracken (2001). Apart from Rapach and Weber (2004), Rapach, Wohar and Rangvid (2005) employ this methodology to examine the predictability of stock returns using macro variables in 12 industrialized countries and find that the interest rates are the most powerful predictors accross countries, while the term spread exhibits some predictive ability in some countries. Moreover, Rapach and Wohar (2006) test whether a set of financial variables exhibits in-sample and out-of-sample forecasting ability on the S&P 500 index and the equal-weighted CRSP portfolio. The authors find that the term spread is a significant predictor of real S&P 500 returns, both in-sample and out-of-sample, at the 5-year horizon, while this ability is limited to in-sample at the 10-year horizon for the CRSP equal-weighted portfolio. In addition, they show that the term spread exhibits no forecasting ability on the S&P 500 returns, while there is in-sample forecastability of the same variable on the CRSP equal-weighted portfolio.

Our results suggest that the SMB, the HML, the reversal and the momentum factors exhibit considerable in-sample and out-of-sample forecasting ability on the CRSP portfolio at specific horizons. Consistent with previous findings, we confirm both the in-sample and out-of sample predictive ability of HML and SMB. More importantly, both the long-term reversal and the momentum factor emerge as useful predictors for stock returns, while the short-term reversal factor hardly improves forecasts. Turning to the financial variables, only the term spread exhibits out-of-sample forecasting ability, while the remaining ones improve in-sample forecasts. Investigating whether any financial factors can act as a proxy for the aforementioned factors, we, indeed, find that there is a link between them with the default spread being the most important proxy.

The remainder of the paper is organized as follows. Section 2 describes in detail the econometric methodology employed. Section 3 presents the data and the empirical results concerning the forecastability of the factors and financial variables at hand. Robustness tests are carried out in Section 4, while Section 5 summarizes and concludes.

2 Econometric methodology

Following Rapach and Weber (2004), the predictive ability of factors and financial variables is evaluated by means of the following predictive AutoRegressive Distributed Lag (ARDL) model:

$$z_{t+h} = a + \sum_{i=0}^{q_1-1} \beta_i \Delta y_{t-i} + \sum_{i=0}^{q_2-1} \gamma_i x_{t-i} + \epsilon_{t+h} \tag{1}$$

where $z_{t+h} = \sum_{i=1}^{h} \Delta y_{t+i}$ is the return to be predicted from period t to $t+h$ with h the forecast horizon, x_t the candidate predictor variable, $\Delta y_t = y_t - y_{t-1}$ the one-period return at time t, ϵ_{t+h} the disturbance term, a the intercept, q_1 and q_2 the data-determined lag orders for Δy_t and x_t.[1] A heteroscedasticity and autocorrelation-consistent (HAC) covariance matrix should be employed when multi-step forecasts are concerned, i.e. $h > 1$, since the returns z_{t+h} overlap and this induces serial correlation to the disturbance term (see e.g. Newey and West, 1987).

In order to test the in-sample forecastability of variables, we employ the whole sample and conduct a Wald test for the null hypothesis that $\gamma_0 = ... = \gamma_{q_2-1} = 0$. If the null hypothesis cannot be rejected at the desirable significance level (s.l.), the variable employed does not have any forecasting ability. In order to study the out-of-sample forecasting ability, the total sample T is divided into the first R in-sample observations and the last P out-of-sample observations. In order to create the first out-of-sample forecast we make use of the in-sample portion of the sample and estimate the OLS parameters a, β_i and γ_i of the ARDL equation via the method of ordinary least squares (OLS) for the unrestricted form of the model, $\widehat{a}_{1,R}$, $\widehat{\beta}_{1,R,i}$, $\widehat{\gamma}_{1,R,i}$. Then the estimated equation $\widehat{z}_{1,R+h} = \widehat{a}_{1,R} + \sum_{i=0}^{q_1-1} \widehat{\beta}_{1,R,i} \Delta y_{R-i} + \sum_{i=0}^{q_2-1} \widehat{\gamma}_{1,R,i} x_{R-i}$ creates the first out-of-sample forecast for the unrestricted form of the model as well as the forecast error $\widehat{u}_{1,R+h} = z_{R+h} - \widehat{z}_{1,R+h}$. Following the same procedure, we estimate the equation for the restricted form of the model: $\widehat{z}_{0,R+h} = \widehat{a}_{0,R} + \sum_{i=0}^{q_1-1} \widehat{\beta}_{0,R,i} \Delta y_{R-i}$, where $\widehat{a}_{0,R}$ and $\widehat{\beta}_{0,R,i}$ are the OLS parameter estimates and compute the forecast error $\widehat{u}_{0,R+h} = z_{R+h} - \widehat{z}_{0,R+h}$. In order to create the next forecasts, we expand recursively the in-sample portion of the sample and repeat the whole procedure through the end of the available sample generating totally $T - R - h + 1$ out-of-sample forecast errors for the unrestricted and the restricted form of the predictive model, $\{\widehat{u}_{1,t+h}\}_{t=R}^{T-h}$ and $\{\widehat{u}_{0,t+h}\}_{t=R}^{T-h}$, respectively.

The variable x_t has forecasting ability for the returns if the unrestricted model forecasts are superior to the restricted ones. A metric that is commonly used for this purpose is Theil's U, which is the ratio of the Mean Squared Forecast Error (MSFE) of the unrestricted model to the MSFE of the restricted one. When $U < 1$, the MSFE of the unrestricted model is less than the MSFE of the restricted model, suggesting that the

[1] The maximum lag value is 8 and is selected by means of the SIC criterion. Alternatively, we could employ the AIC criterion. However, in most cases, the results are not sensitive to the lag selection method as noted by Clark and McCracken (2001).

candidate variable can improve forecasts. In order to statisticaly test the ability of a factor to improve the predictability of the ARDL model, we use the Diebold and Mariano (1995) and West (1996) t-statistic for equal MSFE, the MSE-T statistic, along with a variant of this statistic due to McCracken (2004), the MSE-F statistic. Both statistics test the null hypothesis that the unrestricted model MSFE is equal to the restricted model MSFE against the one-sided (upper-tail) alternative hypothesis that the unrestricted model MSFE is less than the restricted model MSFE.

The MSE-T and MSE-F statistics are expressed as follows:

$$MSE - T = (T - R - h + 1)^{0.5}\overline{d}\widehat{S}_{dd}^{-0.5} \tag{2}$$

$$MSE - F = (T - R - k + 1)\overline{d}/\widehat{MSFE}_1 \tag{3}$$

where $\overline{d} = (T - R - h + 1)^{-1}\sum_{t=R}^{T-h}\widehat{d}_{t+h} = \widehat{MSFE}_0 - \widehat{MSFE}_1$ is the mean loss differential, $\widehat{MSFE}_i = (T - R - h + 1)^{-1}\sum_{t=R}^{T-h}\widehat{u}_{i,t+h}^2 \quad (i = 0, 1)$, $\widehat{d}_{t+h} = \widehat{u}_{0,t+h}^2 - \widehat{u}_{1,t+h}^2$ is the sequence of loss differentials, $\widehat{S}_{dd} = \sum_{j=-J}^{J} K(j/J)\widehat{\Gamma}_{dd}(j)$ is the long-run covariance matrix of $\widehat{d}_{t+h}$, $\widehat{\Gamma}_{dd} = (T - R - h + 1)^{-1}\sum_{t=R+j}^{T-h}(\widehat{d}_{t+h} - \overline{d})(\widehat{d}_{t+h-j} - \overline{d})$ is the covariance of the loss differential $\widehat{d}_{t+h}$ at dispacement j, $\widehat{\Gamma}_{dd}(-j) = \widehat{\Gamma}_{dd}(j)$, k is the number of lags. The estimator of the long-run covariance matrix of $\widehat{d}_{t+h}$, $\Omega = \lim_{j\to\infty}\sum_{-j}^{j} E(\widehat{d}_{t+h}\widehat{d}_{t+h-j}^{\prime})$, is the kernel HAC estimator for Ω of the form $\widehat{S}_{dd} = \sum_{j=-J}^{J} K(j/J)\widehat{\Gamma}_{dd}(j)$. Following Clark and McCracken (2005), we use the Bartlett kernel $K(j/J) = 1 - [j/(J + 1)]$ with bandwidth parameter $J = [1.5h]$ for $h > 1$, where $[\cdot]$ is the nearest integer function.

McCracken (2004) shows that for nested models and for $h = 1$, both statistics have a nonstandard asymptotic distribution which is a function of stochastic integrals of quadratics of Brownian motion $W(\cdot)$ that depends on $\lim_{P,R\to\infty} P/R$. Moreover, Clark and McCracken (2001) show that when we focus on multi-step forecasts, i.e. $h > 1$, the limiting distribution of the statistics is also nonstandard when comparing forecasts from nested models. In this case, unknown nuisance parameters exist in the limiting distribution and both the $MSE - T$ and $MSE - F$ statistics are not asymptotically pivotal. To overcome this, Clark and McCracken (2005) recommend the use of a bootstrap procedure, introduced by Kilian (1999), which enables us to calculate critical values that can yield accurate inferences, especially in the case of multi-step horizons.

An alternative way to evaluate forecasts is based on the notion of forecast encompassing. Let $\widehat{z}_{c,t+h}$ be a combination of the out-of-sample forecasts from the restricted ARDL model $\widehat{z}_{0,t+h}$ and those of the unrestricted model $\widehat{z}_{1,t+h}$ in an optimal way so that $\widehat{z}_{c,t+h} = \lambda\widehat{z}_{1,t+h} + (1 - \lambda)\widehat{z}_{0,t+h}$, $0 \leq \lambda \leq 1$. If the optimal weight attached to the unrestricted model forecast is zero, $\lambda = 0$, then the restricted model forecasts encompass the competing unrestricted model forecasts. In this case we have $\widehat{z}_{c,t+h} = \widehat{z}_{0,t+h}$ from which it is obvious that only the restricted model is important. Transforming the equation $\widehat{z}_{c,t+h} = \lambda\widehat{z}_{1,t+h} + (1-\lambda)\widehat{z}_{0,t+h}$ into $\widehat{u}_{c,t+h} = \lambda(\widehat{u}_{0,t+h} - \widehat{u}_{1,t+h})$ by subtracting $\widehat{z}_{0,t+h}$ from both sides and substituting $\widehat{z}_{1,t+h} - \widehat{z}_{0,t+h} = \widehat{u}_{0,t+h} - \widehat{u}_{1,t+h}$, we conclude that when $\lambda = 1$, then the candidate variable does have predictive power and the covariance between $\widehat{u}_{0,t+h}$ and $\widehat{u}_{0,t+h} - \widehat{u}_{1,t+h}$ will be positive. If $\lambda > 0$, then not only the restricted model forecast, but also the unrestricted model forecast attributes information that is useful and important to the formation of the optimal composite forecast, and as a result the restricted model forecasts do not encompass the unrestricted model forecasts.

In order to test whether the restricted model forecasts encompass or not the unrestricted model forecasts, we employ two statistics; the ENC-T statistic proposed by Harvey et al. (1998) and a variant of ENC-T proposed by Clark and McCracken (2001), ENC-NEW. Both statistics test the null hypothesis of equal forecast accuracy or forecast encompassing, $\lambda = 0$, against the one-sided alternative (upper-tailed) hypothesis that $\lambda > 0$. They are calculated as follows:

$$ENC - T = (T - R - h + 1)^{0.5}\overline{c}\widehat{S}_{cc}^{-0.5} \tag{4}$$

$$ENC - NEW = (T - R - k + 1)\overline{c}/\widehat{MSFE}_1 \tag{5}$$

where $\overline{c} = (T - R - h + 1)^{-1}\sum_{t=R}^{T-h}\widehat{c}_{t+h}$ is the mean of the sequence $\widehat{c}_{t+h}, \widehat{c}_{t+h} = \widehat{u}_{0,t+h}(\widehat{u}_{0,t+h} - \widehat{u}_{1,t+h}), \widehat{S}_{cc} = \sum_{j=-J}^{J} K(j/J)\widehat{\Gamma}_{cc}(j), \widehat{\Gamma}_{cc}(j) = (T-R-h+1)^{-1}\sum_{t=R+j}^{T-h}(\widehat{c}_{t+h} - \overline{c})(\widehat{c}_{t+h-j} - \overline{c})$, and $\widehat{\Gamma}_{cc}(-j) = \widehat{\Gamma}_{cc}(j)$. As previously, we employ the Bartlett kernel $K(j/J) = 1 - [j/(J+1)]$ with a lag truncation parameter $J = [1.5h]$ for $h > 1$, where $[\cdot]$ is the nearest integer function. Clark and McCracken (2001) show that for nested models and $h = 1$, both the ENC-T and ENC-NEW statistics have a nonstandard limiting distribution, since the forecast errors for nested models are asymptotically the same and therefore perfectly correlated. Moreover, for $h > 1$ Clark and McCracken (2005) show that these statistics have a nonstandard asymptotic distribution and are not asymptotically pivotal. As in the case of the MSE-T and MSE-F statistics, Clark and McCracken (2005) recommend the use of a bootstrap procedure which has been introduced by Kilian (1999). The bootstrapped critical values estimated seem to reflect the imprecision of the HAC variance that enters the test statistics, and according to Kilian (1999) this bootstrap method reduces the size distortions of conventional long-horizon regression tests on small samples.[2]

Clark and McCracken (2001, 2005) show that the out-of-sample statistics have good size properties, when inference is based on a bootstrap procedure. The ENC-NEW statistic proves to be the most powerful among all with the ENC-T and MSE-F following, while the least powerful is the MSE-T statistic.

[2] To save space, we do not describe the bootstrap procedure. Please refer to Rapach and Weber (2004).

3 Empirical Results

3.1 Data

The data used in our analysis are monthly observations for the period from July 1963 to October 2009. The returns on the market portfolio (CRSP value-weighted portfolio return), the SMB (Small Minus Big), the HML (High Minus Low), the Short-Term Reversal (ST-Rev), the Long-Term Reversal (LT-Rev) and the Momentum (Mom) factors are taken from Professor Kenneth French's website.

The SMB and HML factors are constructed from 6 value-weighted portfolios formed on size and book-to-market are used. Specifically, the intersections of these portfolios form 6 value-weighted portfolios: small value, small neutral, small growth, big value, big neutral, and big growth portfolio. The average return of the three small portfolios minus that of the three big portfolios forms the SMB portfolio, whereas the average return of the two value portfolios minus the one of the two growth portfolios forms the HML portofolio. The ST-Rev, LT-Rev, and Mom factors are formed from 6 value-weighted portfolios on size and prior returns. The prior-return portfolios are constructed on prior (1-1), (13-60), and (2-12) return, respectively. The average return on the two low prior return portfolios (big and small) minus the average return on the two high prior return portfolios (big and small) form the factors.

In addition, we employ four financial variables which can be thought of as state variables in the context of ICAPM. These are the 3-month T-bill rate, the 1-month T-bill rate, the term spread and the default spread. The term spread is the difference between the yields of a 10-year and a 1-year government bond, while the default spread is the difference between the yields of a long-term corporate Baa bond and a long-term (10-year) government bond. Data on bond yields and the 3-month Treasury Bill is from the FRED database of the Federal Reserve Bank of St. Louis, while the 1-month T-bill rate is from Ibboston and Associates Inc. available at Kenneth French's website.

3.2 The predictive ability of the Fama/French, reversal and momentum factors

We begin our analysis from the HML factor. Using the predictive ARDL model (Equation 1) the in-sample and out-of-sample predictive ability of the factor on the CRSP value-weighted portfolio return is shown in Table 1 through the Wald test and the MSE-T, MSE-F, ENC-T, and ENC-NEW tests, respectively.[3] Specifically, the in-sample and out-of-sample statistics, as well as the bootstrapped p-values associated with these tests (in brackets) for horizons of 1-36 months are reported.

[TABLE 1 AROUND HERE]

[3] For brevity, the values of q_1 and q_2, selected by the SIC, the Theil's U, and the R^2, have been omitted from the table. These results are available from the authors upon request.

The Wald test suggests that the HML factor displays significant, at the 10% level, in-sample predictive ability at horizons of 3, 4, and 6 - 9 months. Furthermore, the out-of-sample predictive ability appears at horizons of 3-10 and 27 months. It is important to note that whenever we have evidence for out-of-sample forecasting ability, all four statistics are significant with the exception of ENC-NEW for the periods of 5 and 10 months. Interestingly, at the horizons of 5, 10, and 27 months there is significant out-of-sample predictive ability without any evidence of in-sample forecastability.

Table 2 reports the same statistics as Table 1 for the SMB factor.

[TABLE 2 AROUND HERE]

The SMB factor displays significant in-sample predictive ability at horizons of 1 and 5 months, while the out-of-sample predictive ability appears at horizons of 1, 3, 4, 5, 6, 8, 9, 10, 13, 14, and 27 months. In the case of the SMB portfolio, we note that not all the statistics appear significant when there is evidence of out-of-sample forecasting ability. In particular, only at the horizons of 5 and 9 months are all the statistics significant, while at the horizons of 4 and 10 months all but the ENC-NEW statistic are significant. Furthermore, there are cases where only one statistic is significant at the 10% level, such as the ENC-NEW statistic at the horizons of 1 and 8 months, and other cases in which only two statistics are significant, such as the horizons of the 3, 6, 13, 14, and 27 months. Moreover, at horizons of 3, 4, 6, 8, 9, 10, 13, 14, and 27 months there is evidence of significant out-of-sample predictive ability without any evidence of significant in-sample forecastability, while the opposite does not appear to happen.

In Table 3 we present the results for the long term reversal factor on the CRSP value-weighted portfolio for horizons of 1-36 months.

[TABLE 3 AROUND HERE]

As the Wald test suggests, this factor displays significant in-sample predictive ability at horizons of 3-8 months, while there is evidence for out-of-sample predictive ability at horizons of 2-8, 27, 32-34 months. Our out-of-sample tests agree on the predictive ability for the LT-Rev portfolio only at horizons of 3, 4, 5, and 27 months, whereas in the other cases, only 1 or 2 of them are significant at the10% level. In particular, at horizons of 6, 7, 33, and 34 months only two of the statistics are significant; namely, the MSE-F and ENC-NEW statistics for the 6 and 7-month horizons and the MSE-T and ENC-T statistic at the 33 and 34-month horizons. In the case of 2, 8, and 32 months ahead, only one test statistic supports the predictive ability of the factor. Moreover, it is interesting to observe that at the horizons of 2, 27, 32, 33, and 34 months there is evidence of significant out-of-sample predictive ability without evidence of significant in-sample forecastability.

Table 4 reports the results for the short term reversal factor. Quite interestingly, this factor does not show any predictive ability, since only the MSE-F statistic is significant at the 10% level at the horizon of 22 months. This is quite interesting given the fact that the ST-Rev factor is the only factor associated with the immediate past of the portfolio returns.

[TABLES 4 & 5 AROUND HERE]

Finally, in Table 5 we give the results for the last factor, the momentum factor. With respect to the in-sample predictive ability of this factor, the Wald test indicates significance at horizons of 4, 5, and 22 months, while out-of-sample predictive ability appears at horizons of 4-6, 9, 12-14 and 16-19 months. It is important to note that whenever there is evidence for out-of-sample forecasting ability, not all of the statistics are significant at the 10% level. In particular, only at horizons of 5, 16 and 19 months are all the statistics significant, while at horizons of 6 months the ENC-NEW statistic is the only one that is not significant. Furthermore, there are cases where only one statistic is significant at the 10% level, such as the MSE-T statistic at the horizon of 14 months, while in the remaining cases that exhibit forecastability only two statistics are significant. Moreover, it is interesting to observe that at horizons of 6, 9, 12-14, 16-18, and 19 months there is evidence of significant out-of-sample predictive ability without any evidence of significant in-sample forecastability, while the opposite appears only at the horizon of 22 months.

Having established the predictability of the book-to-market, size, momentum and reversal factors, we test whether the typically employed financial variables that can be thought of as state variables in the context of ICAPM have any ability to forecast returns.

3.3 Forecastability of the Financial Variables

The most commonly employed financial variables in the forecasting-returns literature are the short term interest rates (3-month T-bill, 1-month T-bill), the term spread and the default spread. Short term interest rates are linked to the current business cycle and monetary policy stance as low interest rates prevail in recessions and vice versa. The term spread signals the future state of the economy, while the default spread signals credit market expectations. Fama and French (1989) find that changes in the term spread and the default spread correspond to short-term and long-term business conditions. Our resulta with respect to the financial variables are reported in Table 6. To save space, we only report the horizons at which we have significant predictive ability for the tests considered.[4] As already mentioned, the period examined is from July 1963 to October 2009 for horizons of 1-36 months.

[TABLE 6 AROUND HERE]

[4] The detailed tables are available from the authors upon request.

All the financial variables with the exception of the term spread show significant in-sample forecasting ability on the CRSP value-weighted portfolio. On the other hand, it is interesting to note that only the term spread exhibits significant predictive ability out-of-sample. In particular, the term spread shows significant predictive ability at long horizons. specifically, at horizons of 19-26, and 28-36 months with the MSE-T and ENC-T statistics being significant. In contrast, the 3-month T_bill, 1-month T_bill, and default spread show only in-sample significant forecasting ability at horizons of 5 and 12-28 months for the 3-month T_bill, 12, 14-20, 22-24, 26, and 27 months for the 1-month T_bill and 5, 14, and 16-18 months for the default spread.

Following the same methodology, Rapach and Wohar (2006) undertake an analysis of both in-sample and out-of-sample tests of the forecasting ability of most frequently employed financial variables in the literature on the CRSP equal-weighted portfolios. In their analysis, they include annual data for the period from 1927 to 1999 for horizons of 1, 5, and 10 years. Among the nine financial variables that they examine are both the term and the default spread. Consistent with our results, they identify that the default spread shows significant in-sample forecasting ability at the horizon of 1 year. They also find in-sample predictive ability for the term spread at the horizon of 10 years. On the other hand, when employing the MSE-F and ENC-NEW out-of-sample statistics, the authors find no evidence of out-of-sample predicting ability, which is consistent with our findings. It seems that the inclusion of the MSE-T and ENC-T tests provides us with significant out-of-sample results.

3.4 Can financial variables proxy for the Fama/French reversal and momentum factors?

The fact that the term spread shows significant forecasting ability at long horizons, while the FF factors do exactly the same, but at shorter horizons, imposes the investigation of the connection between the factors and the financial variables. Hahn and Lee (2006) examine whether the yield spread variables; namely, the term spread and the default spread, could be proxies for the SMB and HML factors for the period from July 1963 to June 2001. In a simple regression framework, they prove that, indeed, the default spread proxies for the SMB factor and the term spread for the HML factor. A different approach is adopted by Petkova (2006) who tests whther these state variables could be proxied by the FF factors . In her analysis, the author investigates whether the SMB and HML factors proxy for the term spread, the default spread, and the 1-month T-bill using monthly data for post-1963 period. Her results show that the SMB factor proxies significantly for the default spread, and the HML factor for the term spread, while the SMB and HML factors have no significant forecasting power on the 1-month T-bill. In a recent paper, In and Kim (2007) investigate how the SMB and HML factors interact with the innovations of state variables over various time scales by means of wavelet analysis. They employ the same state variables for the period from July 1963 to December 2005.

Following much of the procedure adopted by Petkova (2006), they prove, as well, that the SMB factor is a proxy for the default spread at the 5% level of significance, while the HML factor is affected by the term spread at the 10% level of significance. In any case, the 1-month T-bill does not show any significant explanatory power fot the SMB and HML factor. Both the SMB and HML factors exhibit little forecasting ability in the short run, but they display significant ability to predict the state variables in the long run.

Our results, reported in Table 7 (Panels A to E) indicate that there are financial variables that proxy for the FF factors during the period form July 1963 to October 2009 for horizon of 1-36 months. In particular, Panel A shows that only the default spread is out-of-sample proxying the HML factor at horizons of 12-26, and 28-36 months, and in-sample at horizons of 5-36 months. Consistent with In and Kim (2007), the 1-month T-bill shows hardly any predictive ability on the HML factor. Similarly, both the term spread and the 3-month T-bill do not help forecasting the HML factor out of sample, with the latter showing in-sample forecasting ability at horizons of 1, 6, and 7 months. This is in contrast with In and Kim (2007), who find that although at short time scales the HML factor and the term spread indicate no significant relationship, at long time scales such a relationship exists. This finding is in concurrence with Petkova (2007) and Hahn and Lee (2001), who both show that the term spread covaries positively and significantly with the HML factor. With respect to our analysis, the default spread exhibits forecasting ability on the HML factor, which is in agreement with Petkova (2006), and In and Kim (2007). However, our findings contradict those of Hahn and Lee (2001), who show that the default spread cannot be a proxy for the HML factor.

[TABLE 7 AROUND HERE]

Our results for the SMB factor (Table 7, Panel B) show that there is in-sample predictive ability of the default spread on the SMB factor at horizons of 1-22 months, while the out-of-sample forecasting ability of this financial variable shrinks to horizons of 1-3, and 27 months with all the statistics significant with the exception of the MSE-T for the 1-month horizon. Hahn and Lee (2001) also show that the default spread covaries positively with the SMB factor. Turning to the term spread, we find that it proxies out-of-sample for the SMB factor at horizons of 1-4, and 27 months with the MSE-T and ENC-T statistics being significant in each case. In and Kim (2007) also show that the default spread shares more information than the term spread does with the SMB factor, while Petkova (2006) shows that the SMB factor can be a proxy only for the default spread. Furthermore, according to Hahn and Lee (2001), the term spread is not a significant proxy for the SMB factor. In the case of the 1-month T-bill, there is evidence for out-of-sample predicting ability only at the horizon of 2 months with the MSE-T statistic marginaly significant, and there is hardly any evidence for in-sample forecastability. This result is consistent with that of In and Kim (2007), who find that the short-term T-bill does not play an important role on the SMB factor. Regarding the 3-month T_bill, it can only forecast the SMB factor in-sample at horizons of 3 and 4 months .

Panel C of Table 7 reports our findings with respect to the LT-Rev factor. The financial variables that do not proxy for this factor are the two short-term interest rate variables, while the default spread and the term spread show significant predicting out-of-sample ability. Specifically, there is evidence of forecasting ability of the default spread at horizons of 3-13, and 15 months, but only at horizons of 6-10, 12, and 13 months are all the statistics significant. In particular, at horizons of 4, 5, and 11 months the MSE-T statistic is not significant, while at horizon of 3 months only the ENC-NEW statistic is significant at the 10% level. Concerning whether the term spread proxies for the LT-Rev factor, there is evidence only for out-of-sample predictive ability at longer horizons, ranging from 31 to 36 months.

Our results for the ST factor, reported in Table 7 (Panel D), show that with the exception of the default spread, all the remaining financial variables do not proxy for this factor. Specifically, the default spread evinces out-of-sample forecasting ability at horizons of 28, 31, 32, 33, and 35 months on the basis of the MSE-T test. Only at the 31-month horizon is the ENC-T statistic significant.

Finally, Table7 (Panel E) reports the test results of the predictive ability of the financial variables on the momentum factor. Obviously, the default spread displays significant in-sample predictive ability at horizons of 1 and 20 months, while the out-of-sample predictive ability appears at horizons of 1-12, 17-20, and 27 months. More in detail, only at horizons of 1-3, and 27 months are all the statistics significant, while at horizons of 4-10 months the ENC-T statistic is not significant. Furthermore, there are cases where only one statistic is significant at the 10% level, such as the MSE-F statistic at horizons of 11, 12, and 17-20 months. Moreover, it is interesting to observe that only at horizons of 1 and 20 months is there evidence of both in-sample and out-of-sample predictive ability. With respect to the 1-month T_bill, this variable can only proxy for this factor out-of-sample at horizons of 2, and 12 months with the MSE-T statistic being the significant one among the four ones. Similarly, the 3-month T-bill shows significant out-of-sample predictability only at the horizon of 1 month with the MSE-T statistic being significant, while there is no evidence for in-sample forecasting ability at all. On the other hand, the term spread shows only out-of-sample predictive ability on the MOM factor at horizons of 11, and 13-22 months. In particular, at horizons of 11, 13, 15, 16, and 22 months only the MSE-T statistic is significant, while at horizons of 14, and 17-21 months both the MSE-T and ENC-T statistics are significant.

4 Robustness Tests

So far we have shown that there are financial variables that show significant forecasting ability at specific horizons. This section provides two robustness checks with which we test whether these financial variables, the FF, the momentum and reversal factors retain their forecasting ability or they produce results that reflect just a random chance. In the first test, we use weekly observations of the factors and the financial variables for the period from July 5, 1963 to January 31, 2010. For our second check for robustness, we employ monthly observations of the factors for an extended period, from January 1931 to October 2009. These findings are presented in Table 8 who reports just the horizons at which the variables appear significant either in-sample or out-of-sample at the 10% level of significance.

4.1 Weekly Results

In Panel A of Table 8, we present the horizons at which the five factors and the three of the four financial variables show significant in-sample and out-of-sample predictive ability on the CRSP value-weighted portfolio. The default spread has been excluded from our analysis due to data unavailability for the whole period under examination.

As shown in Panel A, HML shows significant in-sample predictive ability on the CRSP value-weighted portfolio at horizons of 1, 6, and 9-24 weeks and out-of-sample predictive ability at horizons of 3, and 5-24 weeks. The SMB factor as well, shows forecastability at horizons of 18-24 weeks in-sample and at 11-24 week horizons out of sample. When considering the remaining FF factors, only the MOM reversal factor exhibits significant in-sample predictability at horizons of 1, 16, and 17 weeks, and at 13, and 16-18 weeks out-of-sample. On the other hand, the long-term and short-term reversal factors show neither in-sample nor out-of-sample ability. Furthermore, the financial variables show only in-sample ability to forecast at horizons of 1-12, and 18-24 weeks for the 3-month T-bill return, at 23 weeks for the 1-month T-bill, and 1-12, 15, 16, and 18-24 weeks for the term spread.

Concerning the financial variables that proxy in-sample and out-of-sample for the FF factors, we note that no financial factor can be a proxy for the HML factor. In addition, there is no evidence of the ability of the financial variables to forecast the LT Rev factor. On the other hand, the momentum factor can only be out-of-sample proxied by the 1-month T-bill and the term spread at horizons of 20, and 22-24 weeks for the former, and 2, 9, and 11-24 weeks for the latter. Furthermore the SMB factor can be proxied by the 3-month T_bill in-sample at horizons of 14-24 weeks, and out-of-sample at horizons of 4-9, 11-12, and 15-18 weeks. The term spread can be a proxy for this factor, as well, with significant in-sample ability at horizons of 1-10, 15-21, 23, and 24 weeks, and significant out-of-sample one at horizons of 1-24 weeks. Finally, the short term reversal factor can be proxied by the term spread only at horizons of 1 and 2 weeks in sample and at horizons of 1-24 weeks out of sample.

[TABLE 8 AROUND HERE]

4.2 Extended Sample

In this section, we examine the robustness of our results employing monthly data for a longer period, namely from January 1931 to October 2009. Panel B of Table 8 reports the horizons at which there is evidence of in-sample or out-of-sample forecasting power of the factors on the CRSP value-weighted portfolio. Employing this extended sample, we conclude that the SMB and long term reversal factors display significant both in-sample and out-of-sample forecasting ability. In particular, at horizons of 4-6, and 13-15 months there is evidence of the forecasting ability of the HML factor on the CRSP value-weighted portfofio, and at horizons of 4-16 months this factor exhibits out-of-sample ability, as well. In addition, this factor evinces significant in-sample ability at horizons of 1 and 5 months, and out-of-sample at 5-8 months. Panel B of Table 8 shows that the HML factor exhibits only in-sample ability to forecast the CRSP portfolio at horizons of 16-23 months, while the ST-Rev and Mom factors evince only out-of-sample forecasting ability at horizons of 21-24 months, and at 9, 12, 13, 18, 19, and 22 months, respectively.

5 Conclusions

In this paper, we examine the forecastability of the SMB, HML, reversal and momentum factors and that of the most-frequently-employed financial variables on the value-weighted CRSP portfolio return. We also investigate the link between these factors and the financial variables. Our results show that, indeed, there is in-sample and out-of-sample forecasting ability of the factors and the variables employed at specific horizons, but the extent to which this forecastability appears differs.

Concerning the in-sample predictive ability of the factors, with the exception of the short term reversal, all the remaining factors display considerable forecasting ability. However, all the factors display out-of-sample ability albeit at differing horizons. Apart from the term spread, the financial variables considered exhibit in-sample predictive ability. Turning to the out-of-sample forecasting ability, only the term spread appears to be a valuable predictor at specific horizons.

Investigating whether the factors are linked with the financial variables, we find that, indeed, there is a link between them. Specifically, the default spread proxies significantly for the HML and the SMB factor in-sample and out-of-sample, while the 3-month T-bill proxies only in-sample for both factors. In addition, the SMB factor is proxied out-of-sample by the 1-month T-bill and the term spread. The momentum factor can be out-of-sample proxied by all the financial variables, but only by the default spread in-sample. Finally, none of the financial variables shows any ability to proxy in-sample for either the short term or the long term reversal factor, while there is evidence that the default spread can be a proxy for both of them and the term spread only for the long term reversal factor. Our robustness tests based on an extended sample and an alternative frequency point to similar conclusions, thus reinforcing our results.

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Table 1
In-sample and out-of-sample predictability test results for horizons 1-36 months, monthly HML portfolio return on the CRSP value-weighted portfolio

Horizon	1		2		3		4		5		6		7		8		9	
Wald	1.77	[0.178]	2.60	[0.148]	4.07	**[0.06]**	3.93	**[0.086]**	2.80	[0.13]	4.50	**[0.054]**	5.40	**[0.042]**	4.81	**[0.064]**	3.16	**[0.09]**
MSE-T	0.03	[0.248]	0.55	[0.136]	1.07	**[0.058]**	1.24	**[0.038]**	0.93	**[0.07]**	1.39	**[0.05]**	1.43	**[0.022]**	1.42	**[0.066]**	1.38	**[0.034]**
MSE-F	0.08	[0.228]	0.82	[0.116]	1.35	**[0.062]**	1.89	**[0.052]**	1.31	**[0.088]**	2.55	**[0.048]**	3.60	**[0.018]**	3.24	**[0.038]**	2.03	**[0.032]**
ENC-T	0.35	[0.246]	1.03	[0.122]	1.54	**[0.05]**	1.55	**[0.056]**	1.17	**[0.1]**	1.58	**[0.068]**	1.63	**[0.042]**	1.64	**[0.09]**	1.61	**[0.05]**
ENC-NEW	0.38	[0.19]	0.75	[0.124]	0.99	**[0.08]**	1.24	**[0.066]**	0.85	[0.128]	1.51	**[0.066]**	2.14	**[0.038]**	1.96	**[0.054]**	1.23	**[0.064]**

Horizon	10		11		12		13		14		15		16		17		18	
Wald	2.24	[0.12]	1.92	[0.222]	0.92	[0.386]	0.62	[0.396]	0.43	[0.55]	0.19	[0.68]	0.04	[0.844]	0.19	[0.702]	0.10	[0.75]
MSE-T	0.99	**[0.07]**	0.57	[0.118]	-0.08	[0.328]	-0.17	[0.3]	-0.16	[0.324]	-0.27	[0.4]	-0.55	[0.472]	-0.57	[0.49]	-0.84	[0.608]
MSE-F	1.25	**[0.074]**	0.71	[0.116]	-0.08	[0.34]	-0.14	[0.328]	-0.18	[0.368]	-0.32	[0.454]	-0.62	[0.598]	-0.83	[0.646]	-0.98	[0.738]
ENC-T	1.18	**[0.094]**	0.74	[0.162]	0.04	[0.372]	-0.06	[0.356]	-0.08	[0.426]	-0.17	[0.452]	-0.50	[0.554]	-0.49	[0.576]	-0.80	[0.658]
ENC-NEW	0.76	[0.114]	0.47	[0.178]	0.02	[0.374]	-0.02	[0.364]	-0.04	[0.444]	-0.10	[0.502]	-0.28	[0.7]	-0.36	[0.73]	-0.46	[0.806]

Horizon	19		20		21		22		23		24		25		26		27	
Wald	0.10	[0.8]	0.04	[0.878]	0.02	[0.914]	0.02	[0.886]	0.01	[0.944]	0.05	[0.85]	0.14	[0.702]	0.10	[0.768]	0.08	[0.828]
MSE-T	-1.20	[0.778]	-1.16	[0.762]	-1.46	[0.8]	-1.70	[0.9]	-1.66	[0.898]	-1.91	[0.916]	-2.51	[0.978]	-2.03	[0.918]	1.07	**[0.058]**
MSE-F	-1.24	[0.83]	-0.84	[0.67]	-0.81	[0.658]	-1.09	[0.75]	-1.20	[0.806]	-0.98	[0.696]	-0.90	[0.69]	-1.05	[0.746]	1.35	**[0.062]**
ENC-T	-1.15	[0.822]	-1.10	[0.814]	-1.39	[0.85]	-1.62	[0.92]	-1.59	[0.916]	-1.86	[0.934]	-2.45	[0.988]	-2.00	[0.944]	1.54	**[0.05]**
ENC-NEW	-0.60	[0.902]	-0.40	[0.78]	-0.38	[0.736]	-0.51	[0.822]	-0.56	[0.868]	-0.47	[0.808]	-0.43	[0.758]	-0.50	[0.812]	0.99	**[0.08]**

Horizon	28		29		30		31		32		33		34		35		36	
Wald	0.09	[0.776]	0.05	[0.852]	0.03	[0.872]	0.00	[0.998]	0.01	[0.928]	0.04	[0.858]	0.14	[0.75]	0.08	[0.812]	0.15	[0.696]
MSE-T	-1.29	[0.754]	-1.19	[0.734]	-0.99	[0.634]	-1.03	[0.666]	-1.01	[0.652]	-1.06	[0.682]	-0.82	[0.632]	-1.06	[0.702]	-1.40	[0.794]
MSE-F	-1.23	[0.776]	-1.09	[0.752]	-0.77	[0.65]	-0.77	[0.65]	-0.72	[0.696]	-0.84	[0.704]	-0.79	[0.698]	-0.55	[0.63]	-0.71	[0.664]
ENC-T	-1.22	[0.802]	-1.09	[0.764]	-0.85	[0.666]	-0.85	[0.69]	-0.84	[0.696]	-0.85	[0.698]	-0.58	[0.662]	-0.89	[0.724]	-1.24	[0.804]
ENC-NEW	-0.55	[0.836]	-0.48	[0.814]	-0.32	[0.706]	-0.31	[0.698]	-0.29	[0.726]	-0.33	[0.728]	-0.27	[0.726]	-0.22	[0.716]	-0.30	[0.714]

HML (High Minus Low) portfolio is the average return on the two value portfolios minus the average return on the two growth portfolios, which include all NYSE, AMEX and NASDAQ stocks for which we have market equity data. Wald is the in-sample F-statistic used to test the null hypothesis that the factor causes returns through the whole period. The MSE-T and MSE-F statistics are used to test the null hypothesis that the unrestricted model out-of-sample MSFE is equal to the restricted model out-of-sample MSFE against the one-sided (upper-tail) hypothesis that the unrestricted model out-of-sample MSFE is lower than the restricted model out-of –sample MSFE. The ENC-T and ENC-NEW statistics are used to test the null hypothesis that the restricted model out-of-sample forecasts encompass the unrestricted model out-of-sample forecasts against the one-sided (upper-tail) hypothesis that the restricted model out-of-sample forecasts do not encompass the unrestricted model out-of-sample forecasts. p-values, computed using the bootstrap procedure, are given in brackets; bold entries indicate significance at the 10% level.

Table 2
In-sample and out-of-sample predictability test results for horizons 1-36 months, SMB portfolio return on the CRSP value-weighted portfolio

Horizon	1		2		3		4		5		6		7		8		9	
Wald	3.23	**[0.072]**	0.01	[0.896]	2.03	[0.184]	2.13	[0.168]	4.35	**[0.064]**	2.08	[0.156]	1.44	[0.248]	3.28	[0.126]	3.14	[0.118]
MSE-T	0.03	[0.26]	-1.51	[0.854]	0.93	**[0.096]**	0.98	**[0.074]**	1.55	**[0.034]**	0.72	[0.104]	0.14	[0.236]	0.23	[0.218]	0.88	**[0.068]**
MSE-F	0.10	[0.242]	-0.64	[0.656]	0.98	[0.108]	1.05	**[0.096]**	2.14	**[0.044]**	0.93	**[0.1]**	0.17	[0.22]	0.57	[0.144]	1.27	**[0.046]**
ENC-T	0.66	[0.178]	-1.42	[0.878]	1.34	**[0.092]**	1.53	**[0.056]**	1.99	**[0.03]**	1.27	**[0.086]**	0.66	[0.192]	1.13	[0.116]	1.49	**[0.04]**
ENC-NEW	1.01	**[0.06]**	-0.30	[0.752]	0.70	[0.136]	0.79	[0.106]	1.45	**[0.058]**	0.75	[0.116]	0.36	[0.188]	1.15	**[0.078]**	1.08	**[0.062]**

Horizon	10		11		12		13		14		15		16		17		18	
Wald	1.75	[0.192]	1.01	[0.352]	1.19	[0.326]	2.08	[0.166]	1.87	[0.196]	0.74	[0.46]	0.22	[0.644]	0.04	[0.874]	0.05	[0.834]
MSE-T	0.91	**[0.078]**	0.33	[0.192]	0.46	[0.208]	0.82	[0.116]	0.67	[0.14]	0.31	[0.27]	0.07	[0.284]	-1.81	[0.91]	-0.94	[0.64]
MSE-F	0.94	**[0.086]**	0.34	[0.176]	0.45	[0.204]	0.98	**[0.08]**	0.87	**[0.082]**	0.34	[0.248]	0.07	[0.274]	-0.71	[0.666]	-0.60	[0.64]
ENC-T	1.42	**[0.066]**	0.84	[0.176]	0.90	[0.202]	1.26	[0.108]	1.10	[0.134]	0.51	[0.314]	0.20	[0.354]	-1.65	[0.926]	-0.81	[0.688]
ENC-NEW	0.73	[0.108]	0.39	[0.178]	0.43	[0.212]	0.82	**[0.098]**	0.78	**[0.098]**	0.29	[0.282]	0.10	[0.318]	-0.33	[0.746]	-0.26	[0.706]

Horizon	19		20		21		22		23		24		25		26		27	
Wald	0.23	[0.67]	0.58	[0.48]	0.48	[0.53]	0.32	[0.624]	0.16	[0.734]	0.43	[0.548]	0.79	[0.404]	0.74	[0.396]	0.50	[0.57]
MSE-T	-1.03	[0.672]	-0.11	[0.336]	0.01	[0.304]	-0.07	[0.374]	-0.39	[0.432]	0.13	[0.294]	0.66	[0.188]	0.53	[0.166]	0.93	**[0.096]**
MSE-F	-0.79	[0.676]	-0.12	[0.366]	0.01	[0.304]	-0.05	[0.382]	-0.20	[0.452]	0.06	[0.298]	0.47	[0.162]	0.30	[0.17]	0.98	[0.108]
ENC-T	-0.83	[0.696]	0.11	[0.382]	0.23	[0.338]	0.12	[0.434]	-0.25	[0.496]	0.37	[0.332]	0.99	[0.216]	0.87	[0.168]	1.34	**[0.092]**
ENC-NEW	-0.32	[0.72]	0.07	[0.344]	0.12	[0.32]	0.05	[0.416]	-0.07	[0.51]	0.09	[0.34]	0.39	[0.186]	0.27	[0.194]	0.70	[0.136]

Horizon	28		29		30		31		32		33		34		35		36	
Wald	0.44	[0.542]	0.67	[0.472]	0.53	[0.53]	1.17	[0.396]	1.52	[0.33]	1.41	[0.312]	1.26	[0.278]	0.84	[0.458]	1.06	[0.38]
MSE-T	0.02	[0.306]	0.48	[0.208]	0.53	[0.208]	0.87	[0.166]	0.97	[0.13]	0.97	[0.152]	1.04	[0.112]	0.55	[0.216]	0.96	[0.154]
MSE-F	0.01	[0.304]	0.29	[0.216]	0.33	[0.212]	0.79	[0.13]	0.69	[0.136]	0.59	[0.152]	0.59	[0.126]	0.17	[0.252]	0.34	[0.182]
ENC-T	0.33	[0.308]	0.77	[0.22]	0.81	[0.242]	1.08	[0.228]	1.27	[0.15]	1.29	[0.16]	1.33	[0.122]	1.07	[0.186]	1.32	[0.15]
ENC-NEW	0.07	[0.344]	0.26	[0.254]	0.28	[0.238]	0.55	[0.174]	0.51	[0.176]	0.45	[0.178]	0.44	[0.136]	0.17	[0.31]	0.26	[0.238]

SMB (Small Minus Big) is the average return on the three small portfolios minus the average return on the three big portfolios constructed using the 6 value-weight portfolios formed on size and BE/ME. Wald is the in-sample F-statistic used to test the null hypothesis that the factor causes returns through the whole period. The MSE-T and MSE-F statistics are used to test the null hypothesis that the unrestricted model out-of-sample MSFE is equal to the restricted model out-of-sample MSFE against the one-sided (upper-tail) hypothesis that the unrestricted model out-of-sample MSFE is lower than the restricted model out-of –sample MSFE. The ENC-T and ENC-NEW statistics are used to test the null hypothesis that the restricted model out-of-sample forecasts encompass the unrestricted model out-of-sample forecasts against the one-sided (upper-tail) hypothesis that the restricted model out-of-sample forecasts do not encompass the unrestricted model out-of-sample forecasts. p-values, computed using the bootstrap procedure, are given in brackets; bold entries indicate significance at the 10% level.

Table 3

In-sample and out-of-sample predictability test results for horizons 1-36 months, monthly long-term reversal factor on the CRSP value-weighted portfolio

	1		2		3		4		5		6		7		8		9	
Wald	2.82	[0.122]	2.60	[0.13]	4.05	**[0.078]**	3.59	**[0.08]**	4.24	**[0.062]**	5.52	**[0.048]**	6.26	**[0.048]**	4.10	**[0.082]**	2.20	[0.164]
MSE-T	-0.15	[0.354]	0.24	[0.194]	1.32	**[0.036]**	1.02	**[0.076]**	0.79	**[0.098]**	0.49	[0.154]	0.45	[0.14]	0.21	[0.22]	0.08	[0.234]
MSE-F	-0.43	[0.584]	0.65	[0.134]	3.27	**[0.02]**	2.54	**[0.032]**	2.55	**[0.04]**	1.80	**[0.056]**	1.76	**[0.072]**	0.84	[0.104]	0.28	[0.192]
ENC-T	0.28	[0.316]	0.65	[0.184]	1.65	**[0.038]**	1.29	**[0.094]**	1.19	**[0.1]**	0.97	[0.13]	0.99	[0.128]	0.69	[0.196]	0.43	[0.256]
ENC-NEW	0.41	[0.186]	0.88	**[0.1]**	2.08	**[0.036]**	1.65	**[0.056]**	1.93	**[0.03]**	1.81	**[0.048]**	1.97	**[0.052]**	1.38	**[0.092]**	0.74	[0.108]

Horizon	10		11		12		13		14		15		16		17		18	
Wald	1.26	[0.294]	1.21	[0.326]	1.40	[0.264]	1.35	[0.298]	1.11	[0.346]	1.35	[0.298]	0.58	[0.468]	0.81	[0.378]	1.24	[0.292]
MSE-T	-0.03	[0.304]	0.00	[0.288]	0.01	[0.314]	-0.09	[0.326]	-0.19	[0.372]	-0.16	[0.344]	-0.36	[0.414]	-0.23	[0.364]	-0.05	[0.336]
MSE-F	-0.11	[0.348]	-0.01	[0.288]	0.04	[0.308]	-0.31	[0.474]	-0.73	[0.656]	-0.59	[0.58]	-1.34	[0.78]	-0.87	[0.698]	-0.18	[0.4]
ENC-T	0.23	[0.33]	0.26	[0.318]	0.31	[0.332]	0.19	[0.364]	0.07	[0.392]	0.11	[0.37]	-0.20	[0.482]	-0.06	[0.396]	0.14	[0.378]
ENC-NEW	0.38	[0.216]	0.38	[0.228]	0.54	[0.19]	0.34	[0.258]	0.15	[0.326]	0.21	[0.278]	-0.37	[0.734]	-0.11	[0.496]	0.24	[0.284]

Horizon	19		20		21		22		23		24		25		26		27	
Wald	1.47	[0.264]	0.94	[0.312]	0.68	[0.442]	0.80	[0.418]	0.93	[0.356]	0.72	[0.444]	0.58	[0.486]	0.83	[0.448]	0.92	[0.382]
MSE-T	0.12	[0.284]	-0.06	[0.324]	-0.10	[0.318]	-0.01	[0.318]	0.09	[0.27]	0.02	[0.32]	-0.07	[0.362]	0.15	[0.298]	1.32	**[0.036]**
MSE-F	0.38	[0.196]	-0.18	[0.392]	-0.21	[0.39]	-0.02	[0.32]	0.16	[0.242]	0.03	[0.312]	-0.07	[0.384]	0.10	[0.292]	3.27	**[0.02]**
ENC-T	0.29	[0.348]	0.09	[0.378]	0.02	[0.372]	0.12	[0.41]	0.22	[0.346]	0.14	[0.392]	0.02	[0.436]	0.26	[0.348]	1.65	**[0.038]**
ENC-NEW	0.46	[0.198]	0.13	[0.32]	0.02	[0.362]	0.12	[0.364]	0.20	[0.29]	0.10	[0.348]	0.01	[0.43]	0.09	[0.35]	2.08	**[0.036]**

Horizon	28		29		30		31		32		33		34		35		36	
Wald	1.60	[0.27]	1.14	[0.336]	1.24	[0.318]	1.22	[0.312]	1.53	[0.244]	1.95	[0.224]	1.65	[0.248]	1.13	[0.3]	1.24	[0.306]
MSE-T	0.82	[0.168]	0.48	[0.206]	0.80	[0.17]	0.65	[0.176]	1.28	**[0.078]**	2.14	**[0.034]**	1.92	**[0.048]**	0.42	[0.238]	0.87	[0.148]
MSE-F	0.50	[0.212]	0.19	[0.244]	0.21	[0.244]	0.23	[0.22]	0.43	[0.18]	0.73	[0.152]	0.42	[0.216]	0.08	[0.288]	0.16	[0.266]
ENC-T	0.96	[0.216]	0.59	[0.274]	0.91	[0.214]	0.77	[0.232]	1.41	[0.122]	2.28	**[0.048]**	2.05	**[0.058]**	0.56	[0.276]	1.00	[0.216]
ENC-NEW	0.30	[0.282]	0.12	[0.32]	0.12	[0.32]	0.14	[0.294]	0.24	[0.256]	0.41	[0.216]	0.24	[0.272]	0.06	[0.352]	0.09	[0.348]

Long-term reversal factor is the average return on the two low prior return portfolios minus the average on the two high prior return portfolios using six value-weight portfolios formed on size and prior (13-60) returns. Wald is the in-sample F-statistic used to test the null hypothesis that the factor causes returns through the whole period. The MSE-T and MSE-F statistics are used to test the null hypothesis that the unrestricted model out-of-sample MSFE is equal to the restricted model out-of-sample MSFE against the one-sided (upper-tail) hypothesis that the unrestricted model out-of-sample MSFE is lower than the restricted model out-of –sample MSFE. The ENC-T and ENC-NEW statistics are used to test the null hypothesis that the restricted model out-of-sample forecasts encompass the unrestricted model out-of-sample forecasts against the one-sided (upper-tail) hypothesis that the restricted model out-of-sample forecasts do not encompass the unrestricted model out-of-sample forecasts. p-values, computed using the bootstrap procedure, are given in brackets; bold entries indicate significance at the 10% level.

Table 4

In-sample and out-of-sample predictability test results for horizons 1-36 months, short-term reversal factor on the CRSP value-weighted portfolio

Horizon	1		2		3		4		5		6		7		8		9	
Wald	0.63	[0.446]	0.03	[0.832]	0.47	[0.474]	0.66	[0.396]	0.63	[0.45]	0.05	[0.848]	0.03	[0.886]	0.22	[0.646]	0.08	[0.792]
MSE-T	-0.69	[0.518]	-1.09	[0.676]	-0.80	[0.55]	-0.77	[0.604]	-1.09	[0.716]	-1.63	[0.882]	-1.72	[0.916]	-1.62	[0.884]	-0.47	[0.414]
MSE-F	-1.34	[0.838]	-0.98	[0.758]	-0.80	[0.73]	-0.94	[0.802]	-1.58	[0.876]	-1.00	[0.776]	-0.36	[0.49]	-0.69	[0.668]	-0.35	[0.532]
ENC-T	-0.36	[0.504]	-0.89	[0.676]	-0.53	[0.54]	-0.50	[0.572]	-0.64	[0.624]	-1.34	[0.856]	-1.56	[0.924]	-1.41	[0.88]	-0.12	[0.404]
ENC-NEW	-0.34	[0.772]	-0.38	[0.788]	-0.25	[0.702]	-0.29	[0.778]	-0.43	[0.84]	-0.37	[0.814]	-0.16	[0.59]	-0.29	[0.718]	-0.04	[0.414]

Horizon	10		11		12		13		14		15		16		17		18	
Wald	1.10	[0.32]	0.03	[0.858]	0.09	[0.768]	0.16	[0.694]	0.12	[0.758]	0.49	[0.548]	0.71	[0.414]	0.54	[0.532]	0.86	[0.394]
MSE-T	-0.02	[0.29]	-1.11	[0.736]	-1.04	[0.678]	-0.99	[0.618]	-1.54	[0.876]	-0.44	[0.468]	-0.55	[0.476]	-0.73	[0.59]	-0.23	[0.438]
MSE-F	-0.02	[0.288]	-0.69	[0.712]	-0.73	[0.726]	-0.34	[0.486]	-0.67	[0.718]	-0.34	[0.524]	-0.48	[0.602]	-0.91	[0.784]	-0.22	[0.532]
ENC-T	0.66	[0.222]	-1.02	[0.78]	-1.01	[0.74]	-0.97	[0.71]	-1.55	[0.922]	-0.27	[0.508]	-0.40	[0.532]	-0.56	[0.61]	0.14	[0.412]
ENC-NEW	0.34	[0.218]	-0.29	[0.766]	-0.33	[0.798]	-0.16	[0.598]	-0.32	[0.786]	-0.09	[0.54]	-0.16	[0.658]	-0.31	[0.8]	0.06	[0.386]

Horizon	19		20		21		22		23		24		25		26		27	
Wald	1.14	[0.304]	1.22	[0.316]	1.51	[0.246]	2.25	[0.178]	1.75	[0.23]	1.35	[0.312]	1.40	[0.294]	1.42	[0.256]	1.36	[0.304]
MSE-T	0.17	[0.232]	-0.16	[0.326]	0.65	[0.122]	0.77	[0.138]	0.54	[0.186]	0.40	[0.202]	-0.50	[0.498]	0.49	[0.196]	-0.80	[0.55]
MSE-F	0.16	[0.214]	-0.21	[0.426]	0.55	[0.104]	0.96	**[0.07]**	0.59	[0.124]	0.31	[0.178]	-0.70	[0.738]	0.24	[0.204]	-0.80	[0.73]
ENC-T	0.58	[0.232]	0.29	[0.334]	1.00	[0.146]	1.22	[0.126]	1.02	[0.186]	0.84	[0.204]	0.09	[0.404]	0.77	[0.232]	-0.53	[0.54]
ENC-NEW	0.27	[0.194]	0.17	[0.27]	0.41	[0.148]	0.73	[0.078]	0.52	[0.138]	0.30	[0.216]	0.06	[0.368]	0.18	[0.246]	-0.25	[0.702]

Horizon	28		29		30		31		32		33		34		35		36	
Wald	1.87	[0.242]	2.21	[0.15]	1.50	[0.262]	1.24	[0.33]	0.60	[0.48]	0.63	[0.414]	0.66	[0.458]	1.14	[0.334]	0.39	[0.562]
MSE-T	1.07	[0.132]	0.74	[0.18]	0.20	[0.302]	1.10	[0.134]	-0.26	[0.426]	-0.69	[0.5]	-0.62	[0.466]	-0.51	[0.484]	-0.93	[0.63]
MSE-F	0.42	[0.168]	0.44	[0.164]	0.11	[0.306]	0.33	[0.194]	-0.06	[0.402]	-0.22	[0.438]	-0.21	[0.45]	-0.11	[0.42]	-0.48	[0.662]
ENC-T	1.26	[0.172]	1.10	[0.174]	0.62	[0.3]	1.35	[0.166]	-0.05	[0.472]	-0.54	[0.54]	-0.41	[0.536]	-0.38	[0.552]	-0.81	[0.666]
ENC-NEW	0.26	[0.232]	0.35	[0.178]	0.18	[0.286]	0.22	[0.264]	-0.01	[0.466]	-0.08	[0.508]	-0.07	[0.51]	-0.04	[0.5]	-0.20	[0.726]

Short-term reversal factor is the average return on the two low prior return portfolios minus the average on the two high prior return portfolios using six value-weight portfolios formed on size and prior (1-1) returns. Wald is the in-sample F-statistic used to test the null hypothesis that the factor causes returns through the whole period. The MSE-T and MSE-F statistics are used to test the null hypothesis that the unrestricted model out-of-sample MSFE is equal to the restricted model out-of-sample MSFE against the one-sided (upper-tail) hypothesis that the unrestricted model out-of-sample MSFE is lower than the restricted model out-of –sample MSFE. The ENC-T and ENC-NEW statistics are used to test the null hypothesis that the restricted model out-of-sample forecasts encompass the unrestricted model out-of-sample forecasts against the one-sided (upper-tail) hypothesis that the restricted model out-of-sample forecasts do not encompass the unrestricted model out-of-sample forecasts. p-values, computed using the bootstrap procedure, are given in brackets; bold entries indicate significance at the 10% level.

Table 5
In-sample and out-of-sample predictability test results for horizons 1-36 months, momentum factor on the CRSP value-weighted portfolio

	1		2		3		4		5		6		7		8		9	
Wald	0.20	[0.662]	0.01	[0.924]	2.57	[0.126]	3.17	**[0.09]**	3.66	**[0.076]**	2.32	[0.154]	0.86	[0.378]	0.38	[0.538]	1.04	[0.32]
MSE-T	-2.21	[0.978]	-1.64	[0.892]	0.16	[0.226]	0.36	[0.152]	0.76	**[0.074]**	1.19	**[0.042]**	0.68	[0.116]	0.17	[0.242]	1.15	**[0.046]**
MSE-F	-1.33	[0.852]	-1.51	[0.888]	0.33	[0.18]	0.83	**[0.08]**	1.66	**[0.034]**	0.97	**[0.07]**	0.20	[0.204]	0.07	[0.264]	0.54	[0.12]
ENC-T	-2.14	[0.988]	-1.50	[0.89]	0.62	[0.194]	0.72	[0.156]	1.04	**[0.082]**	1.30	**[0.064]**	0.75	[0.172]	0.25	[0.314]	1.29	**[0.074]**
ENC-NEW	-0.63	[0.908]	-0.66	[0.922]	0.64	[0.108]	0.87	**[0.08]**	1.19	**[0.042]**	0.57	[0.12]	0.11	[0.298]	0.05	[0.346]	0.30	[0.184]
Horizon	10		11		12		13		14		15		16		17		18	
Wald	0.82	[0.39]	1.20	[0.27]	1.57	[0.244]	2.23	[0.166]	1.42	[0.252]	1.90	[0.176]	2.98	[0.11]	1.49	[0.262]	1.15	[0.348]
MSE-T	0.02	[0.282]	-0.15	[0.324]	1.31	**[0.036]**	1.29	**[0.054]**	0.78	**[0.094]**	0.81	[0.128]	0.90	**[0.09]**	1.49	**[0.038]**	1.72	**[0.036]**
MSE-F	0.01	[0.29]	-0.13	[0.352]	0.59	[0.104]	0.84	[0.112]	0.34	[0.144]	0.58	[0.134]	0.93	**[0.068]**	0.63	[0.106]	0.64	[0.13]
ENC-T	0.25	[0.332]	0.16	[0.314]	1.52	**[0.054]**	1.66	**[0.058]**	0.95	[0.144]	1.13	[0.142]	1.35	**[0.088]**	1.82	**[0.042]**	1.81	**[0.066]**
ENC-NEW	0.07	[0.34]	0.06	[0.318]	0.34	[0.158]	0.52	[0.146]	0.20	[0.218]	0.38	[0.168]	0.67	**[0.088]**	0.39	[0.168]	0.37	[0.188]
Horizon	19		20		21		22		23		24		25		26		27	
Wald	3.48	[0.114]	2.16	[0.158]	1.97	[0.192]	3.70	**[0.064]**	2.11	[0.158]	2.70	[0.136]	1.86	[0.212]	0.65	[0.428]	0.44	[0.56]
MSE-T	1.63	**[0.03]**	0.53	[0.17]	-0.26	[0.342]	0.06	[0.274]	-0.12	[0.324]	0.07	[0.296]	0.03	[0.33]	-0.26	[0.404]	0.16	[0.226]
MSE-F	1.10	**[0.07]**	0.50	[0.118]	-0.27	[0.468]	0.07	[0.252]	-0.11	[0.386]	0.06	[0.294]	0.02	[0.32]	-0.17	[0.484]	0.33	[0.18]
ENC-T	1.93	**[0.038]**	1.14	[0.132]	0.39	[0.292]	0.82	[0.186]	0.65	[0.224]	0.73	[0.238]	0.62	[0.268]	0.29	[0.342]	0.62	[0.194]
ENC-NEW	0.73	**[0.098]**	0.55	[0.114]	0.21	[0.234]	0.45	[0.13]	0.28	[0.182]	0.29	[0.21]	0.23	[0.232]	0.10	[0.302]	0.64	[0.108]
Horizon	28		29		30		31		32		33		34		35		36	
Wald	0.25	[0.652]	0.19	[0.708]	0.91	[0.396]	1.55	[0.3]	0.81	[0.408]	0.55	[0.47]	0.57	[0.466]	0.32	[0.596]	0.49	[0.528]
MSE-T	-0.30	[0.422]	-0.75	[0.552]	-0.44	[0.486]	-0.09	[0.37]	-0.11	[0.384]	-0.46	[0.426]	-0.74	[0.556]	-1.12	[0.668]	-1.34	[0.768]
MSE-F	-0.18	[0.454]	-0.45	[0.622]	-0.41	[0.614]	-0.10	[0.406]	-0.10	[0.412]	-0.24	[0.496]	-0.27	[0.55]	-0.30	[0.54]	-0.34	[0.556]
ENC-T	0.12	[0.416]	-0.18	[0.478]	0.14	[0.416]	0.44	[0.336]	0.34	[0.376]	-0.01	[0.41]	-0.31	[0.518]	-0.84	[0.672]	-1.12	[0.778]
ENC-NEW	0.04	[0.388]	-0.06	[0.504]	0.08	[0.368]	0.29	[0.232]	0.16	[0.29]	0.00	[0.412]	-0.06	[0.538]	-0.12	[0.602]	-0.14	[0.638]

Momentum factor is the average return on the two high prior return portfolios minus the average on the two low prior return portfolios using six value-weight formed on size and prior (2-12) returns. Wald is the in-sample F-statistic used to test the null hypothesis that the factor causes returns through the whole period. The MSE-T and MSE-F statistics are used to test the null hypothesis that the unrestricted model out-of-sample MSFE is equal to the restricted model out-of-sample MSFE against the one-sided (upper-tail) hypothesis that the unrestricted model out-of-sample MSFE is lower than the restricted model out-of –sample MSFE. The ENC-T and ENC-NEW statistics are used to test the null hypothesis that the restricted model out-of-sample forecasts encompass the unrestricted model out-of-sample forecasts against the one-sided (upper-tail) hypothesis that the restricted model out-of-sample forecasts do not encompass the unrestricted model out-of-sample forecasts. p-values, computed using the bootstrap procedure, are given in brackets; bold entries indicate significance at the 10% level.

Table 6
In-sample and out-of-sample predictability test results for horizons of 1-36 months, financial variables on the CRSP value-weighted portfolio

Financial Variables	3-month T_bill	1-month T_bill	term spread	default spread
Wald	5, 12-28	12, 14-20, 22-24, 26, 27	-	5, 14, 16-18
MSE-T	-	-	19-26, 28-36	-
MSE-F	-	-	-	-
ENC-T	-	-	19-26, 28-36	-
ENC-NEW	-	-	-	-

Term spread is the difference between the yields of a 10-year and a 1-year government bond. Default spread is the difference between the yields of a long-term corporate Baa bond and a long-term government bond. The results are based on the following tests: Wald statistic, which is the in-sample F-statistic used to test the null hypothesis that the factor causes returns through the whole period, the MSE-T and MSE-F statistics, which are used to test the null hypothesis that the unrestricted model out-of-sample MSFE is equal to the restricted model out-of-sample MSFE against to the one-sided (upper-tail) hypothesis that the unrestricted model out-of-sample MSFE is lower than the restricted model out-of-sample MSFE, and the ENC-T and ENC-NEW statistics, that are used to test the null hypothesis that the restricted model out-of-sample forecasts encompass the unrestricted model out-of-sample forecasts against the one-sided (upper-tail) hypothesis that the restricted model out-of-sample forecasts do not encompass the unrestricted model out-of-sample forecasts. p-values are computed using the bootstrap procedure; The horizons, given in the table, indicate significance at the 10% level according to the bootstrapped p-values.

Table 7

In-sample and out-of-sample predictability test results for horizons of 1-36 months, financial variables on the Fama/French factors

Panel A: HML factor

Financial Variables	3-month T_bill	1-month T_bill	term spread	default spread
Wald	1, 6, 7	-	-	5-36
MSE-T	-	-	-	21, 23-26, 28-36
MSE-F	-	-	-	19-26, 28-36
ENC-T	-	-	-	12-26, 28-36
ENC-NEW	-	-	-	12-26, 28-36

Panel B: SMB factor

Financial Variables	3-month T_bill	1-month T_bill	term spread	default spread
Wald	3, 4	-	-	1-22
MSE-T	-	2	1-4, 27	2, 3, 27
MSE-F	-	-	-	1-3, 27
ENC-T	-	-	1-4, 27	1-3, 27
ENC-NEW	-	-	-	1-3, 27

Panel C: LT reversal factor

Financial Variables	3-month T_bill	1-month T_bill	term spread	default spread
Wald	-	-	-	-
MSE-T	-	-	31-36	6-10, 12, 13
MSE-F	-	-	31-36	4-13, 15
ENC-T	-	-	31-36	4-13
ENC-NEW	-	-	34, 36	3-13, 15

Panel D: ST reversal factor

Financial Variables	3-month T_bill	1-month T_bill	term spread	default spread
Wald	-	-	-	-
MSE-T	-	-	-	28, 31-33, 35
MSE-F	-	-	-	-
ENC-T	-	-	-	31
ENC-NEW	-	-	-	-

Panel E: Momentum factor

Financial Variables	3-month T_bill	1-month T_bill	term spread	default spread
Wald	-	-	-	1, 20
MSE-T	1	2, 12	11, 13-22	1-10, 27
MSE-F	-	-	-	1-12, 17-20, 27
ENC-T	-	-	14, 17-21	1-3, 27
ENC-NEW	-	-	-	1-10, 27

HML (High Minus Low) portfolio is the average return on the two value portfolios minus the average return on the two growth portfolios, which include all NYSE, AMEX and NASDAQ stocks for which we have market equity data. SMB (Small Minus Big) is the average return on the three small portfolios minus the average return on the three big portfolios constructed using the 6 value-weight portfolios formed on size and BE/ME. Long-term, and short-term reversal factor is the average return on the two low prior return portfolios minus the average on the two high prior return portfolios using six value-weight portfolios formed on size and prior (13-60), and (1-1) returns. Momentum factor is the average return on the two high prior return portfolios minus the average on the two low prior return portfolios using six value-weight formed on size and prior (2-12) returns. Term spread is the difference between the yields of a 10-year and a 1-year government bond. Default spread is the difference between the yields of a long-term corporate Baa bond and a long-term government bond. The results are based on the following tests: Wald statistic, which is the in-sample F-statistic, the MSE-T and MSE-F statistics, which are used to test the null hypothesis that the unrestricted model out-of-sample MSFE is equal to the restricted model out-of-sample MSFE against to the one-sided (upper-tail) hypothesis that the unrestricted model out-of-sample MSFE is lower than the restricted model out-of-sample MSFE, and the ENC-T and ENC-NEW statistics that are used to test the null hypothesis that the restricted model out-of-sample forecasts encompass the unrestricted model out-of-sample forecasts against the one-sided (upper-tail) hypothesis that the restricted model out-of-sample forecasts do not encompass the unrestricted model out-of-sample forecasts. The horizons, given in the table, indicate significance at the 10% level according to the bootstrapped p-values.

Table 8
Robustness tests
Panel A: Weekly frequency

Horizons with significant in-sample test results	HML portfolio return	SMB portfolio return	Long-Term reversal factor	Short-Term reversal factor
CRSP value-weighted portfolio	1, 6, 9-24	18-24	-	-

Horizons with significant in-sample test results	Momentum reversal factor	3-month T_bill return	1-month T_bill	Term Spread
CRSP value-weighted portfolio	1, 16, 17	1-12, 18-24	23	1-12, 15, 16, 18-24

Horizons of weeks with significant out-of-sample test results	HML portfolio return	SMB portfolio return	Long-Term reversal factor	Short-Term reversal factor
CRSP value-weighted portfolio	3, 5-24	11-24	-	-

Horizons of weeks with significant out-of-sample test results	Momentum reversal factor	3-month T_bill return	1-month T_bill	Term Spread
CRSP value-weighted portfolio	13, 16-18	-	-	-

Horizons with significant in-sample test results	3-month T_bill return	1-month T_bill	Term Spread
HML portfolio return	8	-	-
SMB portfolio return	14-24	-	1-10, 15-21, 23, 24
Long-Term reversal factor	-	-	-
Short-Term reversal factor	-	-	1, 2
Momentum reversal factor	-	-	23

Horizons with significant out-of-sample test results	3-month T_bill return	1-month T_bill	Term Spread
HML portfolio return	-	-	-
SMB portfolio return	4-9, 11, 12, 15-18	3-11, 14, 15	1-24
Long-Term reversal factor	-	20, 22-24	-
Short-Term reversal factor	-		1-24
Momentum reversal factor	-	-	2, 9, 11-24

Table 8 (continued)
Panel B: Extended sample- January, 1931 to October, 2009

Horizons with significant in-sample test results	HML portfolio return	SMB portfolio return	Long-Term reversal factor	Short-Term reversal factor	Momentum reversal factor
CRSP value-weighted portfolio	16-23	4-6, 13-15	1, 5	-	-

Horizons with significant out-of-sample test results	HML portfolio return	SMB portfolio return	Long-Term reversal factor	Short-Term reversal factor	Momentum reversal factor
CRSP value-weighted portfolio	-	4-16	5-8	21-24	9, 12, 13, 18, 19, 22

HML (High Minus Low) portfolio is the average return on the two value portfolios minus the average return on the two growth portfolios, which include all NYSE, AMEX and NASDAQ stocks for which we have market equity data. SMB (Small Minus Big) is the average return on the three small portfolios minus the average return on the three big portfolios constructed using the 6 value-weight portfolios formed on size and BE/ME. Long-term, and short-term reversal factor is the average return on the two low prior return portfolios minus the average on the two high prior return portfolios using six value-weight portfolios formed on size and prior (13-60), and (1-1) returns. Momentum factor is the average return on the two high prior return portfolios minus the average on the two low prior return portfolios using six value-weight formed on size and prior (2-12) returns. Term spread is the difference between the yields of a 10-year and a 1-year government bond. The results are based on the following tests: Wald statistic, which is the in-sample F-statistic, the MSE-T and MSE-F statistics, which are used to test the null hypothesis that the unrestricted model out-of-sample MSFE is equal to the restricted model out-of-sample MSFE against to the one-sided (upper-tail) hypothesis that the unrestricted model out-of-sample MSFE is lower than the restricted model out-of-sample MSFE, and the ENC-T and ENC-NEW statistics that are used to test the null hypothesis that the restricted model out-of-sample forecasts encompass the unrestricted model out-of-sample forecasts against the one-sided (upper-tail) hypothesis that the restricted model out-of-sample forecasts do not encompass the unrestricted model out-of-sample forecasts. p-values have been computed using the bootstrap procedure; The horizons, that are given in the table, indicate significance at the 10% level according to the bootstrapped p-values.