No Trade Days and Information Diffusion

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Abstract

This paper shows that information based factors are more successful at pricing industry, size/book-to-market, size/momentum and momentum portfolios than any of the common factors found in the literature. The percentage of days during which an asset did not trade in any given year is used as a proxy for information diffusion on the market. This measure is then used to construct a pricing factor which is shown to be significant in time series regressions. When pricing 30 industry portfolios the no-trade factor outperforms any other multifactor pricing model available in the literature and succeeds at fitting a pricing equation for all but 6 of the portfolios. More interestingly, the same model manages to price correctly 70% of the momentum portfolios.

1 Introduction

Numerous empirical studies show that the Capital Asset Pricing Model (CAPM) fails to account for cross-sectional differences in asset returns. Multifactor pricing models have become the norm in the empirical literature and in industry. While the performance of multifactor models is unquestionable, the cause of this success remains an unanswered question. There have been numerous attempts at explaining these anomalies, but no theoretical consensus

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exists yet. Most of the explanations focus on one of two lines of reasoning: either the factors used are proxies for a source of aggregate risk distinct from the market risk, or investors are not as rational as economists assume them to be. No theoretical model of multiple risk factors rationalizing the empirical results has yet emerged. Behavioral finance has been more successful at developing models reproducing the patterns observed in the data. This success, however, comes at the steep cost of making strong behavioral assumptions about investors that violate the principle of rationality.

A third avenue, presented in Sekeris (2006), suggests that parameter uncertainty might be at the root of at least some of the cross sectional variation observed in the data. The rational expectations (RE) hypothesis has become, since its introduction by Lucas (1978), the gold standard of asset pricing. Under RE, agents make informed predictions of future prices. In other words, their expectations are based on a correct model of the financial markets and the priced asset. In order for agents to make these informed predictions they need to acquire the necessary information, which comes at a cost. Investors will seek this information if they feel that they can benefit from it, i.e. if they can use it to exploit an arbitrage opportunity. The justification for using RE in finance is that the cost of acquiring information about stocks is not too high relative to the benefit of the potential arbitrage opportunity. Financial markets appear to be the perfect setting for RE. However, the hypothesis of RE is only applicable to a stable world where similar types of events occur regularly, so that agents can, through experience, develop a reliable intuition for the values of the relevant variables in most circumstances. If the model is used to describe situations where investors face new and unfamiliar events, then they will not be able to draw on their past experience and on their intuition in order to determine the future distribution of an asset's cash flows.

When considering the market as a whole, the RE hypothesis seems to hold. Investors have observed the market and its reactions to various economic conditions and through these observations have gained a deep understanding of the underlying dynamics. This explains the relative success of the Capital Asset Pricing Model (CAPM) in pricing the market portfolio but also explains why the cross sectional empirical observations are at odds with the predictions of the CAPM. Cross sectional studies are based on the sorting of assets according to a particular characteristic. Two common sorting variables are the size of a stock as measured by its market capitalization and the book-to-market ratio (Fama and French (1992)). Stocks that fall either in the small or in the high book to market categories are typically stocks that are either young or stocks that have gone through rough times. Young stocks are usually not well known to investors and have not been observed in different market conditions. Stocks that have gone through difficult times have been observed in the past but investors cannot necessarily draw on that experience to formulate their beliefs about the stock's future cash flows, they have to re-discover the stock. The common thread among all factors is that they are measures of the quality of information available for the stocks.

Parameter uncertainty will be strongest for assets about which the market either has poor information both in quantity and in quality, or has developed wrong, but strong, beliefs based on past observations. The market capitalization of a stock and its age are good proxies for the quantity of information that is made available to investors outside of the market. Yet, one of the most important vehicles of information remains the market itself. Information is disseminated to all market participants through the price that results from the trades of investors, some of whom have information not available to others. In order for this process to occur, it is necessary for the asset to trade. Despite the depth and the activity of modern markets, daily trading is not a reality for all assets. A significant number of stocks do not trade on at least a day of the year, with some assets going through a whole year and barely seeing a trade. For example, in 2003 4711 stocks were continuously listed on one of the three markets (NYSE, AMEX and NASDAQ). Of those 4711 stocks, 31% did not trade on at least one day, 23% did not trade on at least 5 days and 9% did not trade on at least 50 days (one in 5 trading days). The numbers are even more striking when looking at stocks sorted on their market capitalization. Table **??** shows the number of stocks with at least one no-trade day in 2003 by market capitalization deciles. Only assets listed on every trading day of the year are used (i.e. stocks that went public during that year or that were delisted before the end of the year are excluded).

In the bottom decile, nearly all stocks (422 out of 471) had at least one no-trade day, with one stock not trading for 219 days. In the top deciles, all stocks traded on a daily basis. The only stock that had no trade days in the ninth decile is a stock of Liberty Media, which has four parallel issues on the market. The stark contrast in trading patterns across size deciles suggests that empirical asset pricing tests that use size as a factor are probably capturing information effects. If information is the true driving force behind the patterns observed in the data, then empirical tests should use a measure of information rather than a price-derived measure such as the market cap-

Table 1: Stocks with at least one no-trade day in 2003 by market capitalization deciles

Deciles	# Stocks
1	422
2	382
3	305
4	217
5	84
6	29
7	5
8	1
9	1
10	0

italization. Sekeris (2006) showed that the age of a stock, measured as the number of months the stock had been trading for on a market, is a valid pricing factor. Younger firms have no, or a very small, performance track record and few investors are well informed about them. Consequently, the information available to the market regarding these firms is of much lower quality than that available for the larger ones. This lack of information probably discourages a substantial number of investors from buying stocks of these smaller firms. However, as shown in Table 2, there is no correlation between age and no-trade days. The percentage of stocks that do not trade for at least 1, 5, 50 or 65 days does not change across age categories.

Stocks that have no-trade days outperform other stocks by a wide margin, even after correcting for their higher risk as captured by their larger betas. This result is expected when comparing stocks with large differences in information availability. In this paper, we use the difference in returns as a pricing factor in a cross sectional model. We price various benchmark portfolios with this new factor and with the age factor. We then compare the results to those obtained with the standard Fama and French 3 factor model (FF3). As expected, our model does not perform as well as the FF3 when pricing the 25 size/book-to-market sorted portfolios but our model greatly outperforms the FF3 when pricing industry portfolios. This addresses a common critique of the FF3 model according to which it only prices the cross section of stocks sorted according to some price-derived variable and fails to

Table 2: No-trade days by age category

Age	at least 1 day	at least 5 days	at least 50 days	at least 65 days
$0-24$	30.6%	21.5%	7.4%	5.8%
$25-48$	27.6%	17.0%	5.9%	4.5%
$49-72$	36.3%	26.0%	11.2%	8.8%
$73-96$	37.5%	28.8%	12.1%	9.0%
$97-120$	30.4%	22.1%	7.2%	5.4%
120+	28.0%	20.9%	8.1%	6.3%

price the industry portfolios.

Overall the paper is structured as follows. The next section provides a brief review of the relevant literature. Section 3 describes the methodology followed in constructing the pricing factors and the portfolios to be priced as well as the econometric techniques used to estimate and test the models. In Section 4 we analyze the results for the industry portfolios while Section 5 deals with the results for the size and book-to-market portfolios. Section 6 presents the estimation results when we focus on portfolios sorted partially or entirely on momentum and section 7 concludes. All the tables with the estimation and testing results are gathered in the appendices at the end.

2 Related Literature

This section reviews the large literature that deals with the so called anomalies found in the cross section of stock returns. The characterization of these empirical patterns as anomalies results from the fact that they are inconsistent with the CAPM, which has long been considered as the de facto asset pricing model defining normal returns. Labeling the empirical findings in such terms raises the question, first noted by Fama (1970), of whether the deviations from the CAPM predictions are indicative of market inefficiency, or whether the reference model that is implicitly tested, the CAPM, is deficient. If markets are inefficient and the returns are truly anomalous, then, once detected, arbitrageurs should exploit these deviations and eliminate them. It appears that this is not the case with all the documented anomalies, and that some are still observed today, years after being first documented. This section focuses on the patterns that are still considered a puzzle.

The most well known anomaly is the size effect first documented by Banz

(1981). He shows that stocks with small market capitalizations significantly outperform stocks with large market capitalizations even after controlling for risk. Banz uses all common stocks quoted on the New York Stock Exchange (NYSE) for at least five years between 1926 and 1975 and sorts them into 25 portfolios (5 size quintiles and 5 beta quintiles). He finds a difference in returns between the smallest firms and the remaining firms in the sample of, on average, about .4 percent per month. This result is startling given that according to the CAPM any difference in returns between two portfolios should be the result of their different betas. Portfolios of stocks with higher risk have larger betas and higher returns. What Banz shows is that even when comparing two portfolios with similar betas, the portfolio of smaller stocks will outperform the portfolio of larger ones. The size anomaly has often been used to prove that the CAPM is incorrect, but this is not a fair assessment of its performance because portfolios with higher betas do command larger returns than portfolios with smaller betas. However, what the size effect shows is that there are cross sectional patterns in the returns that cannot be explained by the CAPM.

Another widely documented pattern is the value effect. Basu (1983) shows that firms with high earnings-to-price (E/P) ratios earn returns abnormally larger than those predicted by the CAPM. The value effect encompasses a series of scaled-price ratios such as the dividend-price ratio and the book-to-market ratio, which try to capture some measure of fundamentals. This fundamentals approach has a long history in finance that predates modern finance and the CAPM and can be traced back to at least Graham (1949). At the core of this approach is the idea that some stocks are under or over valued with respect to their fundamentals thus offering an investment opportunity. The most comprehensive analysis of the value effect is Fama and French (1992). They use all stocks traded on the NYSE, AMEX and NASDAQ and group into deciles based on their book-to-market ratios (B/M). They then look at their monthly returns over the year following the portfolio formation and show that from 1963 to 1990 the monthly return of a portfolio of so called value stocks (high B/M) is 1.53% higher than that of growth stocks (low B/M). They find a similar result when sorting stocks according to the E/P ratio. They find a difference in returns of .68%, which is lower that observed for the B/M portfolios but nonetheless significant and anomalous.

Fama and French (1993) use both a size and a value based factor to test various other anomalies that have been identified. They build the Small Minus Big (SMB) factor which is the difference between the returns to portfolios of small and large capitalization firms, holding constant the B/M ratios and the High Minus Low (HML) factor which is the difference between the returns to portfolios of high and low B/M ratio firms holding constant the market capitalization. They then run an augmented CAPM regression to measure abnormal performance defined as an intercept α_i significantly different from 0 in (**??**)

$$(R_{it} - R_{ft}) = \alpha_i + \beta_i (R_{mt} - R_{ft}) + s_i SMB_t + h_i HML_t + \varepsilon_{it}. \qquad (1)$$

They find that their three factor model generates intercepts that are not significantly different from 0 for all value strategies (D/P, E/P and B/M). Fama and French (1996) extend the approach and test for the anomalies documented by Lakonishok, Shleifer and Vishny (1994). Again, when using their three factor model the intercepts are not significantly different from 0 for portfolios sorted on cash flow over price (C/P) ratios and those sorted on the rank of past sales growth rates.

Fama and French (1996) show that close to all known anomalies can be explained by their three factor model dismissing the validity of these other anomalies. However, there is one anomaly that remains unexplained and that has gained the same prominence in the literature as the size and B/M effects: momentum. Jegadeesh and Titman (1993) group all stocks based on their prior six month return and compute the average returns of each decile over the six months after portfolio formation. They find that the portfolio of prior biggest winners significantly outperforms the portfolio of prior biggest losers by an average of 10% (annual). Fama and French are unable to eliminate the abnormal excess return with their three factor model since they obtain intercepts that are strongly significant, especially for past winners.

While the size, B/M and momentum anomalies have been known for a significant number of years, they are still present in the data. This persistence indicates that these patterns are probably not merely anomalies but that they are capturing a persistent deviation from the CAPM predictions. While no sound theoretical explanation has yet been presented it seems certain that the CAPM needs to be enhanced in some way to accommodate for these findings.

3 Methodology

3.1 The Data

We use monthly data from January 1962 to December 2003 of all traded stocks on the NYSE, AMEX and NASDAQ exchanges from the CRSP[1] database and Kenneth French's online data library[2]. We only use common stocks of American companies and exclude all other assets such as REITs and ADRs. We test the validity of the no-trade factor through a series of Fama & French time series regressions, OLS and GLS cross-sectional regressions as well as Fama-MacBeth regressions on 30 industry portfolios, the 25 Fama & French size/book-to-market portfolios, the 25 Fama & French size/momentum portfolios and the 10 Fama & French momentum portfolios. In order to run the regressions we build a mimicking portfolio designed to capture the no-trade effect, which we call the Trade minus No-Trade minus Trade (TMN) factor. TMN is calculated by taking the difference between the average return of stocks that had no-trade days and the average return of stocks that were continuously traded over the whole year. More specifically, we averaged the return of the five quintile portfolios of stocks with no-trade days and subtracted from this average the return of the portfolio of normally traded stocks. Table **??** contains the summary statistics of the Fama & French factors, the age factor (YMO), the no-trade minus trade factor (TMN) and of the one month Treasury bill.

We use the F&F 25 size and BTM portfolios as benchmarks for testing pricing factors because of their wide usage in the literature. Given that these portfolios are sorted according to other variables than the ones tested, it is expected that the new factors will not perform as well as the Fama & French factors on these specific portfolios. However, pricing portfolios sorted according to a different variable is always a good test for a factor's validity. A factor that is capable of pricing different portfolios is more likely to be a valid factor than one that can only price factors sorted according to the variable used to build it. This is the strength of the Fama & French factors that can price a wide range of portfolios other than the F&F 25. The one set of portfolios that the Fama and French factors are not able to price much better than the simple CAPM are the industry portfolios. Regressions using

[1]The CRSP data was downloaded through the Wharton Research Data Services (WRDS) of the Wharton School, at http://wrds.wharton.upenn.edu/.

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

Table 3: Summary Statistics of Factors

	Market-Rf	SMB	HML	YMO	TMN	Rf
Mean (annualized)	5.74	2.91	5.52	−23.97	7.98	5.70
St. Deviation	4.44	3.25	2.95	3.94	3.35	0.23
Correlations						
Market-Rf	1.00					
SMB	0.29	1.00				
HML	−0.42	−0.28	1.00			
YMO	0.26	0.61	−0.48	1.00		
TMN	−0.22	0.39	0.20	0.13	1.00	
Rf Rate	−0.10	−0.08	0.03	−0.14	−0.14	1.00

the information based factors, YMO and TMN, fit very well the industry portfolios suggesting that they are capturing a wide range of cross-sectional patterns and are not limited to explaining variations across portfolios sorted according to information variables.

3.2 Estimation and Testing Procedures

We follow Cochrane (2005) and derive the formulas for estimation and testing as an instance of Hansen's (1982) GMM and we forward the interested reader to this reference for further details. Following Cochrane (2005) and Hamilton (1994), a general overview of the GMM procedure starts by a set of r orthogonality conditions

$$E\left\{h\left(\theta_0, y_t\right)\right\} = 0$$

where y_t is a strictly stationary vector of variables observed at date t, θ_0 is the true values of an unknown $(a \times 1)$ vector of parameters, and $h(\cdot)$ is a differentiable r-dimensional vector-valued function with $r \geq a$. The (first stage) GMM estimate $\widehat{\theta}_T$ is the value of θ that minimizes

$$\left[g\left(\theta; y_T\right)\right]' W \left[g\left(\theta; y_T\right)\right] \tag{2}$$

where W is some arbitrary matrix often taken to be the identity matrix I, and

$$g\left(\theta; y_T\right) \equiv \frac{1}{T}\sum_{t=1}^{T} h\left(\theta; y_t\right).$$

The (second stage) GMM estimate can be treated as if

$$\widehat{\theta}_T \approx N\left(\theta_0, \widehat{V}_T/T\right)$$

where

$$\widehat{V}_T = \left\{\widehat{d}_T \widehat{S}_T^{-1} \widehat{d}'_T\right\}^{-1},$$

$$\widehat{d}'_T = \left.\frac{\partial g\left(\theta; y_T\right)}{\partial \theta'}\right|_{\theta=\widehat{\theta}_T}$$

and $\widehat{S}_T$ is an estimate of

$$S = \lim_{T\to\infty} \frac{1}{T} \sum_{t=1}^{T} \sum_{\nu=-\infty}^{\infty} E\left\{\left[h\left(\theta_0, y_t\right)\right]\left[h\left(\theta_0, y_t\right)\right]'\right\}.$$

The general GMM estimate of θ is obtained by setting some linear combination of sample means of h to zero

$$a_T g_T\left(\theta; y_T\right) = 0$$

which in terms of the minimization in (**??**) sets $a_T = d'W$. Then the asymptotic distribution of the GMM estimate is

$$\sqrt{T}\left(\theta - \widehat{\theta}\right) \to N\left[0, (ad)^{-1} aSa\,(ad)^{-1\prime}\right]$$

while the distribution of the moments $g_T\left(\theta; y_T\right)$ is given by

$$\sqrt{T} g_T\left(\widehat{\theta}\right) \to N\left[0, \left(I - d\,(ad)^{-1} a\right) S \left(I - d\,(ad)^{-1} a\right)'\right].$$

Then, the following test can be used to test whether the g_T are jointly too big

$$T g_T\left(\widehat{\theta}\right)' \left[\left(I - d\,(ad)^{-1} a\right) S \left(I - d\,(ad)^{-1} a\right)'\right]^{-1} g_T\left(\widehat{\theta}\right) \sim \chi^2_{N-K} \qquad (3)$$

where N is the number of orthogonality conditions and K is the number of estimated parameters.

For comparison reasons we estimate our models with two methods: time-series regressions (aka Fama-French regressions) and Fama-MacBeth regressions. We devote the next section to describing each of these procedures. Since the Fama-MacBeth estimation procedure is a generalization of the cross-sectional regression we discuss this procedure as well.

Time-Series Regressions Time-series regressions is the most commonly used procedure for estimating and testing multifactor asset pricing models. It was first suggested by Black, Jensen and Scholes (1972) and it amounts to applying the following OLS regression to each one of the portfolios to be priced

$$R_{i,t}^{e} = \beta_0 + \beta_{1i}' R_t^{p,e} + \varepsilon_{i,t} \tag{4}$$

where $R_{i,t}^{e} = R_{i,t} - R_t^{rf}$ is the excess return of portfolio i at period t, R_t^{rf} is the return of a one month treasury bill in period t and $R_t^{p,e} = R_t^{p} - R_t^{rf}$ is a vector consisting of the excess returns of the factors at period t. Since the factors we are using are also excess returns we can test whether the portfolios are correctly priced by our model by testing whether the regression intercepts are zero. The OLS standard errors can be used for testing such hypotheses about the parameters. In particular, under the assumptions that the errors ε_t^i are uncorrelated and homoscedastic, we can use t-tests to check whether the pricing errors β_0 are in fact zero. However, tests whether all or a subset of the pricing errors are *jointly* equal to zero when the errors are correlated across assets $\left(E\left(\varepsilon_t^i \varepsilon_t^j\right) \neq 0\right)$ require to go beyond the standard OLS formulas. To do so we resort to the GMM procedure.

In the case of time-series regressions the vector $h(\theta_0, y_t)$ is given by $N(K+1)$ OLS orthogonality conditions where K is the number of factors and N is the number of assets (portfolios). Then the vector $g(\theta; y_T)$ is given by

$$g(\theta; y_T) = \begin{bmatrix} \frac{1}{T}\sum_{t=1}^{T}\left(R_t^e - \beta_0 - \beta_1' R_t^{p,e}\right) \\ \frac{1}{T}\sum_{t=1}^{T}\left(R_t^e - \beta_0 - \beta_1' R_t^{p,e}\right) R_{1,t}^{p,e} \\ \cdots \\ \frac{1}{T}\sum_{t=1}^{T}\left(R_t^e - \beta_0 - \beta_1' R_t^{p,e}\right) R_{K,t}^{p,e} \end{bmatrix} = \begin{bmatrix} \frac{1}{T}\sum_{t=1}^{T}\varepsilon_t \\ \frac{1}{T}\sum_{t=1}^{T}\varepsilon_t R_{1,t}^{p,e} \\ \cdots \\ \frac{1}{T}\sum_{t=1}^{T}\varepsilon_t R_{K,t}^{p,e} \end{bmatrix}$$

where $\beta_1 = [\beta_1 \ \beta_2 \ ... \ \beta_N]$ and $\beta_0 = (\beta_{0,1} \ \beta_{0,2} \ ... \ \beta_{0,N})'$. Since the number of equations equals the number of parameters to be estimated, $W = I$. The GMM estimates $\widehat{\beta}_0$ and $\widehat{\beta}_1$ are, of course, the OLS estimates. In our tests we use three different specifications. Assuming no autocorrelation or heteroscedasticity, a χ^2 test is

$$T\left[1 + E_T\left(R_t^{p,e}\right)' \widehat{\Omega}^{-1} E_T\left(R_t^{p,e}\right)\right]^{-1} \widehat{\beta}_0' \widehat{\Sigma} \widehat{\beta}_0 \sim \chi_N^2 \tag{5}$$

where

$$\widehat{\Omega} = \frac{1}{T}\sum_{t=1}^{T}\left[R_t^{p,e} - E_T\left(R_t^{p,e}\right)\right]\left[R_t^{p,e} - E_T\left(R_t^{p,e}\right)\right]'$$

$$\widehat{\Sigma} = \frac{1}{T}\sum_{t=1}^{T}\widehat{\varepsilon}_t\widehat{\varepsilon}_t'.$$

The finite sample F test for the same hypothesis was derived by Gibbons, Ross and Shanken (1989) and is given by

$$\frac{T-N-K}{N}\left[1 + E_T\left(R_t^{p,e}\right)'\widehat{\Omega}^{-1}E_T\left(R_t^{p,e}\right)\right]^{-1}\widehat{\beta}_0'\widehat{\Sigma}\widehat{\beta}_0 \sim F_{N,T-N-K}. \quad (6)$$

Finally, the GMM procedure allows us to generate the required corrections for autocorrelated and heteroscedastic disturbances. The test we are using is

$$\widehat{\beta}_0' var\left(\widehat{\beta}_0\right)^{-1}\widehat{\beta}_0 \sim \chi_N^2 \quad (7)$$

where $var\left(\widehat{\beta}_0\right)$ is the upper left corner of

$$var\left(\begin{bmatrix}\widehat{\beta}_0 \\ \widehat{\beta}_1\end{bmatrix}\right) = \frac{1}{T}d^{-1}Sd^{-1\prime}.$$

For an estimator of the S matrix that guarantees positive semidefiniteness we adopt the one suggested by Newey-West (1987),

$$\widehat{S}_T = \widehat{S}_{0,T} + \sum_{\nu=1}^{q}\left\{1 - \left[\frac{\nu}{q+1}\right]\right\}\left(\widehat{S}_{\nu,T} + \widehat{S}_{\nu,T}'\right) \quad (8)$$

where

$$\widehat{S}_{\nu,T} = \frac{1}{T}\sum_{t=\nu+1}^{T}\left[R_t^e - \widehat{\beta}_0 - \widehat{\beta}_1' R_t^{p,e}\right]\left[R_{t-\nu}^e - \widehat{\beta}_0 - \widehat{\beta}_1' R_{t-\nu}^{p,e}\right].$$

Cross-Sectional OLS and GLS Regressions Here the following *two-pass* approach is applied: at a first step the betas from time-series regressions

$$R_{i,t}^e = \beta_0 + \beta_{1i}' R_t^{p,e} + \varepsilon_{i,t}$$

are obtained and then factor risk premia λ are estimated from a regression of average returns on the betas

$$E_T\left(R_i^e\right) = B_1\lambda + \alpha_i$$

where the residuals α_i are the pricing errors. Under the assumption that the errors $\varepsilon_{i,t}$ are i.i.d. over time and independent of the factors the common GLS and OLS formulas emerge. The statistic used to test whether all pricing errors are zero is

$$\widehat{\alpha}' cov\left(\widehat{\alpha}\right)^{-1}\widehat{\alpha} \sim \chi^2_{N-K}$$

where

$$\widehat{\alpha} = E_T\left(R_i^e\right) - B_1\widehat{\lambda},$$

$$\begin{aligned} cov\left(\widehat{\alpha}\right) &= \tfrac{1}{T}\left[I_N - B_1\left(B_1'B_1\right)^{-1}B_1'\right]\Sigma\left[I_N - B_1\left(B_1'B_1\right)^{-1}B_1'\right]' && \text{for OLS} \\ &= \tfrac{1}{T}\left[\Sigma - B_1\left(B_1'\Sigma^{-1}B_1\right)^{-1}B_1'\right] && \text{for GLS} \end{aligned} \tag{9}$$

and Σ is the variance-covariance matrix of the residuals of the time-series regressions. To account for the fact that the explanatory variables in the cross-sectional regressions are not fixed but estimated, Shanken (1992) proposed the following correction

$$\widetilde{cov}\left(\widehat{\alpha}\right) = cov\left(\widehat{\alpha}\right)\left(1 + \lambda'\Sigma_f^{-1}\lambda\right)$$

where Σ_f is the covariance matrix of the factors and $cov\left(\widehat{\alpha}\right)$ is given in (**??**).

To account for non-i.i.d. disturbances we resort again to GMM. In this case the moment conditions are

$$g\left(\theta; y_T\right) = \begin{bmatrix} \frac{1}{T}\sum_{t=1}^{T}\left(R_t^e - \beta_0 - \beta_1' R_t^{p,e}\right) \\ \frac{1}{T}\sum_{t=1}^{T}\left(R_t^e - \beta_0 - \beta_1' R_t^{p,e}\right)R_{1,t}^{p,e} \\ \cdots \\ \frac{1}{T}\sum_{t=1}^{T}\left(R_t^e - \beta_0 - \beta_1' R_t^{p,e}\right)R_{K,t}^{p,e} \\ \frac{1}{T}\sum_{t=1}^{T}\left(R_t^e - B_1\lambda\right) \end{bmatrix}$$

where

$$B_1 = \begin{bmatrix} \beta_1^{1\prime} \\ \beta_1^{2\prime} \\ \vdots \\ \beta_1^{N\prime} \end{bmatrix}$$

Since the top conditions exactly identify β_0 and B_1 while the bottom N moments identify only K parameters (factor risk premia), the linear combinations to be set to zero is

$$ag(\theta; y_T) = 0$$

where

$$a = \begin{bmatrix} I_N \otimes I_{K+1} & 0 \\ 0 & \gamma' \end{bmatrix}$$

and $\gamma' = B_1'$ for OLS and $\gamma' = B_1'\Sigma^{-1}$ for GLS. Then the sampling distribution of $\widehat{\alpha}$ is given by the bottom right part of the sampling distribution of the moments

$$\left(I - d\,(ad)^{-1}\,a\right) S \left(I - d\,(ad)^{-1}\,a\right)'$$

and the test in (**??**) can be used to test the hypothesis that the pricing errors are jointly zero.

Fama-MacBeth Regressions Fama and MacBeth (1973) suggest the following procedure for running cross-sectional regressions. First, find beta estimates with a time-series regression. They suggest using 5–year rolling windows but the procedure is more directly comparable to the time-series regressions if we use the whole sample. Then, estimate a cross-sectional regression

$$R^e_{i,t} = \beta_{1i}'\lambda_t + \alpha_{i,t}, \quad i = 1, 2, ..., N$$

for each period in the sample. Then estimate λ and α_i by averaging over the cross-sectional regression estimates

$$\widehat{\lambda} = \frac{1}{T}\sum_{j=1}^{T}\widehat{\lambda}_j,\ \widehat{\alpha}_i = \frac{1}{T}\sum_{j=1}^{T}\widehat{\alpha}_{ij}$$

and use the standard deviations of the cross-sectional estimates to generate the sampling errors for these estimates

$$\sigma^2\left(\widehat{\lambda}\right) = \frac{1}{T^2}\sum_{j=1}^{T}\left(\widehat{\lambda}_j - \widehat{\lambda}\right)^2,\ \sigma^2\left(\widehat{\alpha}_i\right) = \frac{1}{T^2}\sum_{j=1}^{T}\left(\widehat{\alpha}_{ij} - \widehat{\alpha}_i\right)^2.$$

To test whether the pricing errors are zero use the statistic

$$\widehat{\alpha}' cov\left(\widehat{\alpha}\right)^{-1}\widehat{\alpha} \sim \chi^2_{N-K}$$

where

$$\widehat{\alpha} = \frac{1}{T}\sum_{j=1}^{T}\widehat{\alpha}_j \text{ and } cov\left(\widehat{\alpha}\right) = \frac{1}{T^2}\sum_{j=1}^{T}\left(\widehat{\alpha}_j - \widehat{\alpha}\right)\left(\widehat{\alpha}_j - \widehat{\alpha}\right)'.$$

Of course any correction discussed in the cross-sectional regressions can be implemented in exactly the same way for the cross-sectional estimates of the factors' risk premia and residuals.

4 Estimation Results

We test the ability of our three factor model to price correctly four sets of portfolios. The 30 industry portfolios whose pricing has been problematic in the literature, the widely used 25 size and book-to-market portfolios constructed by Fama and French, the 25 size and momentum portfolios and the 10 momentum portfolios.

4.1 Pricing Industry Portfolios

4.1.1 Time-Series Regressions

In this subsection, we use several types of regressions with mimicking portfolios and related tests to evaluate the validity of the information based factors. As a first step we apply the regression model (**??**) to each one of the portfolios to be priced. To compute the mimicking portfolios we sort the assets using the variable used as a pricing factor and then we take the difference in returns between portfolios that have different values for that characteristic. For example, in the standard FF3 regression the additional size and BTM factors are the difference in returns between small and large firms and the difference in returns between value and growth firms respectively.

For each set of priced portfolios three different regressions were run: the standard CAPM regression with the market return as the only factor, the FF3 model and a regression with the information factors (TMN and YMO) and the market return. Tables **??**, **??** and **??** present the results of the time series regressions for the 30 industry portfolios using the market portfolio, the F&F factors and the information factors respectively. The shortcomings of the CAPM are clear: out of the 30 portfolios, only one (steel) has an intercept statistically not different from 0. The Fama & French factors fare significantly better with 12 portfolios having an intercept that is not statistically different from 0. This performance is however one of the weakest for the FF3 model which typically fares better when pricing other portfolios. The information factor model (Table **??**) by far outperforms both the CAPM and the FF3 with 24 portfolios being accurately priced. Interestingly, the R-squares of the regressions are not significantly different between the three models. The CAPM tends to have lower R-squares than the two other models but only marginally so. The FF3 and the information model have more or less the same performance from that point of view. Furthermore, the portfolios that are not correctly priced by any of the three models are not the ones with the lowest R-squares. For example, on the one hand, the portfolios of stocks in the business equipment category or in the services category both have R-squares in excess of .7 but both have an intercept that is statistically different from 0. On the other hand, the portfolios of stocks in the coal industry or in the mining industry have very low R-squares around .3 and .15 respectively, but are both accurately priced by the FF3 and the information models.

Next we evaluate the overall performance of the three multifactor models by running tests of whether all or subsets of the pricing errors are *jointly* insignificant. Tables **??**-**??** at the end show the results of four different tests for various subsets of the industry portfolios. The first line corresponds to the χ^2 with i.i.d. errors in (**??**), the second line to the GRS test outlined in (**??**) while the last two lines are the χ^2 tests with GMM errors. The number of lags is the lags used to compute the spectral density matrix in (**??**). By setting the number of lags equal to zero, the standards errors are corrected for heteroscedasticity but not autocorrelation.

In Table **??**, the hypothesis that all pricing errors are jointly zero is tested. As expected, the p-value of the test is zero for all models. However, the value of the statistics for the individual models reveal that the information based model performs significantly better than any other model. For example, the value of the GRS F-test decreases from 14.02 for the FF3 model to 7.7 for the information based model.

Next we run the same set of tests with the 24 portfolios that have a statistically insignificant intercept in the time-series regressions on the market return and the information factors. The results are gathered in Table **??**. There we see dramatic differences in the test statistics between the information based factor model and the other two models. Our model is the only one for which the hypothesis that the pricing errors are jointly zero is accepted at commonly used significance levels. For example, the p-values for the case of i.i.d. errors are 5% and 3% for the χ^2 and the F test while when we correct for heteroscedastic and autocorrelated errors the p-value falls but remains above the 1% level.

Finally, as an additional test of our model in comparison to the FF 3 factor model we run time-series regressions including as explanatory variables all five factors. Table **??** contains the results of the estimation. Out of 30 industry portfolios, the augmented model can price correctly 22, less than the number of portfolios that the information based model can price alone. Then, we use the three models to price these 22 portfolios and test whether the pricing errors are jointly insignificant. The results are startling! Table **??** shows that although for the information based model the p-value never falls below 5% with the highest value of 17% achieved when we correct only for heteroscedasticity, for the FF3 model the p-value is uniformly 0. This leads us to conclude that the ability of the augmented model to price these 22 portfolios is due to the two information factors and not the size and BTM factors.

4.1.2 Fama-MacBeth Cross Sectional Regressions

Tables **??**-**??** contain the estimation results using the procedure suggested by Fama and MacBeth (1973). The results are qualitatively similar to the results obtained by the joint significance tests of the time-series regressions. This similarity can be explained by the fact that in the cross-sectional regressions the estimates of the factors' risk premia (the slopes) are being picked to best fit all points. When we attempt to price all 30 industry portfolios the results are disappointing for all model specifications both in terms of the statistical significance of the factors' premia and the significance of the intercept. In particular, the estimates of the factor risk premia have low t-statistics while the intercept is statistically significant. However, as we move towards the 22 and 24 portfolios that the information factors price reasonably well in the time-series regressions, their statistical significance increases while the statistical significance of the intercept falls.

More specifically, the p-values of the hypothesis that the constant is zero are 0 for any model specification when all portfolios are included. For the 24 portfolios the p-values under the CAPM and the FF3 model are 0 while for our model the p-value is 0.08, a significant improvement. The improvement is even bigger when we move to the 22 portfolios where the p-values for the CAPM and the FF3 model remain the same while for the information based model the null hypothesis cannot be rejected at any significance level lower than 0.14.

As far as the slope coefficients are concerned, they are all statistically insignificant in the 30 portfolios regression confirming the difficulty in pricing the particular portfolios. For the 24 and 22 portfolios regressions, the p-value of the size factor does not fall below the 0.8 level while for the BTM factor the p-values are 0.24 and 0.21 respectively. The picture is much better for the information based factors. The p-vales for the YMO factor are 0.10 and 0.11 for the 24 and 22 portfolios respectively while the corresponding figures for the TMN factor are 0.2 and 0.08. Interestingly, the p-value of the coefficient on Market never falls below 0.55 and has the right (positive) sign only when combined with the information factors.

5 Pricing Size and Book-to-Market Portfolios

We test the validity of our information-based pricing factors by applying them to the Fama and French 25 size and book-to-market portfolios. The reason for this experiment is twofold. First, these portfolios are widely used in the literature and the asset pricing anomalies associated with them led to the introduction of the widely used Fama and French (1992) three factor model that still serves as the point of reference in the relative literature. Second, these portfolios are sorted according to characteristics unrelated to our pricing factors and hence, it would be interesting to see their performance in pricing these portfolios.

We have gathered the time-series regressions results in Tables **??**-**??**. Comparing the information-based model with the CAPM and, most importantly, the FF3 model we see that our factors are statistically significant and the fit of the regressions as described by the coefficient of determination, although slightly worse than the one from the FF3 model, is quite good. More importantly, out of 25 portfolios our model succeeds in pricing correctly 7 while the FF3 model only 1!

The information-based model is particularly successful in pricing large rather than small sized portfolios since all the correctly priced portfolios fall into the two groups of stocks with the biggest size (s4b1 to s5b5). To illustrate this we present the root mean squared errors from the time-series regressions in figures **??** and **??**. Figure **??** presents the mean squared errors of each size category within each book-to-market category, i.e., the lines connect portfolios of different size within each book-to-market category.

As the graph illustrates, holding the book-to-market ratio constant, the root mean squared errors are lower the bigger the size of the firms in the portfolio.

Figure 1: Root Mean Squared Errors for Size Categories.

Figure 2: Root Mean Squared Errors for B/M Categories.

A similar pattern cannot be discerned from figure **??** where each line connects the root mean squared errors of each book-to-market category within each size category. Instead, for all portfolios except the biggest sized ones we observe a U-shaped pattern with the root mean squared errors initially decreasing in the level of the book-to-market ratio and then increasing.

The FF3 model does not display any similar pattern. The only statistically insignificant intercept is the one corresponding to the portfolio with the lowest size and book-to-market ratio while the coefficients of determination are close to 0.9 for all portfolios. The high $\overline{R}^2$ should come as no surprise since the portfolios are sorted according to the factors.

6 Pricing Momentum Portfolios

We conclude the evaluation of our three factor model by considering portfolios sorted entirely or partially on momentum. The two sets of portfolios that we use are the 25 size and momentum portfolios and the 10 momentum portfolios constructed by Fama and French. Again, our three factor model is more successful in pricing these portfolios than the either the Fama and French three factor model or the CAPM.

6.1 Portfolios sorted on Size and Momentum

We begin by considering the 25 size and momentum portfolios and report the results of our estimation in tables **??**-**??** of Appendix D. As expected, using only the market excess return provides the worst pricing benchmark with an average R^2 of .72 and only 5 intercepts statistically equal to zero. The results of the time series regressions are reported in Table **??**. The Fama and French 3 factor model in Table **??** does significantly better in terms of goodness of fit with an average R^2 of .83 but the number of portfolios that are priced correctly is the same as in the CAPM case.

The information based model manages to increase the number of statistically insignificant intercepts to 9, a significant improvement over its two competitors while its average R^2 of .79 is only four percentage points lower than the one obtained by the Fama and French model.

6.2 Portfolios sorted on Momentum

The results become much more interesting when we consider portfolios sorted on momentum only. Tables **??**-**??** illustrate that the three models are equivalent in terms of average goodness of fit. The CAPM continues to provide the worst fit with an average R^2 of .78 compared to .80 for the Fama and French model and .79 for the information based model.

However, as far as the percentage of portfolios that are correctly priced is concerned, the results weigh in favor of the information based model. While the CAPM and the Fama and French models manage to price correctly only 10% of the momentum portfolios, our three factor model prices correctly 70% of the same portfolios.

These results are very important for the explanation of momentum, the premium anomaly as Fama and French (2006) call it. Ever since Jegadeesh and Titman (1993) first documented the momentum anomaly, no satisfactory explanation has been provided as to why short term winners tend to outperform short term losers. With the results of this section we would like to start the debate that superior momentum returns may stem from information problems.

7 Conclusions

In this paper, we have shown that information based factors can be used to produce an augmented CAPM which performs at least as well as the Fama & French model and even significantly outperforms it when pricing industry and momentum portfolios. The new factor introduced in this paper is the no-trade days factor, TMN, which is a significant pricing factor in most regressions. The construction of this factor is directly inspired from the results on parameter uncertainty derived in Sekeris (2006). Parameter uncertainty usually affects stocks that the market does not know very well and for which investors have to guess the parameter (rather than deducing it from the history of the asset). Young stocks are the obvious candidates because of their short history on the market but they are not the only stocks that are unknown to the market. Size could be another proxy for information given that institutional investors will be less inclined to invest in small stocks and hence will not research them. This reduced research is important since the information that institutionals uncover is usually made available to the market either directly by publishing it or indirectly through their trading. Size is, however, an imperfect proxy for information and the no-trade days factor is a much more accurate measure of the quantity of information available. Stocks that are not traded are "neglected" by the market with a small number of investors following them and researching them. This neglect results in the market knowing little about the stocks and exhibiting strong parameter uncertainty.

The strong performance of the information factors is clearly visible when pricing the 30 industry and the 10 momentum portfolios. Both types of portfolios have long been problematic to price and even the FF3 model has had mixed results. The information model proposed in this paper manages to accurately price 24 out of 30 industry portfolios and 7 out of 10 momentum portfolios. This result suggests that the cross sectional mispricing observed in the data might not be the result of an additional risk factor as suggested in the literature but that is caused by parameter uncertainty. In order to validate this argument more testing needs to be done, particularly in refining the variables that are used to capture information effects in the data. A potential variable is the percentage of the stock held by institutional investors. Given that institutional investors, by and large, research extensively the stocks that they purchase, this measure would provide a more accurate measure of the quality of information available to the market. This factor could then be coupled with the existing two information factors and fully capture the impact of parameter uncertainty on the price of assets.

A Industry Portfolios

A.1 Time-Series Regressions

Table 4: Industry Portfolios Priced with CAPM.

	Food	*Beer*	*Smoke*	*Games*	*Books*	*Hshld*	*Cloth*	*Health*	*Chems*	*Txtls*
Const	0.77	0.90	1.33	0.46	0.54	0.61	0.53	0.76	0.44	0.51
t-stat	5.50	4.81	4.80	2.27	3.76	4.11	2.75	5.17	3.28	2.67
Mrkt	0.72	0.79	0.72	1.34	1.07	0.80	1.13	0.87	0.99	0.99
t-stat	23.04	18.95	11.68	29.96	33.30	24.36	26.25	26.54	32.87	23.17
$\overline{R}^2$	0.52	0.42	0.22	0.65	0.69	0.55	0.58	0.59	0.69	0.52

	Cnstr	*Steel*	*FabPr*	*EleEq*	*Autos*	*Carry*	*Mines*	*Coal*	*Oil*	*Util*
Const	0.47	0.32	0.45	0.52	0.46	0.55	0.72	0.86	0.72	0.56
t-stat	4.15	1.71	3.58	4.05	2.46	2.90	2.52	2.40	4.01	3.68
Mrkt	1.10	1.17	1.20	1.08	1.00	1.14	0.84	0.76	0.76	0.53
t-stat	43.78	28.42	43.12	37.62	24.04	27.00	13.30	9.46	18.99	15.65
$\overline{R}^2$	0.80	0.62	0.79	0.74	0.54	0.60	0.26	0.15	0.42	0.33

	Telcm	*Servc*	*BusEq*	*Paper*	*Trans*	*Whlsl*	*Retail*	*Meals*	*Fin*	*Other*
Const	0.51	0.51	0.48	0.54	0.51	0.37	0.63	0.73	0.63	0.52
t-stat	3.66	3.05	2.46	4.03	3.43	3.02	4.27	3.70	5.12	3.92
Mrkt	0.78	1.11	1.45	0.95	1.11	1.01	1.04	1.13	1.02	1.08
t-stat	25.05	30.07	33.56	31.74	33.26	37.67	31.69	25.87	37.46	36.56
$\overline{R}^2$	0.56	0.65	0.70	0.67	0.69	0.74	0.67	0.58	0.74	0.73

Table 5: Industry Portfolios Priced with FF factors

	Food	*Beer*	*Smoke*	*Games*	*Books*	*Hshld*	*Cloth*	*Health*	*Chems*	*Txtls*
Const	0.60	0.88	1.26	0.34	0.40	0.65	0.19	0.98	0.25	0.08
t-stat	4.40	4.69	4.49	1.73	2.78	4.32	1.02	6.89	1.89	0.48
Mrkt	0.84	0.87	0.83	1.27	1.06	0.84	1.18	0.84	1.11	1.03
t-stat	25.16	19.10	12.23	26.64	30.79	22.93	26.55	24.32	34.83	25.23
Size	−0.12	−0.26	−0.28	0.44	0.26	−0.18	0.45	−0.28	−0.08	0.57
t-stat	−2.73	−4.39	−3.16	7.04	5.70	−3.90	7.89	−6.23	−1.88	10.66
B/M	0.32	0.10	0.20	0.10	0.19	−0.02	0.49	−0.31	0.36	0.60
t-stat	6.49	1.45	1.90	1.34	3.63	−0.39	7.38	−5.96	7.46	9.76
$\overline{R}^2$	0.57	0.45	0.24	0.68	0.71	0.56	0.65	0.63	0.72	0.65
	Cnstr	*Steel*	*FabPr*	*EleEq*	*Autos*	*Carry*	*Mines*	*Coal*	*Oil*	*Util*
Const	0.25	−0.03	0.35	0.39	0.09	0.25	0.39	0.52	0.58	0.25
t-stat	2.33	−0.17	2.82	3.08	0.51	1.37	1.40	1.45	3.35	1.87
Mrkt	1.17	1.24	1.17	1.08	1.15	1.23	0.88	0.79	0.89	0.72
t-stat	44.84	29.21	39.40	34.77	26.97	27.27	12.80	9.00	21.09	22.02
Size	0.12	0.31	0.26	0.20	0.07	0.18	0.42	0.47	−0.27	−0.17
t-stat	3.56	5.69	6.63	4.94	1.30	3.03	4.70	4.17	−4.88	−3.90
B/M	0.35	0.52	0.11	0.17	0.62	0.46	0.45	0.47	0.29	0.57
t-stat	8.84	8.08	2.52	3.66	9.58	6.84	4.38	3.59	4.61	11.48
$\overline{R}^2$	0.82	0.67	0.81	0.76	0.61	0.63	0.31	0.19	0.48	0.50
	Telcm	*Servc*	*BusEq*	*Paper*	*Trans*	*Whlsl*	*Retail*	*Meals*	*Fin*	*Other*
Const	0.50	0.83	0.82	0.36	0.27	0.14	0.55	0.55	0.38	0.51
t-stat	3.58	5.42	4.86	2.73	1.86	1.27	3.64	2.80	3.43	3.77
Mrkt	0.84	0.93	1.19	1.05	1.19	1.02	1.05	1.14	1.16	1.13
t-stat	25.05	25.09	29.11	33.17	33.52	38.50	28.85	23.79	42.60	34.74
Size	−0.22	0.09	0.38	−0.06	0.12	0.37	0.08	0.29	−0.08	−0.16
t-stat	−5.10	1.86	7.21	−1.57	2.57	10.72	1.77	4.66	−2.20	−3.72
B/M	0.08	−0.57	−0.67	0.33	0.39	0.30	0.12	0.24	0.44	0.07
t-stat	1.50	−10.24	−10.87	6.92	7.23	7.59	2.19	3.29	10.64	1.36
$\overline{R}^2$	0.59	0.72	0.78	0.70	0.72	0.80	0.67	0.60	0.79	0.74

Table 6: Industry portfolios priced with information factors

	Food	*Beer*	*Smoke*	*Games*	*Books*	*Hshld*	*Cloth*	*Health*	*Chems*	*Txtls*
Const	-0.15	0.12	0.15	0.84	0.31	0.03	-0.07	0.39	-0.16	-0.10
t-stat	-1.03	0.56	0.46	3.69	1.85	0.18	-0.33	2.29	-1.04	-0.47
Mrkt	0.84	0.88	0.87	1.31	1.11	0.88	1.24	0.91	1.07	1.10
t-stat	28.08	20.69	13.69	28.56	32.89	25.65	27.98	26.37	34.62	25.92
YMO	-0.36	-0.32	-0.50	0.26	-0.04	-0.24	-0.14	-0.18	-0.25	-0.11
t-stat	-10.87	-6.88	-7.18	5.02	-0.97	-6.36	-2.90	-4.70	-7.46	-2.34
TMN	0.21	0.12	0.16	0.21	0.21	0.09	0.41	-0.02	0.09	0.51
t-stat	5.52	2.15	1.95	3.48	4.70	2.07	7.15	-0.40	2.16	9.20
$\overline{R}^2$	0.62	0.47	0.29	0.67	0.70	0.58	0.62	0.61	0.72	0.59
	Cnstr	*Steel*	*FabPr*	*EleEq*	*Autos*	*Carry*	*Mines*	*Coal*	*Oil*	*Util*
Const	-0.10	0.07	0.38	0.27	0.02	0.00	0.43	0.22	0.37	-0.28
t-stat	-0.85	0.32	2.57	1.78	0.08	-0.01	1.30	0.52	1.75	-1.65
Mrkt	1.18	1.20	1.21	1.11	1.06	1.22	0.91	0.86	0.79	0.63
t-stat	47.71	27.38	41.10	36.70	24.02	27.48	13.63	10.11	18.76	18.87
YMO	-0.18	-0.07	0.01	-0.07	-0.16	-0.18	0.01	-0.17	-0.17	-0.36
t-stat	-6.46	-1.53	0.32	-2.12	-3.22	-3.68	0.11	-1.82	-3.63	-9.59
TMN	0.26	0.12	0.12	0.13	0.14	0.22	0.41	0.37	-0.02	0.11
t-stat	8.17	2.05	3.19	3.39	2.52	3.89	4.70	3.40	-0.28	2.49
$\overline{R}^2$	0.83	0.62	0.79	0.75	0.55	0.61	0.29	0.17	0.44	0.44
	Telcm	*Servc*	*BusEq*	*Paper*	*Trans*	*Whlsl*	*Retail*	*Meals*	*Fin*	*Other*
Const	0.53	1.46	1.57	-0.19	0.03	-0.03	0.12	0.12	-0.13	0.13
t-stat	3.27	8.09	7.36	-1.28	0.16	-0.22	0.72	0.56	-0.96	0.82
Mrkt	0.76	0.98	1.32	1.04	1.18	1.08	1.11	1.23	1.12	1.13
t-stat	23.16	26.91	30.74	35.00	33.83	40.49	32.56	27.72	42.32	36.44
YMO	-0.04	0.34	0.45	-0.30	-0.16	-0.07	-0.17	-0.13	-0.28	-0.19
t-stat	-1.14	8.50	9.43	-9.16	-4.16	-2.51	-4.41	-2.68	-9.49	-5.53
TMN	-0.15	-0.31	-0.19	0.12	0.19	0.32	0.20	0.43	0.22	-0.01
t-stat	-3.53	-6.59	-3.44	3.13	4.31	9.13	4.57	7.48	6.31	-0.20
$\overline{R}^2$	0.57	0.70	0.74	0.72	0.71	0.78	0.69	0.62	0.79	0.75

Table 7: Industry portfolios priced with all factors

	Food	*Beer*	*Smoke*	*Games*	*Books*	*Hshld*	*Cloth*	*Health*	*Chems*	*Txtls*
Const	-0.10	0.25	0.17	0.69	0.13	0.07	-0.38	0.42	-0.11	-0.42
t-stat	-0.62	1.13	0.52	2.94	0.74	0.40	-1.78	2.56	-0.68	-2.10
Mrkt	0.87	0.90	0.86	1.30	1.08	0.86	1.20	0.86	1.11	1.07
t-stat	26.81	19.60	12.51	26.23	30.10	23.53	26.59	24.76	33.93	25.73
Size	-0.03	-0.20	-0.07	0.26	0.29	-0.11	0.53	-0.19	0.02	0.58
t-stat	-0.64	-2.57	-0.56	3.14	4.73	-1.82	6.90	-3.30	0.28	8.20
B/M	0.13	-0.08	-0.09	0.17	0.11	-0.18	0.33	-0.46	0.27	0.45
t-stat	2.48	-1.08	-0.83	2.12	1.97	-3.11	4.61	-8.26	5.12	6.76
YMO	-0.30	-0.27	-0.51	0.20	-0.12	-0.25	-0.25	-0.25	-0.17	-0.20
t-stat	-7.05	-4.37	-5.52	3.08	-2.46	-5.20	-4.16	-5.40	-3.98	-3.60
TMN	0.20	0.21	0.20	0.08	0.08	0.17	0.16	0.14	0.03	0.21
t-stat	4.57	3.25	2.12	1.20	1.65	3.28	2.54	2.84	0.71	3.72
$\overline{R}^2$	0.62	0.48	0.29	0.68	0.72	0.59	0.67	0.66	0.73	0.66
	Cnstr	*Steel*	*FabPr*	*EleEq*	*Autos*	*Carry*	*Mines*	*Coal*	*Oil*	*Util*
Const	-0.14	-0.14	0.15	0.07	0.14	-0.09	0.33	-0.19	0.70	-0.09
t-stat	-1.11	-0.66	1.04	0.45	0.65	-0.40	0.97	-0.44	3.34	-0.55
Mrkt	1.20	1.21	1.17	1.08	1.16	1.24	0.93	0.80	0.91	0.73
t-stat	46.07	27.44	37.77	33.67	25.90	26.51	13.02	8.78	20.53	21.59
Size	0.12	0.45	0.33	0.30	0.05	0.24	0.27	0.64	-0.35	-0.09
t-stat	2.72	6.04	6.23	5.56	0.61	3.05	2.27	4.21	-4.63	-1.64
B/M	0.23	0.51	0.07	0.09	0.63	0.37	0.40	0.29	0.31	0.48
t-stat	5.45	7.23	1.38	1.81	8.72	4.96	3.51	2.00	4.42	8.80
YMO	-0.15	-0.09	-0.10	-0.16	0.03	-0.16	0.03	-0.34	0.08	-0.16
t-stat	-4.38	-1.57	-2.46	-3.87	0.48	-2.54	0.29	-2.83	1.28	-3.58
TMN	0.18	-0.14	-0.01	0.01	0.01	0.07	0.23	0.09	0.05	0.06
t-stat	4.97	-2.30	-0.20	0.16	0.24	1.07	2.39	0.70	0.89	1.20
$\overline{R}^2$	0.84	0.68	0.81	0.76	0.61	0.64	0.31	0.20	0.48	0.51
	Telcm	*Servc*	*BusEq*	*Paper*	*Trans*	*Whlsl*	*Retail*	*Meals*	*Fin*	*Other*
Const	0.75	1.23	1.07	-0.20	-0.01	-0.29	0.00	-0.05	0.03	0.16
t-stat	4.53	6.95	5.38	-1.31	-0.05	-2.31	0.00	-0.20	0.20	1.03
Mrkt	0.83	0.87	1.13	1.06	1.20	1.04	1.08	1.20	1.20	1.13
t-stat	23.74	23.42	27.20	33.23	32.76	39.23	29.20	24.95	43.79	33.69

Continued on next page

	Cnstr	*Steel*	*FabPr*	*EleEq*	*Autos*	*Carry*	*Mines*	*Coal*	*Oil*	*Util*
Size	-0.24	0.17	0.49	0.08	0.15	0.41	0.16	0.25	-0.10	-0.06
t-stat	-4.13	2.63	6.97	1.42	2.41	9.22	2.49	3.01	-2.18	-0.99
B/M	0.15	-0.43	-0.57	0.19	0.31	0.18	-0.03	0.05	0.32	-0.02
t-stat	2.67	-7.22	-8.49	3.72	5.20	4.23	-0.53	0.59	7.34	-0.30
YMO	0.11	0.13	0.06	-0.27	-0.12	-0.19	-0.24	-0.22	-0.13	-0.17
t-stat	2.33	2.65	1.06	-6.38	-2.49	-5.26	-4.90	-3.41	-3.64	-3.83
TMN	-0.09	-0.29	-0.27	0.06	0.08	0.13	0.15	0.34	0.20	0.02
t-stat	-1.84	-5.70	-4.67	1.33	1.68	3.66	2.98	5.07	5.22	0.33
$\overline{R}^2$	0.59	0.74	0.79	0.73	0.73	0.82	0.69	0.62	0.81	0.75

Table 8: Test that pricing errors are jointly zero - 30 industry portfolios

	CAPM		FAMA - FRENCH		INFORMATION	
	test	p-value	test	p-value	test	p-value
i.i.d. - χ^2	431.17	0.00	450.82	0.00	247.69	0.00
i.i.d. - GRS F	13.47	0.00	14.02	0.00	7.70	0.00
GMM 0 Lags - χ^2	417.96	0.00	460.66	0.00	234.77	0.00
GMM 4 Lags - χ^2	334.14	0.00	402.87	0.00	249.05	0.00

Table 9: Test that pricing errors are jointly zero - 24 industry portfolios

	CAPM		FAMA - FRENCH		INFORMATION	
	test	p-value	test	p-value	test	p-value
i.i.d. - χ^2	137.90	0.00	137.49	0.00	39.35	0.03
i.i.d. - GRS F	5.45	0.00	5.41	0.00	1.55	0.05
GMM 0 Lags - χ^2	135.98	0.00	146.43	0.00	39.33	0.03
GMM 4 Lags - χ^2	121.40	0.00	133.54	0.00	44.35	0.01

Table 10: Test that pricing errors are jointly zero - 22 industry portfolios

	CAPM		FAMA - FRENCH		INFORMATION	
	test	p-value	test	p-value	test	p-value
i.i.d. - χ^2	112.93	0.00	90.79	0.00	31.55	0.09
i.i.d. - GRS F	4.89	0.00	3.92	0.00	1.36	0.13
GMM 0 Lags - χ^2	109.71	0.00	87.77	0.00	28.30	0.17
GMM 4 Lags - χ^2	93.04	0.00	92.80	0.00	33.39	0.06

A.2 Fama-MacBeth Cross Sectional Regressions

Table 11: 30 Industry Portfolios

	Const	**Market**	**Size**	**BE/ME**	**YMO**	**TNT**
coef	1.14	−0.08	–	–	–	–
t-stat	4.08	−0.22	–	–	–	–
coef	1.26	−0.16	−0.02	−0.11	–	–
t-stat	3.61	−0.40	−0.08	−0.61	–	–
coef	0.97	0.06	–	–	−0.18	0.02
t-stat	3.02	0.16	–	–	−0.57	0.05
coef	1.01	0.02	0.02	−0.29	−0.24	0.42
t-stat	2.99	0.05	0.10	−1.44	−0.65	1.11

Table 12: 24 Industry Portfolios

	Const	**Market**	**Size**	**BE/ME**	**YMO**	**TNT**
coef	1.29	−0.23	–	–	–	–
t-stat	4.26	−0.62	–	–	–	–
coef	1.43	−0.26	0.00	−0.30	–	–
t-stat	3.69	−0.61	−0.01	−1.16	–	–
coef	0.74	0.06	–	–	−0.89	0.44
t-stat	1.75	0.14	–	–	−1.64	1.28
coef	0.89	0.02	−0.11	−0.06	−0.63	0.58
t-stat	2.08	0.05	−0.46	−0.27	−1.21	1.39

Table 13: 22 Industry Portfolios

	Const	**Market**	**Size**	**BE/ME**	**YMO**	**TNT**
coef	1.30	-0.23	–	–	–	–
t-stat	4.30	-0.62	–	–	–	–
coef	1.50	-0.32	0.05	-0.30	–	–
t-stat	3.71	-0.75	0.17	-1.25	–	–
coef	0.63	0.14	–	–	-0.85	0.70
t-stat	1.48	0.34	–	–	-1.57	1.72
coef	0.76	0.08	0.09	-0.07	-0.80	0.70
t-stat	1.88	0.19	0.30	-0.31	-1.39	1.66

B Size and Book-to-Market Portfolios

Table 14: Size and B/M Portfolios Priced with CAPM

	const	**t-stat**	**Market**	**t-stat**	$\overline{R}^2$
s1b1	0.10	0.42	1.45	28.07	0.62
s1b2	0.74	3.66	1.23	27.34	0.60
s1b3	0.86	5.20	1.07	29.12	0.63
s1b4	1.12	7.10	0.99	28.03	0.61
s1b5	1.22	7.07	1.01	26.45	0.59
s2b1	0.20	1.16	1.43	37.06	0.74
s2b2	0.60	4.29	1.16	37.61	0.74
s2b3	0.90	7.10	1.02	36.23	0.73
s2b4	1.00	7.92	0.97	34.27	0.70
s2b5	1.06	7.01	1.04	31.03	0.66
s3b1	0.26	1.78	1.36	42.05	0.78
s3b2	0.70	6.55	1.10	46.48	0.81
s3b3	0.74	6.96	0.96	40.49	0.77
s3b4	0.93	8.33	0.91	36.34	0.73
s3b5	1.07	7.65	0.98	31.81	0.67
s4b1	0.43	3.91	1.25	51.62	0.84
s4b2	0.48	5.38	1.06	53.64	0.85
s4b3	0.76	7.71	0.97	44.36	0.80
s4b4	0.93	8.94	0.91	38.98	0.76
s4b5	0.91	6.66	0.99	32.50	0.68
s5b1	0.44	5.67	1.01	57.92	0.87
s5b2	0.52	6.65	0.95	54.78	0.86
s5b3	0.60	6.32	0.85	40.64	0.77
s5b4	0.70	6.37	0.78	31.97	0.67
s5b5	0.69	4.86	0.83	26.50	0.59

Table 15: Size and B/M Portfolios Priced with FF

	const	**t-stat**	**Market**	**t-stat**	**size**	**t-stat**	**B/M**	**t-stat**	$\overline{R}^2$
s1b1	0.09	0.81	1.07	40.01	1.38	39.60	−0.31	−7.73	0.92
s1b2	0.51	6.39	0.97	49.70	1.32	52.29	0.07	2.50	0.94
s1b3	0.53	8.35	0.92	59.63	1.10	54.67	0.30	12.96	0.95
s1b4	0.71	11.36	0.90	59.03	1.03	51.91	0.46	20.21	0.94
s1b5	0.67	10.40	0.98	62.58	1.08	53.30	0.69	29.31	0.95
s2b1	0.30	3.77	1.12	58.30	0.99	39.68	−0.39	−12.71	0.95
s2b2	0.37	5.19	1.03	59.40	0.86	38.34	0.18	6.98	0.94
s2b3	0.55	8.35	0.98	60.75	0.75	35.86	0.42	17.19	0.93
s2b4	0.56	9.02	0.98	64.73	0.70	35.48	0.59	25.83	0.93
s2b5	0.49	7.59	1.08	69.21	0.83	41.02	0.78	33.11	0.94
s3b1	0.42	5.59	1.08	59.23	0.73	30.78	−0.45	−16.31	0.94
s3b2	0.49	6.17	1.06	54.19	0.51	20.13	0.23	7.74	0.90
s3b3	0.39	5.18	1.01	55.58	0.42	17.87	0.51	18.51	0.89
s3b4	0.49	7.06	1.01	59.63	0.39	17.56	0.67	26.13	0.90
s3b5	0.50	6.20	1.11	56.31	0.51	20.07	0.84	28.40	0.89
s4b1	0.63	8.59	1.05	58.67	0.37	15.99	−0.44	−16.38	0.93
s4b2	0.30	3.63	1.10	54.43	0.20	7.56	0.26	8.61	0.88
s4b3	0.45	5.62	1.08	55.75	0.16	6.27	0.50	17.16	0.88
s4b4	0.54	7.39	1.04	58.28	0.19	8.20	0.63	23.32	0.89
s4b5	0.39	4.15	1.17	50.93	0.25	8.23	0.84	24.14	0.86
s5b1	0.70	12.01	0.96	67.40	−0.26	−14.15	−0.38	−17.77	0.93
s5b2	0.47	6.78	1.04	61.49	−0.23	−10.42	0.14	5.43	0.89
s5b3	0.46	5.75	0.98	50.55	−0.24	−9.40	0.29	9.93	0.84
s5b4	0.37	5.34	1.00	58.98	−0.22	−9.98	0.62	24.16	0.88
s5b5	0.24	2.35	1.07	42.76	−0.10	−2.99	0.79	20.85	0.79

Table 16: Size and B/M Portfolios Priced with information factors

	const	t-stat	Market	t-stat	YMO	t-stat	TMN	t-stat	$\overline{R}^2$
s1b1	1.71	9.27	1.30	35.16	0.89	21.61	0.36	7.55	0.83
s1b2	1.60	8.59	1.17	31.25	0.56	13.53	0.44	9.05	0.76
s1b3	1.21	7.73	1.08	34.29	0.33	9.62	0.49	11.94	0.77
s1b4	1.29	8.53	1.01	33.47	0.26	7.64	0.51	13.01	0.75
s1b5	1.32	8.15	1.05	32.35	0.26	7.10	0.59	13.98	0.74
s2b1	1.10	6.68	1.36	40.97	0.52	14.10	0.27	6.23	0.83
s2b2	0.74	5.16	1.18	41.29	0.20	6.25	0.38	10.18	0.81
s2b3	0.74	5.80	1.08	41.98	0.08	2.70	0.43	12.97	0.80
s2b4	0.74	5.50	1.03	38.03	0.01	0.40	0.39	11.00	0.76
s2b5	0.84	5.19	1.10	33.73	0.05	1.32	0.42	9.95	0.72
s3b1	1.04	7.19	1.29	44.40	0.42	13.09	0.15	4.04	0.85
s3b2	0.52	4.52	1.15	49.64	0.02	0.84	0.30	9.98	0.85
s3b3	0.29	2.53	1.04	45.51	−0.10	−3.94	0.33	11.00	0.81
s3b4	0.38	3.13	0.99	41.00	−0.15	−5.69	0.31	9.84	0.78
s3b5	0.56	3.64	1.07	34.64	−0.11	−3.30	0.35	8.82	0.72
s4b1	0.89	7.37	1.20	49.49	0.23	8.42	0.02	0.65	0.86
s4b2	−0.03	−0.27	1.14	60.09	−0.15	−7.13	0.25	10.17	0.88
s4b3	0.10	0.92	1.06	51.49	−0.23	−10.08	0.23	8.68	0.85
s4b4	0.32	2.80	0.99	43.47	−0.22	−8.78	0.19	6.58	0.80
s4b5	0.22	1.47	1.09	35.55	−0.24	−6.97	0.25	6.31	0.72
s5b1	0.48	5.43	0.99	55.73	−0.04	−1.86	−0.15	−6.64	0.88
s5b2	0.09	1.11	1.00	59.36	−0.20	−10.60	0.01	0.44	0.89
s5b3	0.17	1.61	0.90	43.36	−0.21	−9.24	−0.03	−1.00	0.81
s5b4	−0.02	−0.13	0.87	37.71	−0.32	−12.45	0.06	1.93	0.75
s5b5	0.13	0.81	0.90	27.76	−0.24	−6.68	0.06	1.51	0.62

C Size and Momentum Portfolios

Table 17: Size and Momentum Portfolios Priced with CAPM

	const	**t-stat**	**Market**	**t-stat**	$\overline{R}^2$
s1m1	−0.27	−1.13	1.31	24.56	0.55
s1m2	0.71	4.30	1.00	27.13	0.60
s1m3	1.00	6.63	0.95	28.44	0.62
s1m4	1.14	7.60	0.98	29.41	0.64
s1m5	1.47	7.66	1.20	28.18	0.62
s2m1	−0.24	−1.27	1.39	32.67	0.68
s2m2	0.53	3.82	1.07	34.70	0.71
s2m3	0.80	6.73	0.99	37.53	0.74
s2m4	1.03	8.41	1.03	38.10	0.75
s2m5	1.24	7.42	1.29	34.73	0.71
s3m1	−0.04	−0.21	1.33	32.19	0.68
s3m2	0.48	4.11	1.05	40.39	0.77
s3m3	0.68	6.46	0.97	41.65	0.78
s3m4	0.79	7.74	0.98	43.12	0.79
s3m5	1.19	8.10	1.23	37.66	0.74
s4m1	−0.02	−0.10	1.27	30.90	0.66
s4m2	0.47	4.09	1.07	41.45	0.78
s4m3	0.56	5.99	0.98	46.57	0.82
s4m4	0.78	9.15	1.00	52.56	0.85
s4m5	1.08	8.31	1.16	39.99	0.76
s5m1	0.09	0.53	1.16	30.09	0.65
s5m2	0.48	4.01	0.90	34.05	0.70
s5m3	0.35	4.33	0.89	48.83	0.83
s5m4	0.57	6.92	0.89	47.92	0.82
s5m5	0.81	6.81	1.04	39.35	0.76

Table 18: Size and Momentum Portfolios Priced with FF

	const	t-stat	Market	t-stat	size	t-stat	B/M	t-stat	$\overline{R}^2$
s1m1	−0.64	−3.76	1.14	27.61	1.24	23.11	0.34	5.47	0.78
s1m2	0.27	3.02	0.94	42.58	0.97	33.70	0.52	15.70	0.89
s1m3	0.58	7.47	0.91	48.33	0.89	36.68	0.51	18.17	0.91
s1m4	0.77	10.25	0.91	49.63	0.92	38.95	0.42	15.31	0.91
s1m5	1.26	11.66	0.99	37.66	1.15	33.63	0.09	2.39	0.88
s2m1	−0.48	−3.32	1.25	35.34	0.92	20.16	0.19	3.60	0.83
s2m2	0.19	2.08	1.03	46.34	0.73	25.33	0.41	12.21	0.88
s2m3	0.47	6.48	0.97	55.24	0.64	28.16	0.42	15.65	0.91
s2m4	0.72	10.77	0.98	60.95	0.72	34.36	0.37	15.02	0.93
s2m5	1.14	11.05	1.08	43.09	0.93	28.67	−0.05	−1.29	0.89
s3m1	−0.22	−1.26	1.25	30.02	0.57	10.54	0.17	2.70	0.74
s3m2	0.19	1.97	1.07	46.74	0.45	15.20	0.40	11.67	0.86
s3m3	0.36	4.75	1.00	54.06	0.44	18.29	0.44	15.71	0.89
s3m4	0.51	6.44	1.00	51.93	0.40	16.02	0.39	13.27	0.88
s3m5	1.16	10.50	1.06	39.34	0.68	19.58	−0.11	−2.68	0.86
s4m1	−0.18	−0.97	1.27	28.26	0.29	4.92	0.21	3.06	0.68
s4m2	0.23	2.14	1.14	43.21	0.15	4.30	0.38	9.52	0.81
s4m3	0.30	3.70	1.06	53.84	0.14	5.66	0.42	14.09	0.87
s4m4	0.58	7.46	1.06	56.08	0.13	5.43	0.32	11.14	0.88
s4m5	1.08	9.24	1.04	36.63	0.42	11.40	−0.10	−2.27	0.82
s5m1	0.07	0.38	1.21	28.00	−0.12	−2.08	0.07	1.08	0.65
s5m2	0.40	3.48	1.00	36.15	−0.23	−6.28	0.19	4.57	0.74
s5m3	0.30	4.09	0.98	53.81	−0.22	−9.39	0.14	5.04	0.87
s5m4	0.57	7.59	0.96	52.91	−0.26	−11.15	0.08	2.76	0.86
s5m5	0.93	7.77	1.00	34.30	−0.05	−1.43	−0.19	−4.39	0.77

Table 19: Size and Momentum Portfolios Priced with Information Factors

	const	t-stat	Market	t-stat	YMO	t-stat	TMN	t-stat	$\overline{R}^2$
s1m1	0.74	3.32	1.24	27.57	0.66	13.15	0.51	8.69	0.72
s1m2	0.77	5.13	1.04	34.44	0.24	7.22	0.61	15.41	0.76
s1m3	1.00	7.44	1.00	36.94	0.21	6.85	0.58	16.42	0.79
s1m4	1.27	9.49	1.02	37.81	0.25	8.51	0.55	15.74	0.80
s1m5	2.20	12.42	1.16	32.79	0.50	12.84	0.47	10.12	0.77
s2m1	0.39	1.91	1.35	33.06	0.40	8.81	0.29	5.43	0.75
s2m2	0.40	2.81	1.12	39.35	0.09	2.99	0.44	11.99	0.78
s2m3	0.50	4.21	1.07	44.82	0.01	0.47	0.44	14.29	0.82
s2m4	0.93	7.59	1.08	44.11	0.10	3.59	0.41	12.95	0.82
s2m5	1.84	10.57	1.24	35.53	0.37	9.59	0.25	5.46	0.78
s3m1	0.41	1.91	1.29	30.03	0.25	5.20	0.10	1.88	0.70
s3m2	0.15	1.17	1.12	43.40	−0.04	−1.51	0.32	9.63	0.80
s3m3	0.22	2.04	1.05	49.00	−0.08	−3.57	0.37	13.33	0.84
s3m4	0.40	3.75	1.05	49.26	−0.06	−2.71	0.34	12.37	0.84
s3m5	1.65	10.24	1.19	36.77	0.27	7.62	0.16	3.73	0.78
s4m1	0.15	0.68	1.26	28.52	0.10	1.98	0.05	0.86	0.66
s4m2	−0.09	−0.73	1.15	44.43	−0.19	−6.56	0.23	6.71	0.81
s4m3	−0.08	−0.84	1.07	54.90	−0.21	−9.89	0.26	10.21	0.86
s4m4	0.24	2.69	1.07	59.49	−0.18	−8.85	0.22	9.25	0.88
s4m5	1.25	8.32	1.15	38.27	0.13	3.86	0.14	3.70	0.78
s5m1	−0.11	−0.54	1.18	28.60	−0.11	−2.40	−0.04	−0.75	0.65
s5m2	0.02	0.13	0.95	35.41	−0.23	−7.63	−0.03	−0.84	0.74
s5m3	−0.02	−0.22	0.93	51.35	−0.18	−8.95	−0.01	−0.40	0.85
s5m4	0.26	2.78	0.92	49.14	−0.16	−7.67	−0.03	−1.17	0.84
s5m5	0.99	7.03	1.02	35.86	0.06	2.07	−0.06	−1.62	0.76

D Momentum Portfolios

Table 20: Momentum Portfolios Priced with CAPM

	const	t-stat	Market	t-stat	$\overline{R}^2$
m1	−0.53	−2.62	1.35	30.15	0.65
m2	0.21	1.46	1.13	34.73	0.71
m3	0.41	3.37	0.98	36.39	0.73
m4	0.47	4.75	0.93	41.86	0.78
m5	0.37	4.62	0.90	49.93	0.84
m6	0.47	5.71	0.93	51.14	0.84
m7	0.53	6.52	0.90	50.14	0.84
m8	0.73	8.92	0.92	50.50	0.84
m9	0.79	8.33	0.99	46.63	0.82
m10	1.14	7.73	1.20	36.49	0.73

Table 21: Momentum Portfolios Priced with FF

	const	t-stat	Market	t-stat	size	t-stat	B/M	t-stat	$\overline{R}^2$
m1	−0.60	−3.08	1.26	26.46	0.44	7.18	0.03	0.39	0.68
m2	0.09	0.62	1.16	32.13	0.12	2.48	0.18	3.36	0.72
m3	0.26	2.18	1.06	36.29	−0.02	−0.65	0.26	5.91	0.75
m4	0.35	3.60	1.01	42.65	−0.07	−2.35	0.23	6.46	0.80
m5	0.25	3.30	0.97	52.06	−0.07	−2.79	0.22	7.90	0.86
m6	0.37	4.64	1.00	52.49	−0.09	−3.46	0.20	6.84	0.86
m7	0.45	5.87	0.98	52.80	−0.15	−6.03	0.17	6.11	0.86
m8	0.68	8.29	0.97	48.88	−0.09	−3.30	0.11	3.81	0.85
m9	0.75	7.73	1.02	43.58	−0.05	−1.72	0.09	2.59	0.82
m10	1.24	9.20	1.05	31.76	0.36	8.51	−0.27	−5.38	0.78

Table 22: Momentum Portfolios Priced with Information Factors

	const	t-stat	Market	t-stat	YMO	t-stat	TMN	t-stat	$\overline{R}^2$
m1	-0.01	-0.05	1.30	28.14	0.28	5.56	0.12	2.01	0.67
m2	0.02	0.11	1.16	33.23	-0.06	-1.63	0.08	1.81	0.71
m3	-0.05	-0.37	1.04	37.15	-0.18	-5.87	0.10	2.72	0.75
m4	-0.01	-0.05	0.99	44.04	-0.20	-8.12	0.07	2.35	0.81
m5	-0.06	-0.62	0.95	52.97	-0.17	-8.60	0.09	3.76	0.86
m6	0.06	0.65	0.98	53.49	-0.16	-8.02	0.08	3.46	0.86
m7	0.11	1.24	0.96	52.83	-0.17	-8.44	0.08	3.25	0.86
m8	0.46	4.84	0.96	50.01	-0.11	-5.08	0.06	2.30	0.85
m9	0.59	5.28	1.01	45.01	-0.07	-2.84	0.07	2.26	0.82
m10	1.66	10.00	1.14	34.41	0.27	7.25	0.07	1.53	0.76

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