Factor covariances predict factor returns

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Abstract

We examine low-turnover zero-investment "factor" portfolios constructed from various stock characteristics previously shown to predict returns. The nine different factor portfolios all exhibit negative market betas. Our central result is that a more negative beta across factors predicts higher factor returns over the next two years. Similarly, the average relative volatility of the factor returns, as well as the cross-sectional variance of the betas and volatilities, predicts future factor returns. While the results are difficult to reconcile with standard risk-based explanations, they are consistent with the existence of a time-varying mass of naïve investors, whose trading affects the returns to characteristics-based factor portfolios. Indeed, the average beta across factors is highly negatively correlated across time with the Baker and Wurgler (2006) investor sentiment measure.

Key Words: Factor Returns, Factor Covariances, Investor Sentiment, Time-Series Predictability

JEL Codes: G12, G02 -

1. Introduction

A wide range of firm characteristics predict stock returns. These include valuation ratios, profitability measures, long-term price changes, level of investment, level of external financing, accounting accruals changes, and bloated balance sheets. The standard rational explanation is that such predicability reflects differences in risk. By contrast, the standard sub-rational explanation is that naïve investors have excess demand (driven by preferences or biased information processing) for high-characteristic stocks, say stocks with high market-to-book ratios, high assets growth, or high accruals growth. This leads to overpricing in the current period and low future returns, as prices revert to fundamental values.

Fortunately, the two explanations yield diametrically opposite predictions for the risk-return relationship. In particular, if the trading of the naïve investors is positively correlated with aggregate market movements, then the high-characteristic stocks will exhibit high market betas, even though they have low expected returns due to the overpricing. Two channels would lead to such a positive correlation. First, by the assumption that naïve investors affect prices, their trading will move both the aggregate market and the high-characteristic stocks. Since they disproportionately hold the high-characteristic stocks, these stocks will have greater price movements and thus high market betas. A second channel is based on the assumption that naïve investors are subject to the *house money effect*, consistent with models such as Constantinides (1990) and Barberis, Huang, and Santos (2001). That is, their risk preferences will change dynamically according to their level of wealth. When aggregate prices increase, they will become less risk averse, increasing their allocation to stocks and driving up the price of the high-characteristic stocks relative to the market. If both directions of causation hold, there will be a positive-feedback loop from the trading of the naïve investors, to market prices, and back to the naïve investors. The high-characteristic stocks will have high market betas and low subsequent returns, the opposite of what is predicted by the standard risk-based explanation.

We test this prediction for portfolios based on nine different characteristics previously shown to predict returns: Book-to-market, long-term reversals, cash earnings yield, net stock issuance, the accruals measure proposed by Sloan (1996), the accruals measure proposed by Richardson, Sloan, Soliman, and Tuna (2005), net operating assets, asset growth, and investment-to-assets. We use these characteristics to construct long-short "factor" portfolios based on U.S. stocks in a manner similar to Fama and French (1993). We focus on low-turnover portfolios that are formed annually, since the sub-rational explanation for the returns to higher frequency portfolios is distinct and typically based on the delayed reaction to specific signals.[1] We then regress the factor portfolio returns on the overall market returns using daily and monthly returns to obtain the factor portfolio betas. We find that all nine factor portfolios exhibit significantly negative betas at either the daily or monthly level, implying that high-characteristic stocks exhibit higher betas than do low-characteristic stocks. Specifically, seven of the nine portfolios exhibit significantly negative betas using daily data, and eight portfolios exhibit significantly negative betas using monthly data. A Composite Factor portfolio constructed by equal-weighting the nine portolios exhibits a beta of -0.09 (t-statistic = 16.9) at the daily level and -0.13 (t-statistic = 7.9) at the monthly level.

The betas of the factor portfolios exhibit considerable time variation. Figure 1 shows that the Composite Factor beta varies from -0.34 to 0.14 (inverted

[1] We apply two further criteria in selecting portfolios. First, the portfolios must be sufficiently distinctive. When portfolios are highly correlated, such as those based on different earnings measures, we only include the portfolio generating the highest Sharpe ratio. Second, the factor returns must be significantly positive at the 5% level during the sample period 1967–2010. The size-based Fama-French portfolio, SMB, failed to meet this criterion, yielding insignificant average returns over the sample period (t-statistic = 1.60). Still, because it is the subject of interest among researchers, we performed the analysis on SMB. The results (not reported) were generally not consistent with those of the remaining variables. This suggests that any possible return differential across size portfolios is unrelated to the trading of naïve investors.

scale) between July 1967 and December 2010, using one-year rolling estimates with daily data. Moreover, Figure 1 shows a striking negative relationship between the level of the Baker and Wurgler (2006) measure of investor sentiment and the Composite Factor beta. This is consistent with the notion that when investor sentiment is high, more naïve investors participate in the stock market, and their impact on prices becomes stronger. As such, the average factor beta can be interpreted as alternative proxy for investor sentiment. Interestingly, the two measures seem to diverge in the post-financial crisis period, in that the Baker-Wurgler investor sentiment measure is neutral while the beta-measure indicates low participation by naïve investors.

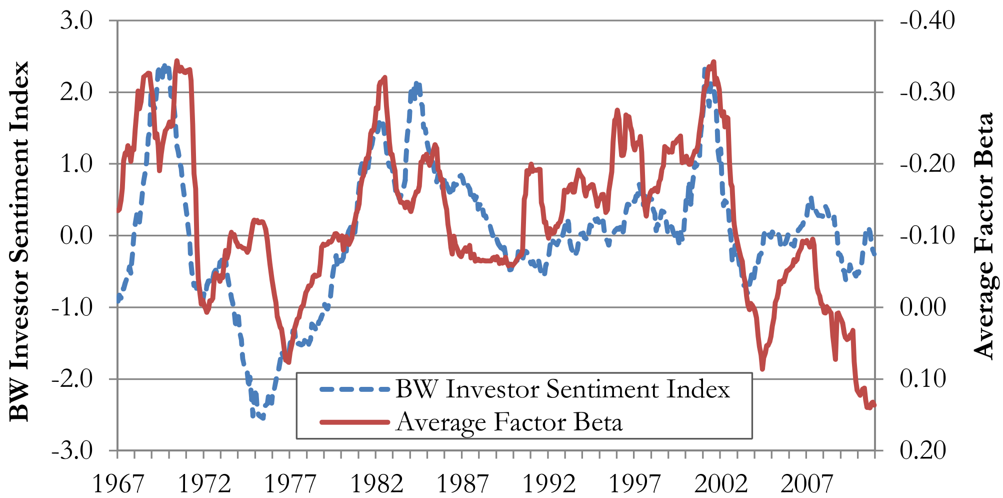

Figure 1: Investor Sentiment and the Average Factor Beta. The Average Factor Beta is the average beta the nine factor portfolios. The beta is updated monthly based on daily returns over the previous 12 months. The BW Investor Sentiment Index is from Jeffrey Wurgler's website, and is constructed as the first principal component of six series: NYSE trading volume; the dividend premium; the closed-end fund discount; the number of IPOs; the first-day return on IPOs; and the equity share in new issues.

If the trading of naïve investors affects systematic risk in the manner suggested, the key prediction is that factor returns will be higher following periods with strongly negative factors betas than following periods with less negative (or positive) factor betas. Consistent with this prediction, time series regressions show that future factor returns are negatively related to the level of beta.

This predictability appears up to two years in the future in that we estimate betas using a one-year rolling window to predict one-month returns up to one year later.

These findings are inconsistent with the standard Sharpe-Lintner CAPM framework, in which the expected excess return on asset i is related to the market excess return r^m by $E[r^i] = \beta^i E[r^m]$. Our Composite Factor has a monthly excess return of 0.344% and a beta of -0.132, which simplistically implies a market excess return of -2.61% per month. The time series regressions with factor returns depending on the level of beta can be interpreted as tests of the Sharpe-Lintner CAPM, with the market excess return as the test statistic. Running the regression $r^i_{t+1} = \beta^i_t E[r^m]$, with the Composite Factor return depending on the prior month's beta (estimated based on daily observations), generates a coefficient estimate of -1.703% (std.error = 0.599%, constant = 0.150%).[2] Forcing the constant term to zero generates a coefficient estimate of -2.268% (std.error = 0.488%). These estimates are significantly different from the observed market excess return of 0.429% per month during our sample period. These tests can be extended to account for the correlation between beta and the market excess return by incorporating interaction terms, and the results are quantitatively very similar.[3]

In addition to the betas of the factor portfolios, we examine other variables related to the impact of naïve investors. First, we expect the volatility of the factors relative to the market volatility to proxy for the impact of naïve traders. This only requires that naïve investors affect relative prices. Their trading need not be correlated with aggregate market movements. Secondly, we expect the dispersion in beta and relative volatility across factors to proxy for the im-

[2]We include many regressions of this form. The constant terms capture the higher-order terms discussed by Lewellen and Nagel (2006).

[3]For example, running the regression $r^i_t = a.\beta^i_{t-1} + b.r^m_t + c.\beta^i_{t-1} r^m_t$ generates a coefficient estimate a of -1.972% (std.error = 0.353%). If instead we use the following month's market excess return as an estimate it's expected value, we can run the regression $r^i_t = a.\beta^i_{t-1} + b.r^m_{t+1} + c.\beta^i_{t-1} r^m_{t+1}$, generating a coefficient estimate a of -2.274% (std.error = 0.475%). These results are not further reported.

pact of naïve investors. The argument is that the characteristics most strongly correlated with the holdings of the biased traders will vary over time. When there are few biased traders, then the corresponding portfolios will not deviate from fundamentals, with a low volatility and a neutral market beta. But when there are many biased traders, then the corresponding portfolios deviate from fundamentals, with high (and varied) volatilities and low (and varied) market betas, and the variation depends on which characteristics are most correlated with the holdings of the biased traders.

Thus far, we have four predictive variables, and the final variable is the first principal component of the four time series. We find that all five variables strongly predict future returns, the most successful being the principal component. In terms of economic magnitude, a one standard deviation move in the level of the principal components translates into a move in the Composite Factor return of 27.6 basis points per month. This compares to the average monthly return on the Composite Factor of 34.4 basis points.

We also examine the ability of the predictive variables to price various portfolios using two-stage Fama-MacBeth regressions. In the first stage, we use time series regressions to estimate the loading of each portfolio on the lagged predictive variable. In the second stage, we use the estimated loadings as the explanatory variable in cross-sectional regressions. We find strong pricing abilities of the predictive variables. For instance, using the 25 Fama-French size/book-to-market portfolios supplemented with 30 industry portfolios, suggested by Lewellen, Nagel, and Shanken (2010), we find that a univariate regression with the first principal component yields an R^2 of 34.9%. By comparison, the Fama-French 3-factor model yields an R^2 of 28.4%.

The paper perhaps closest to ours is Stambaugh, Yu, and Yuan (2012). They demonstrate that the Baker and Wurgler (2006) measure of investor sentiment significantly predicts the short decile of many factors, a finding that we replicate when we examine decile portfolios. They analyze both low- and high-turnover portfolios, but do not analyze factors based on the book-to-market ratio or long-term stock return reversals.[4] The BW Investor Sentiment measure and our covariance measures are correlated and both appear to proxy for the extent to which prices have deviated from fundamentals. We include the BW Investor Sentiment measure as an alternate predictive variable in our tests and find it to have limited predictive ability. Hence our covariance measure appears to be a better proxy for the deviation of prices from fundamentals and as such is useful as a proxy for investor sentiment.

Two other papers use measures of sentiment to predict the value premium specifically. Ben-Rephael, Kandel, and Wohl (2012) base their measure on the investor reallocation between equity and bond funds, and find that a reallocation towards equity funds is followed by a higher value premium. Yu (2011) bases his measure on the dispersion in individual stock analyst forecasts, and similarly finds greater dispersion leads to a higher value premium.

Other papers find that the returns to value-growth sorted portfolios are inconsistent with the Sharpe-Lintner CAPM, including Lewellen and Nagel (2006), Ang and Kristensen (2012), and Roussanov (2010).[5] Campbell and Vuolteenaho (2004) attempt to resolve this by decomposing the market beta into a (transitory) discount-rate news beta and a (permanent) cash-flow news beta. This appears helpful, in that the trading of naïve investors is more strongly correlated with the discount-rate news.[6] However, naïve investors also cause prices to deviate from fundamentals, potentially impacting the return earned for cash-flow risk. Indeed, Campbell and Vuolteenaho find that the price of cash-flow risk is 58%-69% per year (their Table 7), an order of

[4]As mentioned above, we exclude high-turnover portfolios, like Momentum, because such returns are likely driven by the under-reaction to specific signals. Indeed, Stambaugh, Yu, and Yuan (2012) find that BW Investor Sentiment does not significantly predict Momentum returns.

[5]Note that the CAPM relationship can be weakened by time-varying liquidity constraints (Holmström and Tirole, 2001; Acharya and Pedersen, 2005; Brunnermeier and Pedersen, 2009) or leverage constraints (Frazzini and Pedersen, 2010).

[6]Using data downloaded from the American Economic Review website, our Composite Factor has a correlation of 0.581 with their monthly discount-rate news and 0.239 with their cash-flow news.

magnitude greater than the equity premium, which should bound its return.[7]

This paper is related to several further strands of the finance literature. First is the literature on limits to arbitrage.[8] Naïve investors will cause greater price deviations in stocks with stronger limits to arbitrage. Consistent with this, the value premium is stronger for stocks that have low institutional ownership (Nagel, 2005), no analyst coverage (Griffin and Lemmon, 2002), and high idiosyncratic volatility (Ali, Hwang, and Trombley, 2003). Also, stocks with a high idiosyncratic volatility have greater return predictability based on accounting accruals (Mashruwala, Rajgopal, and Shevlin, 2006) or asset growth (Lipson, Mortal, and Schill, 2011; Lam and Wei, 2011) .

Second is the literature on investor heterogeneity and ability. Since the naïve investors achieve negative risk-adjusted returns, we may expect them to have relatively low levels of expertise, experience, and intelligence. Using trade size as a proxy for expertise, Hvidkjaer (2008) finds that stocks with intense small-trade buying activity, relative to selling activity, tend to have had high historic long-term returns and low book-to-market ratios. These stocks subsequently have higher market betas, load negatively on HML, and have low risk-adjusted returns, as also shown by Barber, Odean, and Zhu (2009). Consistent with this, Battalio, Lerman, Livnat, and Mendenhall (2012) find that stocks with an increase in accounting accruals experience small-investor buying pressure. Less experienced investors generally make worse choices and be more prone to biases, and this holds for both individual investors (Feng and Seasholes, 2005) and institutional investors (Greenwood and Nagel, 2009). Indeed, Seru, Shumway, and Stoffman (2010) follow the complete trading records of investors in Finland for eight years and describe a Darwinian process in which some investors learn and become less biased, while others exit the mar-

[7]The cross-sectional price of risk should approximate the time-series price of risk. The equity premium is a return for cash-flow risk and discount-rate risk but, as Campbell and Vuolteenaho argue, long-term investors care primarily about cash-flow risk. Hence the cross-sectional price of cash-flow risk should approximate, but be bounded by, the equity premium.

[8]See also Nagel's (2012) recent review of empirical cross-sectional asset pricing.

ket due to their poor trading performance. Finally, less intelligent investors exhibit worse stock selection ability and enter the the market when aggregate prices are high (Grinblatt, Keloharju, and Linnainmaa, 2012) — they bought technology stocks just as the market reached its peak in 1999–2000, for example.

Third is the literature on dynamic risk preferences, as used in two explanations of the equity premium puzzle. Constantinides (1990) uses a habit-formation model to motivate a fall in investors' risk aversion when asset prices increase. Barberis, Huang, and Santos (2001) present a prospect theory setting in which the degree of loss aversion depends on prior investment performance, which again results in investors' risk aversion falling when asset prices increase. Both explanations result in positive-feedback trading and excess market volatility, and are consistent with the house money effect of Thaler and Johnson (1990), which is so-named due to the tendency of gamblers to increase their stakes when they are winning. This effect appears to be triggered by anything that alters the mood of the market participants, even national sporting events and the local weather (Edmans, Garcia, and Norli, 2007; Hirshleifer and Shumway, 2003).[9]

2. Data and factor portfolio construction

We focus on portfolios formed using characteristics that change only slowly. We use the Book-to-Market Factor, HML, of Fama and French (1993) as the

[9]The neurological evidence for the house-money effect is striking. In the brain, the dopamine system corresponds to pleasure and positive reinforcement, while the insular cortex is more related to pain and negative emotions. Activation of the dopamine system precedes risk-seeking mistakes, while insular cortex activation can be seen before risk-averse mistakes (Kuhnen and Knutson, 2005). Artificially stimulating the dopamine system results in subjects making riskier choices (Knutson, Wimmer, Kuhnen, and Winkielman, 2008), and Parkinsons patients who receive drugs to stimulate dopamine production are prone to becoming compulsive gamblers (Dodd, Klos, Bower, Geda, Josephs, and Ahlskog, 2005). Finally, patients with brain damage to the insular cortex and other emotional processing areas are no longer prone to the house money effect, in contrast to patients with brain damage to other regions (Shiv, Loewenstein, Bechara, Damasio, and Damasio, 2005).

archetype of an anomalous factor based on such a characteristic. All factor portfolios that we construct are based on the method used for HML, with portfolios formed at the end of June each year based on the prior year's accounting data, 70/30 split points based on NYSE stocks only, value-weighted returns calculated for small and large stocks separately, and then the factor being calculated as the average difference between the two low- characteristic portfolios and the two high-characteristic portfolios. We use the standard set of U.S. stocks, with data downloaded from CRSP and Compustat unless otherwise noted, and with returns covering the period July 1967 – December 2010.

Our choice of characteristics to include in the analysis is dictated by three criteria. First, we focus on low-turnover portfolios, i.e., portfolios formed on a yearly basis. Second, when different characteristics are highly correlated, such as different earnings measures, we only include the characteristic generating the highest Sharpe ratio. Third, the corresponding factor portfolio must yield significantly positive returns at the 5% level over the sample period. The series used are:

Book-to-Market. The book-to-market effect was first documented by Stattman (1980) and Rosenberg, Reid, and Lanstein (1985), and has become central to cross-sectional asset pricing following the seminal work of Fama and French (1992, 1993). We use the HML series from Kenneth French's website under the Fama/French Factors series.

Long-Term Reversal. De Bondt and Thaler (1985) find a negative serial correlation in the long-term returns to individual stocks. We use the corresponding factor from Kenneth French's website under the Long-Term Reversal Factor series.

Cash Earnings Yield. Basu (1983) first documented the ability of the earnings-to-price ratio to predict cross-sectional asset prices. We use Operating Income Before Depreciation (Compustat OIBDP) for the year ending in year $t-1$, divided by market value at the end of June in year t. Other profitability/revenue measures were tested and found to generate lower returns and smaller Sharpe Ratios.[10]

Net Stock Issuance. Firms that repurchase equity experience high subsequent returns (Ikenberry, Lakonishok, and Vermaelen, 1995), while firms that issue secondary equity experience low subsequent returns (Spiess and Affleck-Graves, 1995). This inspired Daniel and Titman (2006) to construct a composite equity issuance measure. We follow Fama and French (2008) and define Net Stock Issuance as the percentage change in split-adjusted shares outstanding in the previous year (Compustat CSHO $\times$ ADJEX_C).

Sloan Accruals. Sloan (1996) argues that investors do not fully appreciate the extent to which the accruals component of earnings is transitory, leading high-accruals growth firms to subsequently underperform. We follow his Eq.(1) and define accruals as the change in non-cash working capital, less depreciation, divided by average total assets during the year. Where an item is missing, the change in that item is taken to be zero.

Richardson Accruals. Richardson, Sloan, Soliman, and Tuna (2005) argue that some components of accounting accruals have a greater degree of subjectivity in their measurement, and that these low-reliability accruals are better at predicting future profitability. We use the coefficients from their multivariate regression predicting Return on Assets (Table 5, Panel C, last row) as weights to apply to the different components of accruals (their ΔCOA, ΔCOL, ΔNCOA, ΔNCOL, ΔSTI, ΔLTI, and ΔFINL, scaled by average total assets during the year). This measure of accruals does not include depreciation and the correlation with the Sloan Accruals factor is lower than some of the other factors. Where an item is missing, the change in that item is taken to be zero.

[10] The other numerators tested were Dividends (Compustat DV, or DVC if available), Net Income (Compustat NI), Operating Income After Depreciation (Compustat OIADP), and Sales (Compustat SALE). The other denominators tested were Book Value (Compustat CEQ + TXDITC (if available) – Preferred Stock (PSTKRV, PSTKL, or PSTK, in that order)), and Total Assets (Compustat AT, averaged over the year).

Net Operating Assets. Hirshleifer, Hou, Teoh, and Zhang (2004) argue that investors focus too much on accounting profitability rather than cash flow, implying that net operating assets will negatively predict returns — i.e., that investors overvalue bloated balance sheets. We follow their Eqs.(4)–(6) in defining Net Operating Assets as the difference between operating assets and operating liabilities, scaled by lagged total assets. Except for total assets, where an item is missing, its value is taken to be zero.

Assets Growth. Titman, Wei, and Xie (2004b) argue that investors underreact to the empire building implications of investment expenditures, leading high-investment firms to subsequently underperform. One simple measure of this proposed by Cooper, Gulen, and Schill (2008) is the rate of assets growth, who we follow in defining Assets Growth as the percentage change in Total Assets (Compustat AT) during the year.

Investment-to-Assets. Another proxy for empire-building behaviors is investment expenditures scaled by assets. We follow Chen, Novy-Marx, and Zhang (2011) and define Investment-to-Assets as the annual change in Property, Plant and Equipment (Compustat PPEGT) plus the annual change in Inventories (Compustat INVT), divided by lagged total assets Compustat AT). Where an item is missing, the change in that item is taken to be zero.

Composite Factor. This is calculated as the simple average of the daily (or monthly) returns on the above factors.

Other factors were considered but not included. Financial Distress was estimated using the predictors of Ohlson (1980, Table 4, Model 1), but was found not to generate significant returns using the above methodology. Momentum, Short-Term Reversal, Standardized Unexpected Earnings (Bernard and Thomas, 1989), and Abnormal Capital Investment (Titman, Wei, and Xie, 2004a) were excluded because the underlying characteristics change too rapidly (SUE and ACI are both calculated as the deviation from a trend). External Financing (Bradshaw, Richardson, and Sloan, 2006) was excluded because it overlaps too greatly with Net Stock Issuance, Assets Growth, and Investment-to-Assets.

We use other series as control variables:

Market Premium. This is the Mkt-RF series downloaded from Kenneth French's website under the Fama/French Factors series.

Size. This is the SMB series downloaded from Kenneth French's website under the Fama/French Factors series. This series does not generate significant returns at the 5% level during the time period studied and we do not include it as a factor return to be explained.

Momentum. This is the MOM series downloaded from Kenneth French's website.

Where the risk-free rate is required, we use the one-month Treasury bill rate downloaded from Kenneth French's website under the Fama/French Factors series.

Table 1 shows the summary statistics for the factor returns. The Cash Earnings Yield gives the highest average return with 0.431% per month, comparable to the Market return premium at 0.429% per month. While the other constructed factors yield a lower premium than the market, they all yield a higher Sharpe ratio than the market factor. The low volatility of the factor portfolios contructed from the Richardson Accruals and Net Operating Assets results in those yielding the highest Sharpe ratios among the individual factors at 0.775 and 0.769, respectively. The composite factor yields an average return of 0.344% per month and a Sharpe ratio at 0.783 that is higher than any of the individual factors.

Table 2 presents correlations of the factor returns on both a daily (Panel A) and monthly (Panel B) basis. The table shows that the correlation between most factors is positive and relatively large. Indeed, the average of the 36 correlations in Panel B is 0.354. The correlation is not driven by a common price denominator, as only two of the factors are scaled by stock price (HML and Cash Earnings Yield). Such a positive correlation is clearly consistent with standard risk models, but is it also predicted by the hypothesis that the factor returns are driven by similar underlying investor behavior.

The Sloan Accruals exhibit the lowest correlations with the other factors, followed by the Net Operating Assets. The correlation between the daily returns on the Sloan and the Richardson Accruals factors is a relatively low 0.349, while it is 0.502 using monthly returns.

3. Results

Below we first establish the negative market betas of the factors constructed in Section 2. Then, we turn to constructing the predictive variables in Section 3.2 and examine their predictive value in Section 3.3. In Section 3.4, we examine the cross-sectional evidence of the predictive variable to price various portfolios. Finally, in Section 3.5 we examine possible factor timing strategies based on the signal strengths.

3.1. Factor betas

We establish the negative market beta of the factors in Table 3. As discussed above, this is consistent with the presence of naïve investors who systematically misinterpret firm-specific information and whose trading is positively correlated with the aggregate market return: their trading pushes up the price of high-characteristic stocks when the market increases, resulting in the high-characteristic stocks having high betas and the long-short factor portfolios having negative betas. We find that all nine factor portfolios exhibit significantly negative betas at either the daily or monthly level. Specifically, seven of the nine portfolios exhibit significantly negative betas using daily data, and eight portfolios exhibit significantly negative betas using monthly data. Of the 18 beta estimates, only one is positive, namely that of Net Operating Assets on a daily basis. However, it exhibits a significantly negative beta on a monthly basis. Net Stock Issuance exhibits the most negative beta on both the daily and monthly basis. The composite factor portfolio exhibits a beta of -0.09 (t-statistic = 16.9) at the daily level and -0.13 (t-statistic = 7.9) at the monthly level.

3.2. Construction of predictive variables

Our central research question is whether the time-varying mass of naïve investors predicts future returns. Our first proxy for the mass of naïve investors is the market beta of the factor portfolios. The argument is simple: if naïve investors cause the factor market betas to be negative, then the more negative the factor market betas, the greater the mass of naïve investors. We construct the proxy on a monthly basis using daily returns data for the month, taking the simple average of the market betas of the nine factor portfolios within the month. This generates a monthly non-overlapping series which we summarize in Table 4. The time-series average of the monthly beta values are close to the full-period beta values presented in Table 3. Moreover, there is substantial autocorrelation in the monthly beta values for all factors.

The second proxy for the mass of naïve investors is the relative volatility of the factor portfolios. The argument is again simple: if naïve investors cause common price movements in stocks with similar characteristics, then the higher the volatility of characteristic-sorted portfolios relative to the market, the greater the mass of naïve investors. We construct this proxy on a monthly basis using daily returns data for the month, taking the simple average of the volatilities of the nine factor portfolios within the month, normalized by the volatility of the market. We summarize this series in Table 4.

Baker and Wurgler (2006) develop a measure of investor sentiment which they argue proxies for the level of uninformed demand in the market. Their BW Investor Sentiment measure is constructed as the first principal component of six series: the closed-end fund discount; the equity share in new issues; the number of IPOs; the first-day return on IPOs; NYSE trading volume; and the dividend premium. The latter three series are lagged by 12 months. The BW Investor Sentiment measure is intended to capture a similar type of investor demand as do our proxies, but the construction of the measures is quite different, since we use factor covariances with the market. Figure 1 showed a very strong negative correlation between the composite factor beta and the BW Investor Sentiment measure. Table 5 shows that this correlation extends to the individual factor betas as well as the relative volatilities of the individual factors. We also include betas and relative volatilities that are calculated using daily observations over 12 months – this is reported monthly and so has overlapping observations. Almost all of these proxies are correlated with BW Investor Sentiment, as expected, and the 12-monthly series are more strongly correlated. Only the beta of the Sloan Accruals factor does not appears to be correlated with the BW Invester Sentiment measure. The beta of the Composite Factor exhibits the second-highest correlation with BW Investor Sentiment; only the Long-Term Reversal factor exhibits a higher correlation. This suggests that information is gained from considering all factors jointly rather than investigating the betas of each factors separately.

We construct two further proxies for the mass of naïve investors. One proxy is based on the dispersion between the factor betas and the other is based on the dispersion between the factor volatilities, relative to the market volatility. These require the assumption that the preferences of naïve investors vary over time, such that sometimes accruals better reflect naïve investor trading, while at other times it may be the book-to-market ratio, for example. Then, when there are few naïve investors, the factors will have low volatilities with little dispersion (due to their small magnitude), but when there are many naïve investors, the factors will have high volatilities with high dispersion. The argument about the dispersion in factor betas is analogous. These proxies are also constructed monthly, based on the dispersion between the factors in the market betas and relative volatilities during the month.

Our final proxy for the mass of naïve investors is the first principal component of the other four proxies, which is calculated from the four time series over the period 1967–2010. We thus have six series on which we focus: (i) Average Factor Beta; (ii) Average Factor Relative Volatility; (iii) Standard Deviation(Factor Betas); (iv) Standard Deviation(Factor Relative Volatilities); (v) First Principal Component of (i)–(iv); and (vi) the Baker and Wurgler (2006) Investor Sentiment measure. Summary statistics for these series are presented in Table 6. In the rest of this paper, we investigate the extent to which the mass of naïve investors predicts future factor returns.

3.3. Prediction of factor returns

The initial set of tests are simple time series regressions predicting the return on the various factors. When there is a high mass of naïve investors, prices of high-characteristic stocks have deviated further from fundamentals, and future returns on factors will be higher as prices revert towards fundamentals. This basic argument is tested in Table 7 and the evidence in favor is strong. All of our five Predictive Variables predict the return for most factors. Focusing on the First Principal Component, we see that it significantly predicts seven of the nine factors at the 1% level (t-statistic between 3.05 and 4.87), with the two accruals variables being the exceptions. For control variables, we use the market excess return, the size factor (SMB), and the momentum factor, all of which are downloaded from Kenneth French's website. We do not include a HML as a control, since it is a factor explained by our Predictive Variables and so would confound the regressions. We present results both with and without the controls, and they are found to have relatively little influence on the statistical significance. The BW Investor Sentiment variable does not appear generally to predict factor returns.

We now turn to the longer-horizon predictability of the factors using our proxies for the mass of naïve investors. Such predictability would follow from our basic argument if prices slowly revert to fundamentals. We focus on predicting the Composite Factor return (i.e., the simple average of the factors), since it is less noisy than the individual factors. To avoid the problem of estimating significance with overlapping return periods, we have extended and delayed formation periods for the Predictive Variables. For example, we calculate the Predictive Variables using daily observations for the period two to seven months prior to the Composite Factor return. We present the results in Table 8. The first column of each Panel uses the Predictive Variables with a lag of one month and so reproduces the regressions from Table 7 with the Composite Factor return as the dependent variable. Without exception, our five Predictive Variables significantly predict the Composite Factor return for lag periods of 1 month, 2–7 months, 1–12 months, and 13–24 months. With a lag of 25–36 months, the results are no longer significant, although the regression coefficients retain the anticipated sign. Overall, these findings are consistent with prices slowly reverting to fundamentals following price pressure from the naïve investors. As in table 7, BW Investor Sentiment does not predict future composite factor returns.[11]

We can also use Tables 7 and 8 to assess the economic significance of the predictive regressions. The First Principal Component series are normalized to unit standard deviation over the full time period. Hence the regression coefficients for the First Principal Component series can be interpreted as the change in expected monthly return (in basis points) for a one standard deviation difference in the level of the First Principal Component.[12] From Table 8 we see that the effect varies from 21.0–27.6 basis points. This compares to the

[11]The results in table 8 are qualitatively identical if we exclude the control variables (unreported).

[12]Note that the series are persistent and so the coefficients are not the effect of a one standard deviation shock to the monthly autoregressive processes.

average monthly return on the Composite Factor of 34.4 basis points for the period considered. Clearly, the effect is large. We investigate the market timing implications in more detail later in this section.

As a robustness check, we determine the extent to which the factor returns are predicted by the individual factor covariances, rather than the aggregated factor covariances. E.g., to what extent are the returns to HML predicted by the beta of HML? We present the analysis in Table 9, with monthly factor returns depending on the prior month's covariances from daily observations. While many of the coefficients are not statistically significant, all nine factor returns are negatively predicted by their market betas, and eight of nine are positively predicted by their relative volatilities. This is consistent with the pattern in Table 7. The significance levels are generally much lower than in Table 7, which implies that there is little factor-specific information and that averaging the betas and relative volatilities reduces the amount of noise. This is consistent with the averaged covariances being better proxies for a general mass of naïve investors, whose trading causes price deviations and positive expected returns for each of the factors.

Various authors use decile portfolios in asset pricing papers. For example, Stambaugh, Yu, and Yuan (2012) use decile portfolios to analyze the power of BW Investor Sentiment. In Table 10 we present the average excess returns on decile portfolios formed using the stock characteristics described in the previous section. The portfolios are formed annually at the end of June each year based on the prior year's accounting data, and the break points use only NYSE listed firms. In Table 11 we present the regression coefficients for the Average Factor Beta, First Principal Component, and BW Investor Sentiment predicting the return on each decile portfolio with a one month lag. The overall pattern is similar to Table 7. BW Investor Sentiment has a relatively weak ability to predict the decile returns, although it does significantly predict the short leg (Decile 1) for four of the five anomalies that are also analyzed by Stambaugh, Yu, and Yuan (2012). The other Predictive Variables have a stronger ability to predict the decile returns, including long-short portfolios that are analogous to the factors in Table 7.[13]

3.4. Cross-sectional evidence

So far, we have used aggregation to reduce noise, having factor returns as the dependent variables. An alternative is to use the cross-sectional variation in the decile portfolios, with the 90 decile portfolios in Table 10 as test assets for Fama-MacBeth regressions. This method corrects for cross-sectional correlation in the panel (see Petersen, 2009), which would otherwise be a concern with our portfolio construction. Our approach is standard. We first run time series regressions for each portfolio to determine the sensitivity ("beta") of the portfolio to the factors. We use lagged Predictive Variables to capture the time-variation in portfolio expected return according to the mass of naïve investors. To risk-adjust the portfolio returns, we also include controls for the contemporaneous market excess return (RmRf), the size factor (SMB), and the momentum factor (MOM). In the second step, we run cross-sectional regressions for each month to estimate the factor risk premia ("lambda") as the coefficient on the betas. In the third step, we average the lambdas over time and estimate standard errors.[14] The final step is to regress the average return of portfolio depending on its predicted return–from the Fama-Macbeth procedure–to determine the goodness-of-fit, the regression R^2, of the overall model.

We present the results of the Fama-MacBeth procedure in Table 12, Panel A. With the exception of BW Investor Sentiment, the Predictive Variables all perform well at pricing the decile portfolios. The Predictive Variable t-statistics are all significant, and the R^2 from the regressions of actual average decile re-

[13]The patterns for the other three Predictive Variables (Average Factor Relative Volatility, StDev(Factor Betas), and StDev(Factor Relative Vols)) are almost identical.

[14]We follow the advice of Cochrane (2005) to correct the standard errors for serial correlation and heteroskedasticity. The errors-in-variables correction of Shanken (1992) would be small due to the number of monthly observations.

turn depending on predicted varies from 40.0%–58.3% for the univariate cases. When lagged BW Investor Sentiment is added as a control to the first- and second-stage regressions, it is not significant, it does not reduce the power of the other Predictive Variables, and there is little change to the reported regression R^2 statistics. Similarly, the fitted models do not improve appreciably when we include controls for the contemporaneous market excess return (RmRf), the size factor (SMB), and the momentum factor (MOM).

Lewellen, Nagel, and Shanken (2010) criticize this form of model testing due to generally weak power and the choice of easy test assets to price — from Tables 10 and 11, we know that Average Factor Beta positively predicts the deciles with low returns, and negatively predicts the deciles with high returns, for example. They suggest using the 5×5 Fama-French size/book-to-market portfolios supplemented with 30 industry portfolios as a more rigorous test. We follow their suggestion in Panel B of Table 12. In this case, BW Investor Sentiment has very little predictive power, while the other Predictive Variables perform well. The univariate t-statistics and reported R^2 statistics vary from 1.46 and 10.6% for Average Factor Beta, to 2.41 and 35.8% for StDev (Factor Betas). The First Principal Component statistics are 2.30 and 34.9%. Since these are univariate regressions, the t-statistics also reflect the level of significance of the R^2 statistics. While the power is reduced compared to Panel A, this is not surprising given the large idiosyncratic component of industry returns. Adding BW Investor Sentiment and other controls increases the R^2 statistic somewhat, although Lewellen, Nagel, and Shanken (2010) argue this is a mechanical effect from having more factors. In their Table 1, they report comparable OLS R^2 statistics for other asset-pricing models that are -2% for CAPM 1-factor models, 8% for a 2-factor model, and from 0% to 42% for 3-factor models. They report a Fama-French 3-factor model (Rm, SMB, HML) as having a 31% R^2, which is close to the 28.4% that we find for that model (result not reported). In comparison, three out of four basic Predictive Variables in univariate regressions out-perform the Fama-French 3-factor model, and all four basic Predictive Variables out-perform six out of seven additional asset pricing models analyzed by Lewellen et al. Hence the Predictive Variables perform well in pricing these portfolios.

Overall, the cross-sectional evidence is consistent with the Predictive Variables being proxies for the mass of naïve investors: when there are many such investors, the price of some portfolios deviate far from fundamentals; these portfolios exhibit low (or negative) returns at such times, and low returns on average over the entire time period. The converse holds for portfolios with high expected returns when there are many naïve investors. These patterns are not affected by the contemporaneous movements of the market premium, SMB, or Momentum. Hence the cross-sectional evidence supports the time-series argument that the trading of naïve investors explains the return to factor portfolios.

3.5. Factor timing

Our final analysis considers factor timing strategies, which we present in Table 13. In Panel A we consider portfolio returns which are sorted according to the decile of the prior month's First Principal Component. Since the factors presented in Table 1 follow the Fama-French HML methodology, we can form composite long, medium, and short portfolios that are deconstructed from the factor calculations. Including the medium portfolio allows us to see the relative contribution of the long- and short-sides to the factor sensitivity. Various patterns are noteworthy. The volatility of the long-short portfolio increases with signal strength from 1.254% per month (Low Decile) to 1.967% per month (High Decile), a trend that is less clear in the long-only portfolios. The 3-factor alpha (RmRf, SMB, MOM) is small for the long-short portfolio with low signals, but does not become negative. The market beta of the long-short portfolio becomes more negative with higher signal strength, as expected. Finally, the long- and medium-portfolios appear quite similar, and the divergence of with the short portfolio is increasing with the signal strength, consistent with short-sale constraints limiting arbitrage against the naïve investors. We also include the signal strength from BW Investor Sentiment (Panel B) and the results appear somewhat weaker.

While Table 13 indicates time-varying expected factor returns, the usefulness of these measures for factor timing is unclear. For long-only investors, the primary insight is that the short portfolio is always unattractive, having a higher beta, a higher volatility, and a lower 3-factor alpha, compared to the other portfolios. For long-short investors, the primary insight is that the factor portfolios always have positive expected returns, with those returns being smallest when the factor portfolios have the lowest volatility. Hence this analysis does not indicate a strong benefit from market timing, and we do not attempt to develop implementable trading strategies based on the First Principal Component series.[15]

4. Conclusion

We analyze the hypothesis that returns of portfolios based on characteristics such as asset growth are driven by the behavior of naïve investors whose trading is positively correlated with aggregate market returns. Because they have a preference for stocks with certain characteristics, say high asset growth, we expect such stocks to exhibit high systematic risk. The equivalent long-short portfolio will thus exhibit negative systematic risk.

We examine the market betas of factor portfolios based on nine different characteristics: Book-to-market, long-term reversals, cash earnings yield, net stock issuance, Sloan accruals, Richardson accruals, net operating assets, asset growth, and investment-to-assets. All factor portfolios exhibit negative betas

[15]Both the weights for the First Principal Component series and the decile break points use data for the entire period, so timing strategies from Table 13 are not ex ante implementable.

at either the daily or monthly level. Moreover, the average negative beta is highly correlated with the Baker and Wurgler (2006) investor sentiment index, consistent with the notion that when sentiment is high, the mass of naïve investors is also high.

If the trading behavior of naïve investors drive the returns to factor portfolios, then we expect that a more negative betas results in future higher returns. Indeed, we find strong and robust evidence of such predictability. We also find the factor returns are predicted by the average relative volatility of the factor portfolios, and the dispersion of the factor betas and relative volatilities.

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Table 1: Factor Summary Statistics. This table presents the mean, minimum, maximum, and standard deviation of the percentage monthly return, together with the calculated Sharpe Ratio, for the factors and the Market Premium. The Market Premium, HML, and Long-Term Reversal series are from Kenneth French's website. All other factors are calculated using the same basic methodology of HML. The Composite Factor is calculated as the simple average of the monthly returns of the other factors. The returns are for the period July 1967 to December 2010. (n. obs. = 522)

	Mean	t(Mean)	Std.Dev.	Min	Max	Sharpe
Market Premium (Rm-Rf)	0.429	(2.10)	4.66	−23.1	16.1	0.319
Book-to-Market (HML)	0.404	(3.04)	3.04	−12.9	13.9	0.461
Long-Term Reversal	0.330	(2.88)	2.61	−7.8	14.5	0.438
Cash Earnings Yield	0.431	(3.02)	3.26	−21.8	12.9	0.458
Net Stock Issuance	0.368	(3.82)	2.20	−14.9	9.0	0.579
Sloan Accruals	0.272	(3.45)	1.80	−6.7	6.4	0.524
Richardson Accruals	0.328	(5.11)	1.47	−5.4	5.9	0.775
Net Operating Assets	0.319	(5.07)	1.44	−6.3	6.4	0.769
Assets Growth	0.378	(4.24)	2.03	−6.5	8.7	0.644
Investment-to-Assets	0.268	(2.69)	2.28	−9.3	8.8	0.408
Composite Factor	0.344	(5.16)	1.52	−4.8	6.8	0.783

Table 2: Factor Cross-Correlations. This table presents the cross correlations of the factor returns on a daily and monthly basis. The HML and Long-Term Reversal series are from Kenneth French's website. All other factors are calculated using the same basic methodology as HML. The returns are for the period July 1967 to December 2010. (Significance levels: * = 10%, ** = 5%, and *** = 1%; n.obs. = 10,950 in Panel A and 522 in Panel B.)

Panel A: Correlations Based on Daily Observations

	HML	LTRev	CEY	NSI	SAccr	RAccr	NOA	AssetGr	ItoA
Book-to-Market (HML)	1.000								
Long-Term Reversal	0.436***	1.000							
Cash Earnings Yield	0.861***	0.285***	1.000						
Net Stock Issuance	0.467***	0.225***	0.507***	1.000					
Sloan Accruals	−0.106***	−0.012	−0.196***	−0.078***	1.000				
Richardson Accruals	0.300***	0.350***	0.211***	0.353***	0.349***	1.000			
Net Operating Assets	0.065***	0.216***	0.050***	0.086***	−0.099***	0.361***	1.000		
Assets Growth	0.590***	0.510***	0.463***	0.589***	0.153***	0.573***	0.199***	1.000	
Investment-to-Assets	0.643***	0.433***	0.626***	0.494***	−0.299***	0.439***	0.471***	0.580***	1.000

Panel B: Correlations Based on Monthly Observations

	HML	LTRev	CEY	NSI	SAccr	RAccr	NOA	AssetGr	ItoA
Book-to-Market (HML)	1.000								
Long-Term Reversal	0.421***	1.000							
Cash Earnings Yield	0.898***	0.285***	1.000						
Net Stock Issuance	0.620***	0.160***	0.631***	1.000					
Sloan Accruals	0.020	0.085*	−0.092**	−0.077*	1.000				
Richardson Accruals	0.411***	0.288***	0.311***	0.385***	0.502***	1.000			
Net Operating Assets	0.026	0.184***	−0.073*	0.116***	−0.020	0.372***	1.000		
Assets Growth	0.718***	0.500***	0.597***	0.617***	0.212***	0.631***	0.261***	1.000	
Investment-to-Assets	0.678***	0.345***	0.629***	0.636***	−0.186***	0.513***	0.429***	0.696***	1.000

Table 3: Factor Market Betas. This table presents factor market betas, with observations taken either daily or monthly. The Market Premium, HML, and Long-Term Reversal series are from Kenneth French's website. All other factors are calculated using the same basic methodology of HML. The Composite Factor is calculated as the simple average of the returns of the other factors. The returns are for the period July 1967 to December 2010. (robust t-statistics in parentheses, n.obs.=10,950 for Daily Observations and 522 for Monthly Observations.)

	Daily Observations		Monthly Observations	
	Beta	(t-statistic)	Beta	(t-statistic)
Book-to-Market (HML)	−0.155	(−12.28)	−0.207	(−5.29)
Long-Term Reversal	−0.067	(−5.79)	−0.035	(−0.96)
Cash Earnings Yield	−0.126	(−9.04)	−0.189	(−4.69)
Net Stock Issuance	−0.192	(−28.23)	−0.243	(−11.30)
Sloan Accruals	−0.008	(−1.33)	−0.048	(−2.23)
Richardson Accruals	−0.065	(−15.08)	−0.095	(−6.16)
Net Operating Assets	0.021	(4.37)	−0.041	(−2.71)
Assets Growth	−0.147	(−19.91)	−0.180	(−8.54)
Investment-to-Assets	−0.108	(−11.18)	−0.146	(−6.02)
Composite Factor	−0.094	(−16.92)	−0.132	(−7.89)

Table 4: Monthly Variables Based on Daily Observations. This table presents summary statistics for the Market Beta and Relative Volatility series for the factors, calculated monthly using daily returns data from within the month. The Market Premium, HML, and Long-Term Reversal series are from Kenneth French's website. All other factors are calculated using the same basic methodology of HML. The Composite Factor is calculated as the simple average of the returns of the other factors. The returns are for the period July 1967 to December 2010. (n.obs.=522.)

	Market Beta			Relative Volatility		
	Mean	StDev	Autocor	Mean	StDev	Autocor
Book-to-Market (HML)	−0.226	0.256	0.748	0.497	0.189	0.560
Long-Term Reversal	−0.046	0.269	0.781	0.471	0.181	0.479
Cash Earnings Yield	−0.208	0.256	0.693	0.525	0.219	0.593
Net Stock Issuance	−0.187	0.170	0.685	0.392	0.175	0.732
Sloan Accruals	−0.013	0.132	0.539	0.337	0.133	0.476
Richardson Accruals	−0.075	0.139	0.656	0.315	0.134	0.559
Net Operating Assets	0.027	0.120	0.475	0.318	0.130	0.432
Assets Growth	−0.146	0.192	0.741	0.404	0.179	0.636
Investment-to-Assets	−0.148	0.185	0.656	0.414	0.178	0.621
Composite Factor	−0.114	0.132	0.759	0.408	0.137	0.593

Table 5: BW Investor Sentiment and Factor Covariances. This table presents the correlation between BW Investor Sentiment and the Market Betas of the individual factors (Panel A) and the Relative Volatilities of the individual factors (Panel B). The Market Betas and Relative Volatilities are calculated using daily observations from the month (left columns) or from the 12 months ending with the focal month (right columns). The Market Premium, HML, and Long-Term Reversal series are from Kenneth French's website. All other factors are calculated using the same basic methodology of HML. The Composite Factor is calculated as the simple average of the returns of the other factors. The BW Investor Sentiment measure is from Jeffrey Wurgler's website. The returns are for the period July 1967 to December 2010. (robust t-statistics from the corresponding regression are in parentheses; Significance levels: *=10%, ** = 5%, and *** = 1%; n.obs.=522.)

	Monthly		12-Monthly	
	Correlation	t-statistic	Correlation	t-statistic
Panel A: BW Investor Sentiment and Factor Market Betas				
Book-to-Market (HML)	−0.397	(−9.86)***	−0.488	(−12.75)***
Long-Term Reversal	−0.608	(−17.45)***	−0.630	(−18.48)***
Cash Earnings Yield	−0.249	(−5.85)***	−0.432	(−10.93)***
Net Stock Issuance	−0.234	(−5.48)***	−0.304	(−7.27)***
Sloan Accruals	−0.056	(−1.28)	−0.006	(−0.14)
Richardson Accruals	−0.223	(−5.22)***	−0.250	(−5.90)***
Net Operating Assets	−0.279	(−6.62)***	−0.335	(−8.11)***
Assets Growth	−0.416	(−10.43)***	−0.462	(−11.88)***
Investment-to-Assets	−0.299	(−7.16)***	−0.448	(−11.44)***
Composite Factor	−0.486	(−12.68)***	−0.566	(−15.67)***
Panel B: BW Investor Sentiment and Factor Relative Volatilities				
Book-to-Market (HML)	0.346	(8.40)***	0.507	(13.40)***
Long-Term Reversal	0.132	(3.05)***	0.239	(5.61)***
Cash Earnings Yield	0.260	(6.15)***	0.437	(11.07)***
Net Stock Issuance	0.247	(5.81)***	0.342	(8.30)***
Sloan Accruals	0.119	(2.72)***	0.262	(6.20)***
Richardson Accruals	0.151	(3.49)***	0.239	(5.61)***
Net Operating Assets	0.075	(1.72)*	0.216	(5.05)***
Assets Growth	0.335	(8.11)***	0.452	(11.54)***
Investment-to-Assets	0.242	(5.69)***	0.398	(9.88)***
Composite Factor	0.274	(6.49)***	0.433	(10.96)***

Table 6: Predictive Variables. This table presents combinations of the factor covariances which will be used as Predictive Variables. All covariances are calculated monthly, based on daily observations of factor returns within the month. The factors used to calculate averages are: HML, Long-Term Reversal, Cash Earnings Yield, Net Stock Issuance, Sloan Accruals, Richardson Accruals, Net Operating Assets, Assets Growth, and Investment-to-Assets. The Average Factor Beta is the average of the market betas of the factors. The Average Factor Relative Volatility is the average of the daily volatilities of the factors divided by the market premium daily volatility. The Standard Deviation Factor Betas: for each factor and each month, the market beta is calculated based on daily observations within the month, and the standard deviation is then calculated across the factors. The Standard Deviation Factor Relative Volatility: for each factor and each month, the volatility relative to the market premium is calculated based on daily observations within the month, and the standard deviation is then calculated across the factors. The First Principal Component is the first principal component of the four variables described above (i.e., not including BW Investor Sentiment). The BW Investor Sentiment measure is from Jeffrey Wurgler's website. The returns are for the period July 1967 to December 2010. (n.obs. = 522; Significance levels: * = 10%, ** = 5%, and *** = 1%.)

Panel A: Summary Statistics

	Mean	Std.Dev.	Autocorr
Average Factor Beta	−0.114	0.132	0.759***
Average Fact Relative Vol	0.408	0.137	0.593***
Stdev (Factor Betas)	0.167	0.072	0.496***
Stdev (Fact Relative Vols)	0.120	0.057	0.555***
First Principal Component	0.000	1.000	0.609***
BW Investor Sentiment	0.058	0.983	0.992***

Panel B: Correlation Coefficients

	AFB	AFRVol	SDFB	SDFRV	FPC
Average Factor Beta	1.000				
Average Fact Relative Vol	−0.443***	1.000			
Stdev (Factor Betas)	−0.204***	0.535***	1.000		
Stdev (Fact Relative Vols)	−0.331***	0.710***	0.700***	1.000	
First Principal Component	−0.560***	0.868***	0.798***	0.899***	1.000
BW Investor Sentiment	−0.486***	0.274***	0.059	0.275***	0.320***

Table 7: Factor Covariances Predict Factor Returns. This table presents regressions with factor returns depending on the prior month's Predictor and the current month's control variables (Market Premium, Size, and Momentum). The control variables are downloaded from Kenneth French's website. The regression coefficients on the Predictor are presented, along with the regression R^2. The Predictors are all calculated based on daily observations within the month, except for BW Investor Sentiment, which is from Jeffrey Wurgler's website. The factors used to calculate averages and standard deviations are: HML, Long-Term Reversal, Cash Earnings Yield, Net Stock Issuance, Sloan Accruals, Richardson Accruals, Net Operating Assets, Assets Growth, and Investment-to-Assets. The Predictors are: (i) Average Factor Beta: the average of the market betas of the factors; (ii) Average Factor Relative Volatility: the average of the daily volatilities of the factors divided by the market premium daily volatility; (iii) Standard Deviation Factor Betas: for each factor and each month, the market beta is calculated based on daily observations within the month, and the standard deviation is then calculated across the factors; (iv) Standard Deviation Factor Relative Volatilities: for each factor and each month, the volatility relative to the market premium is calculated based on daily observations within the month, and the standard deviation is then calculated across the factors. (v) First Principal Component: the first principal component (normalized to unit standard deviation) of the four series (i)–(iv) above; and (vi) BW Investor Sentiment. The returns are for the period July 1967 to December 2010. (n.obs. = 522; robust t-statistics in parentheses; significance levels: * = 10%, ** = 5%, and *** = 1%.)

$$R_t = c + d\cdot\text{Predictor}_{t-1} + e\cdot\text{RmRf}_t + f\cdot\text{SMB}_t + g\cdot\text{MOM}_t + u_t$$

	With Controls			Without Controls			With Controls			Without Controls		
	d	t(d)	R^2	d	t(d)	R^2	d	t(d)	R^2	d	t(d)	R^2
	Predictor: Average Factor Beta						Predictor: Average Factor Relative Volatility					
Book-to-Market (HML)	−2.056	(−1.82)*	0.174	−1.723	(−1.51)	0.006	2.751	(3.11)***	0.181	3.081	(3.19)***	0.019
Long-Term Reversal	−2.246	(−2.17)**	0.107	−2.010	(−1.92)*	0.010	1.951	(2.56)**	0.105	1.971	(2.44)**	0.011
Cash Earnings Yield	−2.290	(−2.06)**	0.256	−1.506	(−1.29)	0.004	2.958	(3.24)***	0.263	3.214	(3.15)***	0.018
Net Stock Issuance	−1.855	(−2.89)***	0.412	−2.071	(−2.41)**	0.015	1.662	(3.27)***	0.411	2.116	(3.26)***	0.017
Sloan Accruals	1.108	(1.44)	0.046	0.848	(1.17)	0.004	−0.801	(−1.30)	0.043	−0.690	(−1.13)	0.003
Richardson Accruals	−0.890	(−1.66)*	0.140	−1.090	(−2.02)**	0.009	0.385	(0.86)	0.136	0.574	(1.23)	0.003
Net Operating Assets	−2.093	(−4.11)***	0.068	−2.226	(−4.25)***	0.041	1.315	(3.19)***	0.048	1.397	(3.33)***	0.018
Assets Growth	−2.079	(−2.80)***	0.196	−2.077	(−2.63)***	0.018	1.469	(2.45)**	0.188	1.781	(2.70)***	0.014
Investment-to-Assets	−3.523	(−4.07)***	0.170	−3.474	(−3.86)***	0.040	2.855	(4.34)***	0.159	3.107	(4.37)***	0.035
Composite Factor	−1.769	(−3.15)***	0.222	−1.703	(−2.84)***	0.021	1.616	(3.75)***	0.220	1.839	(3.84)***	0.027

	With Controls			Without Controls			With Controls			Without Controls		
	d	t(d)	R^2	d	t(d)	R^2	d	t(d)	R^2	d	t(d)	R^2
	Predictor: StDev (Factor Betas)						Predictor: StDev (Factor Relative Vols)					
Book-to-Market (HML)	5.008	(2.51)**	0.180	5.781	(2.59)***	0.019	7.202	(3.02)***	0.184	8.716	(3.20)***	0.027
Long-Term Reversal	3.318	(2.02)**	0.103	3.881	(2.25)**	0.011	6.066	(2.91)***	0.112	6.562	(2.95)***	0.020
Cash Earnings Yield	5.175	(2.35)**	0.261	6.199	(2.49)**	0.018	6.819	(2.69)***	0.262	8.542	(2.86)***	0.022
Net Stock Issuance	3.417	(2.75)***	0.412	3.723	(2.11)**	0.015	5.075	(3.30)***	0.417	6.341	(3.04)***	0.027
Sloan Accruals	−2.117	(−1.52)	0.046	−2.184	(−1.64)	0.008	−1.841	(−1.10)	0.042	−1.720	(−1.04)	0.003
Richardson Accruals	−0.001	(0.00)	0.134	0.045	(0.05)	0.000	1.499	(1.34)	0.138	1.912	(1.65)*	0.005
Net Operating Assets	1.624	(1.89)*	0.039	1.626	(1.79)*	0.007	3.666	(3.24)***	0.053	3.792	(3.17)***	0.022
Assets Growth	2.219	(1.76)*	0.184	2.759	(1.96)*	0.009	4.465	(2.97)***	0.194	5.610	(3.23)***	0.025
Investment-to-Assets	4.219	(3.02)***	0.147	4.547	(2.83)***	0.020	7.185	(4.06)***	0.162	8.051	(3.93)***	0.040
Composite Factor	2.540	(2.80)***	0.213	2.931	(2.83)***	0.019	4.459	(4.09)***	0.227	5.312	(4.12)***	0.039
	Predictor: First Principal Component						Predictor: BW Investor Sentiment					
Book-to-Market (HML)	0.449	(3.27)***	0.188	0.504	(3.23)***	0.028	0.051	(0.35)	0.166	0.139	(0.92)	0.002
Long-Term Reversal	0.355	(3.08)***	0.113	0.373	(3.04)***	0.020	0.050	(0.39)	0.095	0.004	(0.03)	0.000
Cash Earnings Yield	0.462	(3.09)***	0.268	0.510	(3.02)***	0.024	0.134	(0.92)	0.249	0.221	(1.50)	0.004
Net Stock Issuance	0.313	(3.80)***	0.420	0.374	(3.20)***	0.029	0.133	(1.68)*	0.403	0.264	(2.74)***	0.014
Sloan Accruals	−0.155	(−1.59)	0.047	−0.142	(−1.52)	0.006	−0.171	(−2.25)**	0.048	−0.145	(−1.92)*	0.006
Richardson Accruals	0.074	(1.20)	0.137	0.099	(1.50)	0.005	−0.044	(−0.73)	0.135	0.007	(0.10)	0.000
Net Operating Assets	0.234	(4.03)***	0.058	0.245	(4.02)***	0.029	0.165	(3.23)***	0.045	0.177	(3.33)***	0.015
Assets Growth	0.270	(3.05)***	0.196	0.321	(3.16)***	0.025	0.050	(0.55)	0.179	0.112	(1.09)	0.003
Investment-to-Assets	0.479	(4.87)***	0.174	0.515	(4.56)***	0.051	0.186	(1.87)*	0.136	0.256	(2.46)**	0.012
Composite Factor	0.276	(4.37)***	0.232	0.311	(4.19)***	0.042	0.062	(0.90)	0.201	0.115	(1.51)	0.005

Table 8: Longer-Horizon Return Predictability. This table determines the extent to which various measures predict the monthly Composite Factor return, with the Predictors calculated over various horizons. The Predictors are calculated as in Table 6, but using daily observations from month L_a to month L_b prior to the return month. For example, in Column 3, each Predictor is calculated based on daily observations over the prior 2–7 months and then used to predict the monthly Composite Factor return with an OLS regression with controls for RmRf, SMB, and MOM. The First Principal Component series are normalized to unit standard deviation. The returns are for the period July 1967 to December 2010. (Robust t-statistics in parentheses; significance levels: * = 10%, ** = 5%, and *** = 1%; n.obs. = 522.)

$$R_t = c + d \cdot [L_a\text{–}L_b]\text{Predictor} + e \cdot \text{RmRf}_t + f \cdot \text{SMB}_t + g \cdot \text{MOM}_t + u_t$$

	Predictor Calculated Over Month Lags:				
Predictor	1	2–7	1–12	13–24	25–36
Average Factor Beta	−1.769	−1.392	−1.280	−1.289	−0.885
	(−3.15)***	(−2.29)**	(−1.99)**	(−2.12)**	(−1.45)
Avg Factor Relative Volatility	1.616	1.474	1.582	1.876	0.254
	(3.75)***	(2.45)**	(2.39)**	(2.89)***	(0.42)
StDev (Factor Betas)	2.540	4.032	4.862	4.258	0.699
	(2.80)***	(3.00)***	(3.10)***	(2.72)***	(0.60)
StDev (Factor Relative Vols)	4.459	5.088	6.636	4.468	0.305
	(4.09)***	(3.37)***	(3.77)***	(2.57)**	(0.22)
First Principal Component	0.276	0.238	0.248	0.210	0.041
	(4.37)***	(3.38)***	(3.35)***	(3.01)***	(0.72)
BW Investor Sentiment	0.062	0.058	0.062	0.009	−0.030
	(0.89)	(0.85)	(0.90)	(0.16)	(−0.56)

Table 9: Individual Factor Covariances Predict Factor Returns. This table presents regressions with factor returns depending on the prior month's factor covariance and the current month's control variables (Market Premium, Size, and Momentum). The control variables are from Kenneth French's website. The regression coefficients on the factor covariances, d, are presented. The returns are for the period July 1967 to December 2010. (n.obs.=522; robust t-stats in parentheses; significance levels: * = 10%, ** = 5%, and *** = 1%.)

$$R_t = c + d \cdot \text{FactorCovar}_{t-1} + e \cdot \text{RmRf}_t + f \cdot \text{SMB}_t + g \cdot \text{MOM}_t + u_t$$

	With Controls			Without Controls			With Controls			Without Controls		
	d	t(d)	R^2	d	t(d)	R^2	d	t(d)	R^2	d	t(d)	R^2
	Factor Covariance: Factor Beta						Factor Covariance: Factor Relative Volatility					
Book-to-Market (HML)	−1.110	(−1.68)*	0.174	−0.941	(−1.43)	0.006	2.003	(2.82)***	0.182	2.312	(3.02)***	0.021
Long-Term Reversal	−0.605	(−1.19)	0.098	−0.608	(−1.17)	0.004	1.731	(2.63)***	0.109	1.753	(2.59)***	0.015
Cash Earnings Yield	−1.370	(−2.17)**	0.259	−1.056	(−1.43)	0.007	1.194	(1.93)*	0.254	1.561	(2.02)**	0.011
Net Stock Issuance	−1.172	(−2.37)**	0.408	−1.398	(−2.06)**	0.012	1.207	(2.68)***	0.409	1.683	(2.71)***	0.018
Sloan Accruals	−0.218	(−0.30)	0.039	−0.038	(−0.05)	0.000	−0.192	(−0.32)	0.039	−0.144	(−0.23)	0.000
Richardson Accruals	−0.748	(−1.32)	0.139	−0.694	(−1.17)	0.004	0.103	(0.20)	0.134	0.119	(0.21)	0.000
Net Operating Assets	−0.141	(−0.25)	0.032	−0.240	(−0.43)	0.000	0.036	(0.07)	0.032	0.075	(0.15)	0.000
Assets Growth	−1.423	(−2.64)***	0.196	−1.452	(−2.47)**	0.019	1.299	(2.60)***	0.191	1.517	(2.68)***	0.018
Investment-to-Assets	−2.369	(−3.32)***	0.166	−2.223	(−3.04)***	0.032	1.747	(2.83)***	0.148	1.719	(2.53)**	0.018

Table 10: Decile Portfolio Average Excess Returns. This table presents the mean monthly return of decile portfolios in excess of the risk free rate. The Long-Term Reversal deciles and the risk free rate are from Kenneth French's website. The other deciles are formed at the end of June each year based on accounting data from the prior year. The break points use only NYSE listed firms. Since the long-short portfolios are zero-investment, they are not adjusted for the risk free rate. The Slope*10 portfolio is based on the slope each month in the decile returns, and is equivalent to investing an amount proportional to the distance from the center point (5.5). The returns are for the period July 1967 to December 2010. (Robust t-statistics in parentheses; significance levels: * = 10%, ** = 5%, and *** = 1%; n.obs.=522.)

		Decile							Long–Short			
	Order	1	2	3	...	8	9	10	10–1		Slope*10	
Book-to-Market	L–H	0.337	0.439	0.448		0.633	0.722	0.789	0.452	(2.07)**	0.450	(2.28)**
Long-Term Reversal	H–L	0.376	0.394	0.493		0.690	0.701	0.872	0.496	(2.19)**	0.461	(2.11)**
Cash Earnings Yield	L–H	0.304	0.361	0.447		0.604	0.843	0.752	0.448	(2.11)**	0.532	(2.74)***
Net Stock Issuance	H–L	0.104	0.219	0.468		0.461	0.669	0.720	0.616	(5.33)***	0.493	(3.75)***
Sloan Accruals	H–L	0.163	0.356	0.312		0.546	0.405	0.510	0.347	(2.28)**	0.293	(1.98)**
Richardson Accruals	H–L	0.132	0.278	0.396		0.473	0.621	0.665	0.533	(4.49)***	0.468	(4.18)***
Net Operating Assets	H–L	0.039	0.446	0.315		0.571	0.507	0.570	0.531	(4.21)***	0.428	(4.17)***
Assets Growth	H–L	0.145	0.410	0.433		0.598	0.702	0.693	0.548	(3.81)***	0.481	(3.22)***
Investment-to-Assets	H–L	0.232	0.364	0.427		0.622	0.538	0.676	0.445	(3.10)***	0.388	(2.55)**
Composite		0.203	0.363	0.415		0.601	0.640	0.665	0.462	(4.69)***	0.438	(4.46)***

Table 11: Predicting Decile Portfolio Returns. This table determines the extent to which various measures predict the monthly excess return on decile portfolios. The Predictors are calculated as in Table 6, using daily observations from the prior month. Since the long-short portfolios are zero-investment, they are not adjusted for the risk free rate. The Slope*10 portfolio is based on the slope each month in the decile returns, and is equivalent to investing an amount proportional to the distance from the center point (5.5). The returns are for the period July 1967 to December 2010. (* = 5% significance level; ** = 1% significance level; n.obs.=522.)

Estimates of coefficient d from time series regressions of decile excess return:

$$R_t - Rf_t = c + d{\cdot}\text{Predictor}_{t-1} + e{\cdot}\text{RmRf}_t + f{\cdot}\text{SMB}_t + g{\cdot}\text{MOM}_t + u_t$$

	Decile							Long–Short	
	1	2	3	...	8	9	10	10–1	Slope*10
Panel A: Portfolio Return Predicted by Average Factor Beta									
Book-to-Market	1.218*	−0.152	−0.884*		−1.364	−1.375	−2.045	−3.263 (−1.77)*	−2.565 (−1.60)
Long-Term Reversal	1.766**	0.015	−0.213		−1.370	−3.186***	−1.078	−2.844 (−1.52)	−3.493 (−1.96)**
Cash Earnings Yield	1.068	0.587	−0.712		−1.630*	−1.559*	−1.793	−2.861 (−1.64)	−2.953 (−1.96)**
Net Stock Issuance	0.829	0.702	0.482		−1.149	−2.541***	−1.048*	−1.877 (−2.07)**	−3.092 (−3.33)***
Sloan Accruals	−0.031	−0.525	−1.342**		0.210	−0.100	2.224**	2.255 (1.58)	1.996 (1.34)
Richardson Accruals	1.603**	0.919*	−0.455		−0.413	−1.376**	0.459	−1.144 (−1.21)	−1.505 (−1.64)
Net Operating Assets	2.129***	−0.548	0.858		−1.005	−0.699	−1.681***	−3.810 (−4.03)***	−2.810 (−3.33)***
Assets Growth	2.610***	0.220	−0.270		−1.627***	−0.877	−0.826	−3.436 (−2.61)***	−2.844 (−2.20)**
Investment-to-Assets	2.390***	1.824***	1.300*		−2.349***	−2.353***	−1.051	−3.440 (−2.81)***	−4.955 (−3.55)***
Composite Factor	1.509***	0.338	−0.137		−1.343***	−1.397***	−0.771*	−2.280 (−2.71)***	−2.451 (−2.88)***

	Decile							Long–Short			
	1	2	3	...	8	9	10	10–1		Slope*10	
Panel B: Portfolio Return Predicted by First Principal Component											
Book-to-Market	−0.223**	0.021	0.156*		0.254*	0.319**	0.296*	0.519	(2.48)**	0.470	(2.56)**
Long-Term Reversal	−0.289***	0.032	0.015		0.250**	0.379***	0.387**	0.675	(3.10)***	0.626	(3.09)***
Cash Earnings Yield	−0.277***	−0.033	0.115		0.298**	0.312**	0.318*	0.595	(2.39)**	0.561	(2.73)***
Net Stock Issuance	−0.314***	−0.138*	0.016		0.047	0.278**	0.104	0.418	(3.92)***	0.463	(4.31)***
Sloan Accruals	0.083	−0.061	0.102		−0.015	−0.089	−0.318***	−0.400	(−2.32)**	−0.279	(−1.47)
Richardson Accruals	−0.309***	−0.043	0.084		−0.033	0.176**	−0.126	0.183	(1.62)	0.153	(1.37)
Net Operating Assets	−0.338***	0.007	−0.140		0.078	0.184**	0.262***	0.600	(4.68)***	0.493	(5.13)***
Assets Growth	−0.397***	−0.012	0.110		0.150*	0.128	0.181*	0.578	(3.49)***	0.385	(2.29)**
Investment-to-Assets	−0.344***	−0.266***	−0.203**		0.336***	0.284***	0.108	0.452	(3.31)***	0.659	(3.78)***
Composite Factor	−0.268***	−0.055	0.028		0.177***	0.200***	0.128**	0.396	(3.87)***	0.388	(3.89)***
Panel C: Portfolio Return Predicted by BW Investor Sentiment											
Book-to-Market	0.005	0.038	0.059		−0.033	−0.072	−0.019	−0.024	(−0.11)	−0.108	(−0.54)
Long-Term Reversal	−0.061	−0.048	−0.013		0.069	0.062	−0.051	0.010	(0.04)	0.060	(0.27)
Cash Earnings Yield	−0.030	−0.030	0.008		−0.034	0.078	−0.038	−0.008	(−0.03)	0.024	(0.11)
Net Stock Issuance	−0.258***	−0.023	0.068		0.094	0.134	−0.048	0.211	(1.83)*	0.168	(1.35)
Sloan Accruals	−0.019	0.027	0.049		−0.127*	−0.145*	−0.131	−0.112	(−0.74)	−0.179	(−1.21)
Richardson Accruals	−0.117	0.043	0.138**		0.046	−0.018	−0.157*	−0.040	(−0.35)	−0.078	(−0.70)
Net Operating Assets	−0.306***	0.101	0.018		0.079	0.092	0.117	0.423	(3.87)***	0.238	(2.64)***
Assets Growth	−0.287***	−0.012	0.087		0.029	−0.106	−0.197*	0.090	(0.58)	−0.007	(−0.05)
Investment-to-Assets	−0.169**	−0.069	0.011		0.071	0.113	−0.050	0.119	(0.88)	0.184	(1.16)
Composite Factor	−0.138**	0.003	0.047*		0.026	−0.005	−0.048	0.090	(0.85)	0.035	(0.33)

Table 12: Fama-MacBeth Regressions Predicting Portfolio Returns. This table presents Fama-MacBeth regression coefficients and corresponding t-statistics for the 90 decile portfolios in Table 9, excluding the Composite portfolios (Panel A), and the 55 Fama-French portfolios, comprising 25 size-B/M portfolios together with 30 industry portfolios (Panel B). The Predictor variable is included in each first-stage regression with a 1-month lag, as is BW Investor Sentiment. The Predictors are calculated as in Table 5, using daily observations during the month, and are all normalized to zero mean and unit standard deviation. The control variables, RmRf, SMB, and MOM, are included contemporaneously. Each row of the table corresponds to a separate Fama-MacBeth regression including different Predictor and control variables. The adjusted R^2 reported is from a cross-sectional regression with the average return on each of the portfolios depending on its predicted return from the Fama-MacBeth coefficients. The control variables and Fama-French portfolios are from Kenneth French's website and the BW Investor Sentiment measure is from Jeffrey Wurgler's website. The returns are for the period July 1967 to December 2010. (Newey-West t-statistics with 6 lags in parentheses; significance levels: * = 10%, ** = 5%, and *** = 1%; no.portfolios=90 (Panel A) and 55 (Panel B); no.periods=522.)

First Stage: Time-Series Regressions for each portfolio i:

$$R_{i,t} - Rf_t = c_i + \beta_{Pi} \cdot \text{Predictor}_{t-1} + \beta_{Ii} \cdot \text{InvSent}_{t-1} + \beta_{Rmi} \cdot \text{RmRf}_t + \beta_{Si} \cdot \text{SMB}_t + \beta_{Mi} \cdot \text{MOM}_t + u_{i,t}$$

Second Stage: Cross-Sectional Regressions for each month t:

$$R_{i,t} - Rf_t = \lambda_{0t} + \lambda_{Pt} \cdot \beta_{Pi} + \lambda_{It} \cdot \beta_{Ii} + \lambda_{Rmt} \cdot \beta_{Rmi} + \lambda_{St} \cdot \beta_{Si} + \lambda_{Mt} \cdot \beta_{Mi} + v_{i,t}$$

Third Stage: Compare Actual Average to Predicted Return for each Portfolio i:

$$\overline{R_i - Rf} = \overline{\lambda_{0t}} + \overline{\lambda_{Pt}} \cdot \beta_{Pi} + \overline{\lambda_{It}} \cdot \beta_{Ii} + \overline{\lambda_{Rmt}} \cdot \beta_{Rmi} + \overline{\lambda_{St}} \cdot \beta_{Si} + \overline{\lambda_{Mt}} \cdot \beta_{Mi} + w_i$$

Panel A: 90 Decile Portfolios as Test Assets											
Predictor	$\overline{\lambda_{Pt}}$		$\overline{\lambda_{It}}$		$\overline{\lambda_{Rmt}}$		$\overline{\lambda_{St}}$		$\overline{\lambda_{Mt}}$		R^2
Average Factor Beta	−0.691	(−2.59)***									0.400
	−0.720	(−2.72)***	0.170	(0.71)							0.422
	−0.535	(−3.01)***	0.236	(1.22)	−0.685	(−1.82)*	0.342	(1.63)	0.145	(0.38)	0.549
Avg Factor Relative Volatility	0.721	(2.60)***									0.486
	0.747	(2.67)***	0.086	(0.36)							0.494
	0.582	(3.01)***	0.152	(0.80)	−0.681	(−1.76)*	0.283	(1.33)	0.150	(0.41)	0.546
StDev (Factor Betas)	0.620	(2.55)**									0.475
	0.620	(2.54)**	0.034	(0.14)							0.475
	0.452	(2.56)**	0.099	(0.51)	−0.668	(−1.75)*	0.299	(1.41)	0.013	(0.03)	0.522
StDev (Factor Relative Vols)	0.615	(2.75)***									0.583
	0.632	(2.82)***	0.009	(0.04)							0.599
	0.611	(3.49)***	0.091	(0.48)	−0.362	(−0.97)	0.183	(0.86)	0.033	(0.08)	0.609
First Principal Component	0.570	(2.65)***									0.539
	0.579	(2.69)***	0.028	(0.12)							0.554
	0.511	(3.14)***	0.095	(0.50)	−0.508	(−1.34)	0.251	(1.18)	0.137	(0.37)	0.579
BW Investor Sentiment	0.365	(1.43)									0.089
	0.328	(1.66)*			−1.036	(−2.52)**	0.381	(1.81)*	−0.217	(−0.50)	0.437
(None)					−1.160	(−2.77)***	0.336	(1.59)	−0.170	(−0.39)	0.411

Panel B: FF25 + 30 Industry Portfolios as Test Assets											
Predictor	$\overline{\lambda_{Pt}}$		$\overline{\lambda_{It}}$		$\overline{\lambda_{Rmt}}$		$\overline{\lambda_{St}}$		$\overline{\lambda_{Mt}}$		R^2
Average Factor Beta	−0.419	(−1.46)									0.106
	−0.480	(−1.97)**	0.121	(0.46)							0.124
	−0.368	(−1.64)	0.192	(0.72)	−0.407	(−1.32)	0.130	(0.90)	0.175	(0.39)	0.233
Avg Factor Relative Volatility	0.653	(2.26)**									0.293
	0.695	(2.57)**	0.072	(0.28)							0.312
	0.753	(3.30)***	0.300	(1.14)	−0.234	(−0.76)	0.119	(0.82)	0.394	(0.88)	0.420
StDev (Factor Betas)	0.659	(2.41)**									0.358
	0.656	(2.42)**	0.057	(0.22)							0.358
	0.683	(2.64)***	0.266	(1.02)	−0.205	(−0.68)	0.149	(1.02)	0.340	(0.75)	0.464
StDev (Factor Relative Vols)	0.636	(2.27)**									0.355
	0.721	(2.70)***	−0.011	(−0.04)							0.409
	0.844	(3.47)***	0.224	(0.84)	−0.085	(−0.29)	0.130	(0.89)	0.298	(0.66)	0.488
First Principal Component	0.591	(2.30)**									0.349
	0.628	(2.55)**	0.048	(0.18)							0.381
	0.700	(3.24)***	0.261	(0.99)	−0.149	(−0.51)	0.130	(0.89)	0.370	(0.83)	0.459
BW Investor Sentiment	0.100	(0.38)									−0.004
	0.191	(0.71)			−0.526	(−1.57)	0.139	(0.95)	0.079	(0.17)	0.187
(None)					−0.598	(−1.74)*	0.125	(0.85)	0.025	(0.05)	0.166

Table 13: Market Timing Strategies. This table analyses investment strategies that depend on the decile of a signal strength in the prior month. The signals are the First Principal Component (Panel A), and the level of BW Investor Sentiment (Panel B). The Composite Long Portfolio is the simple average monthly return on the long legs of the following factors: HML, Long-Term Reversal, Cash Earnings Yield, Net Stock Issuance, Sloan Accruals, Richardson Accruals, Net Operating Assets, Assets Growth, and Investment-to-Assets. The Composite Medium Portfolio is the simple average of the corresponding medium portfolios (which are excluded from the factor calculations), and the Composite Short Portfolio is the simple average of the corresponding short legs. The Composite Long–Short Factor Portfolio is the Composite Portfolio calculated previously. All other portfolios are calculated using the same basic methodology of HML. (Robust t-statistics in parentheses; significance levels: * = 10%, ** = 5%, and *** = 1%; no.obs. averages 52.2 per decile)

Estimates of α_i from time series regressions:

$$R_t - Rf_t = \alpha_i + e_i{\cdot}\mathrm{RmRf}_t + f_i{\cdot}\mathrm{SMB}_t + g_i{\cdot}\mathrm{MOM}_t + u_t$$

And estimates of β_i from time series regressions:

$$R_t - Rf_t = a_i + \beta_i{\cdot}\mathrm{RmRf}_t + u_t$$

both given $\mathrm{PredictorStrength}_{t-1} \in \mathrm{Decile}_i$

	Low		Signal Strength (Decile)				High	Timing Benefit	
	1	2	3	4–7	8	9	10	10–1	Slope*10
Panel A: Signal Strength from First Principal Component									
Composite Long Portfolio									
Mean Excess Return	1.835	−0.007	0.030	0.805	0.224	1.862	−0.120	−1.955	−0.121
StDev / (t-statistic)	5.365	7.176	4.461	4.794	5.246	4.132	4.381	(−2.05)**	(−0.15)
3-Factor Alpha	0.190	0.063	0.067	0.244	0.187	0.261	0.711	0.520	0.607
(t-statistic)	(1.66)*	(0.45)	(0.74)	(3.55)***	(1.61)	(1.84)*	(4.68)***	(2.73)***	(3.99)***
Market Beta	1.007	1.116	1.066	1.059	1.110	0.967	0.883	−0.124	−0.164
(t-statistic of $\beta = 1$)	(0.09)	(1.99)**	(1.38)	(2.00)**	(2.23)**	(−0.73)	(−2.12)**	(−1.34)	(−2.24)**
Composite Medium Portfolio									
Mean Excess Return	1.677	0.008	0.082	0.715	0.143	1.733	−0.216	−1.892	−0.244
StDev / (t-statistic)	5.034	6.743	4.089	4.483	4.802	3.913	3.797	(−2.18)**	(−0.33)
3-Factor Alpha	0.134	0.066	0.090	0.146	0.090	0.206	0.513	0.379	0.456
(t-statistic)	(2.20)**	(0.63)	(1.74)*	(3.41)***	(1.06)	(1.87)*	(2.88)***	(2.01)**	(3.01)***
Market Beta	0.966	1.057	0.992	1.013	1.018	0.932	0.751	−0.214	−0.194
(t-statistic of $\beta = 1$)	(−0.58)	(1.21)	(−0.28)	(0.59)	(0.45)	(−1.67)*	(−4.42)***	(−2.64)***	(−2.97)***
Composite Short Portfolio									
Mean Excess Return	1.784	−0.165	−0.089	0.493	−0.127	1.755	−1.515	−3.299	−0.997
StDev / (t-statistic)	5.884	7.365	4.681	5.331	5.443	5.210	5.806	(−2.89)***	(−1.10)
3-Factor Alpha	0.006	−0.122	−0.069	−0.212	−0.208	−0.215	−0.398	−0.404	−0.303
(t-statistic)	(0.09)	(−1.58)	(−0.85)	(−4.46)***	(−2.46)**	(−1.69)*	(−4.27)***	(−3.53)***	(−3.10)***
Market Beta	1.137	1.153	1.133	1.197	1.149	1.177	1.199	0.062	0.041
(t-statistic of $\beta = 1$)	(2.87)***	(3.65)***	(4.18)***	(7.99)***	(3.27)***	(2.91)***	(3.98)***	(0.89)	(0.74)
Composite Long–Short Factor Portfolio									
Mean Excess Return	0.051	0.158	0.118	0.313	0.351	0.107	1.395	1.344	0.876
StDev / (t-statistic)	1.254	1.291	1.002	1.464	1.383	1.890	1.967	(4.17)***	(3.57)***
3-Factor Alpha	0.184	0.185	0.136	0.457	0.395	0.476	1.109	0.924	0.910
(t-statistic)	(1.15)	(1.03)	(0.87)	(4.48)***	(2.18)**	(2.18)**	(6.60)***	(3.99)***	(4.70)***
Market Beta	−0.130	−0.037	−0.066	−0.138	−0.039	−0.210	−0.316	−0.186	−0.205
(t-statistic of $\beta = 0$)	(−3.31)***	(−1.07)	(−1.82)*	(−4.96)***	(−0.92)	(−4.31)***	(−7.08)***	(−3.12)***	(−3.87)***

	Low		Signal Strength (Decile)				High	Timing Benefit	
	1	2	3	4–7	8	9	10	10–1	Slope*10
Panel B: Signal Strength from BW Investor Sentiment									
Composite Long Portfolio									
Mean Excess Return	1.097	1.448	1.410	0.387	1.018	1.852	−1.317	−2.414	−1.101
StDev / (t-statistic)	5.822	5.336	5.268	4.690	5.674	4.601	4.733	(−2.33)**	(−1.37)
3-Factor Alpha	0.232	0.209	0.033	0.135	0.188	0.668	0.309	0.077	0.255
(t-statistic)	(1.72)*	(1.57)	(0.31)	(2.02)**	(1.79)*	(5.56)***	(2.12)**	(0.39)	(1.71)*
Market Beta	1.025	1.252	1.144	1.044	1.023	0.926	0.956	−0.068	−0.218
(t-statistic of $\beta = 1$)	(0.25)	(5.84)***	(2.96)***	(1.66)*	(0.46)	(−2.52)**	(−0.76)	(−0.59)	(−2.53)**
Composite Medium Portfolio									
Mean Excess Return	0.879	1.095	1.247	0.390	0.963	1.910	−1.351	−2.231	−0.794
StDev / (t-statistic)	5.480	4.812	4.661	4.323	5.468	4.363	4.478	(−2.29)**	(−1.05)
3-Factor Alpha	0.205	−0.034	−0.035	0.120	0.143	0.803	0.203	−0.002	0.406
(t-statistic)	(1.84)*	(−0.33)	(−0.64)	(2.50)**	(1.68)*	(4.55)***	(1.71)*	(−0.01)	(2.84)***
Market Beta	0.988	1.139	1.034	0.974	0.998	0.870	0.905	−0.083	−0.159
(t-statistic of $\beta = 1$)	(−0.15)	(3.19)***	(1.00)	(−1.23)	(−0.05)	(−3.04)***	(−1.57)	(−0.83)	(−2.17)**
Composite Short Portfolio									
Mean Excess Return	0.552	1.150	1.459	0.235	0.577	1.259	−2.300	−2.851	−1.637
StDev / (t-statistic)	6.052	5.456	5.273	5.120	6.506	6.035	6.025	(−2.42)**	(−1.80)*
3-Factor Alpha	−0.079	−0.158	0.018	−0.164	−0.402	−0.243	−0.181	−0.102	−0.219
(t-statistic)	(−1.41)	(−2.14)**	(0.26)	(−3.86)***	(−3.55)***	(−2.19)**	(−1.90)*	(−0.92)	(−2.27)**
Market Beta	1.109	1.283	1.162	1.151	1.148	1.199	1.248	0.138	0.035
(t-statistic of $\beta = 1$)	(2.07)**	(4.85)***	(4.44)***	(6.40)***	(3.87)***	(4.21)***	(4.99)***	(1.91)*	(0.61)
Composite Long–Short Factor Portfolio									
Mean Excess Return	0.545	0.298	−0.049	0.153	0.441	0.593	0.983	0.438	0.536
StDev / (t-statistic)	1.256	1.221	1.092	1.415	1.697	1.857	2.030	(1.33)	(2.17)**
3-Factor Alpha	0.311	0.366	0.014	0.298	0.590	0.911	0.490	0.179	0.475
(t-statistic)	(2.11)**	(2.20)**	(0.09)	(3.08)***	(3.00)***	(5.86)***	(2.35)**	(0.70)	(2.40)**
Market Beta	−0.084	−0.032	−0.018	−0.107	−0.125	−0.273	−0.291	−0.207	−0.253
(t-statistic of $\beta = 0$)	(−1.54)	(−0.77)	(−0.47)	(−3.79)***	(−3.29)***	(−6.95)***	(−6.10)***	(−2.84)***	(−4.40)***