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The time-series relations among expected return, risk, and book-to-market☆

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Abstract

This paper examines the time-series relations among expected return, risk, and book-to-market (B/M) at the portfolio level. I find that B/M predicts economically and statistically significant time-variation in expected stock returns. Further, B/M is strongly associated with changes in risk, as measured by the Fama and French (1993) (Journal of Financial Economics, 33, 3–56) three-factor model. After controlling for risk, B/M provides no incremental information about expected returns. The evidence suggests that the three-factor model explains time-varying expected returns better than a characteristics-based model.

JEL classification: G12; G14

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1. Introduction

Empirical research consistently finds a positive cross-sectional relation between average stock returns and the ratio of a firm's book equity to market equity (B/M). Stattman (1980) and Rosenberg et al. (1985) document the association between expected returns and B/M, which remains significant after controlling for beta, size, and other firm characteristics (Fama and French, 1992). The explanatory power of B/M does not appear to be driven entirely by data snooping or survival biases; it is found in stock markets outside the United States (Chan et al., 1991; Haugen and Baker, 1996) and in samples drawn from sources other than Compustat (Davis, 1994). As a whole, the evidence provides considerable support for the cross-sectional explanatory power of B/M.

At least two explanations have been offered for the empirical evidence. According to asset-pricing theory, B/M must proxy for a risk factor in returns. The significance of B/M in competition with beta contradicts the capital asset pricing model (CAPM) of Sharpe (1964), Lintner (1965), and Black (1972), or more precisely, the mean-variance efficiency of the market proxy. However, the evidence might be consistent with the intertemporal models of Merton (1973) and Breeden (1979). In these models, the market return does not completely capture the relevant risk in the economy, and additional factors are required to explain expected returns. If a multifactor model accurately describes stock returns, and B/M is cross-sectionally correlated with the factor loadings, then the premium on B/M simply reflects compensation for risk.

A positive relation between B/M and risk is expected for several reasons. Chan and Chen (1991) and Fama and French (1993) suggest that a distinct 'distress factor' explains common variation in stock returns. Poorly performing, or distressed, firms are likely to have high B/M. These firms are especially sensitive to economic conditions, and their returns might be driven by many of the same macroeconomic factors (such as variation over time in bankruptcy costs and access to credit markets). In addition, following the arguments of Ball (1978) and Berk (1995), B/M might proxy for risk because of the inverse relation between market value and discount rates. Holding book value constant in the numerator, a firm's B/M ratio increases as expected return, and consequently risk, increases.

Alternatively, B/M might provide information about security mispricing. The mispricing view takes the perspective of a contrarian investor. A firm with poor stock price performance tends to be underpriced and have a low market value relative to book value. As a result, high B/M predicts high future returns as the underpricing is eliminated. Lakonishok et al. (1994) offer a rationale for the association between past performance and mispricing. They argue that investors naively extrapolate past growth when evaluating a firm's prospects. For example, investors tend to be overly pessimistic about a firm which has had low or negative earnings. On average, future earnings exceed the market's expectation, and the stock does abnormally well. Thus, the mispricing argument says that B/M captures biases in investor expectations.

Fama and French (1993) provide evidence of a relation between B/M and risk. Using the time-series approach of Black et al. (1972), they examine a multifactor model consisting of market, size, and book-to-market factors, where the size and book-to-market factors are stock portfolios constructed to mimic underlying risk factors in returns. If the model explains cross-sectional variation in average returns, the intercepts will be zero when excess returns are regressed on the three factors. Fama and French find, as predicted by the risk-based view, that the model does a good job explaining average returns for portfolios sorted by size, B/M, earnings-price ratios, and other characteristics. Further, they document a strong association between a stock's B/M ratio and its loading on the book-to-market factor.

More recently, Daniel and Titman (1997) argue in favor of a characteristics-based model, consistent with the mispricing view. They suggest that the three-factor model does not *directly* explain average returns. Instead, the model appears to explain average returns only because the factor loadings are correlated with firms' characteristics (size and B/M). To disentangle the explanatory power of the factor loadings from that of the characteristics, Daniel and Titman construct test portfolios by sorting stocks first on B/M ratios and then on factor loadings. This sorting procedure creates independent variation in the two variables. Consistent with the mispricing story, Daniel and Titman find a stronger relation between expected returns and B/M than between expected returns and factor loadings. Daniel and Titman conclude that firm characteristics, in particular B/M, and not covariances determine expected stock returns.

In this paper, I provide further evidence on the risk- and characteristics-based stories. In contrast to Fama and French (1993) and Daniel and Titman (1997), I focus on the time-series relations among expected return, risk, and B/M. Specifically, I ask whether a portfolio's B/M ratio predicts time-variation in its expected return, and test whether changes in expected return can be explained by changes in risk. Recently, Kothari and Shanken (1997) and Pontiff and Schall (1998) find that B/M forecasts stock returns at the aggregate level, but the predictive ability of B/M for individual stocks or portfolios has not been explored.

The time-series analysis is a natural alternative to cross-sectional regressions. An attractive feature of the time-series regressions is that they focus on changes in expected returns, not on average returns. The mispricing story suggests that a stock's expected return will vary over time with B/M, but it says little about average returns if mispricing is temporary. Cross-sectional regressions, however, can pick up a relation between average returns and B/M. The time-series regressions also highlight the interaction between B/M and risk, as measured by time-variation in market betas and the loadings on the Fama and French

(1993) size and book-to-market factors. Further, I can directly test whether the three-factor model explains time-varying expected returns better than the characteristics-based model. These results should help distinguish between the risk and mispricing stories.

The empirical tests initially examine B/M's predictive ability without attempting to control for changes in risk. I find that a portfolio's B/M ratio tracks economically and statistically significant variation in its expected return. An increase in B/M equal to twice its time-series standard deviation forecasts a 4.6% (annualized) increase in expected return for the typical industry portfolio, 8.2% for the typical size portfolio, and 9.3% for the typical book-to-market portfolio. The average coefficient on B/M across all portfolios, 0.99, is approximately double the cross-sectional slope, 0.50, found by Fama and French (1992, p. 439). B/M explains, however, only a small fraction of portfolio returns, generally less than 2% of total volatility.

Return predictability indicates that either risk or mispricing changes over time. Of course, we cannot distinguish between these explanations without some model of risk. Following Daniel and Titman (1997), I examine B/M's explanatory power in competition with the Fama and French (1993) three-factor model. The multifactor regressions employ the conditional asset-pricing methodology of Shanken (1990), which allows both expected returns and factor loadings to vary over time with B/M. In these regressions, time-variation in the intercepts measures the predictive ability of B/M that cannot be explained by changes in risk. The mispricing view suggests that the intercepts will be positively related to B/M; the risk-based view implies that changes in the factor loadings will eliminate B/M's explanatory power, assuming the Fama and French factors are adequate proxies for priced risk in the economy.

Empirically, the factors absorb much of the volatility of portfolio returns, which permits relatively powerful tests of the competing stories. I find that B/M explains significant time-variation in risk, but does not provide incremental information about expected return. In general, the loadings on the size and book-to-market factors vary positively with a portfolio's B/M ratio, and statistical tests strongly reject the hypothesis of constant risk. The results for market betas are more difficult to characterize: across different portfolios, B/M predicts both significant increases and significant decreases in beta. Overall, B/M contains substantial information about the riskiness of stock portfolios.

In contrast, the intercepts of the three-factor model do not vary over time with B/M. For the industry portfolios, the average coefficient on B/M (that is, variation in the intercept) has the opposite sign predicted by the overreaction hypothesis and is not significantly different from zero. Across the 13 portfolios, eight coefficients are negative and none is significantly positive at conventional levels. The results are similar for size and book-to-market portfolios: the average coefficients are indistinguishable from zero, and roughly half are negative. Importantly, the inferences from the multifactor regressions are not driven by low power. For all three sets of portfolios, statistical tests can reject economically large coefficients on B/M. In short, the three-factor model measures risk sufficiently well to explain time-variation in expected returns.[1]

As an aside, I find that the book-to-market factor, HML, explains common variation in returns that is unrelated to its industry composition. Daniel and Titman (1997) argue that HML does not proxy for a distinct risk factor, but explains return covariation only because similar types of firms become mispriced at the same time. For example, a bank with high B/M will covary positively with HML simply because the factor is weighted towards underpriced financial firms. The time-series regressions provide evidence to the contrary. As an alternative to HML, I estimate the regressions with an 'industry-neutral' book-to-market factor. This factor is constructed by sorting stocks on their industry-adjusted B/M ratios, defined as the firm's B/M minus the industry average, so the factor should never be weighted towards particular industries. The results using the industry-neutral factor are similar to those with HML. Thus, HML's explanatory power does not appear to be driven by industry factors in returns.

The remainder of the paper is organized as follows. Section 2 introduces the time-series regressions. Section 3 describes the data to be used in the empirical tests. Section 4 estimates the simple relation between expected returns and B/M, and Section 5 tests whether the predictive ability of B/M can be explained by changes in risk, as measured by the Fama and French (1993) three-factor model. Section 6 summarizes the evidence and concludes.

2. Distinguishing between characteristics and risk

Book-to-market explains cross-sectional variation in average returns after controlling for beta. Fama and French (1993) provide evidence that B/M relates to common risk factors in returns. In contrast, Daniel and Titman (1997) argue that the Fama and French factors appear to be priced only because the loadings are correlated with firm characteristics, like B/M. This section introduces the time-series methodology used in the current paper and discusses, more generally, asset-pricing tests of the risk and mispricing stories.

[1] I also replicate the empirical tests using size in place of B/M, with similar results. There is some evidence that size and expected returns are negatively related in time series. In conditional three-factor regressions, size captures significant time-variation in risk, but does not contain additional information about expected returns. Details are available on request. I thank Ken French for suggesting these tests.

2.1. Time-series methodology

The empirical tests initially examine the simple relation between expected returns and B/M. The explanations that have been offered for the cross-sectional evidence also suggest that expected returns will vary over time with B/M. According to the risk-based view, B/M should capture information about changes in risk, and consequently, expected return. The mispricing view says that B/M is related to biases in investor expectations, and will contain information about under- and overpricing. Thus, both explanations predict a positive slope coefficient in the regression

$$R_i(t) = \gamma_{i0} + \gamma_{i1} B/M_i(t-1) + e_i(t), \tag{1}$$

where R_i is the portfolio's excess return and B/M_i is its lagged book-to-market ratio. Note that Eq. (1) specifies a separate time-series regression for each portfolio, with no constraint on the coefficients across different portfolios. The regressions focus only on the time-series relation between expected returns and B/M, and do not pick up any cross-sectional relation.

Eq. (1) makes no attempt to understand the source of time-varying expected returns. According to traditional asset-pricing theory, a positive slope in Eq. (1) must be driven by an association between B/M and risk. It follows that the predictive power of B/M should be eliminated if the regressions control adequately for changes in risk. The characteristics-based story, on the other hand, suggests that B/M will capture information about expected returns that is unrelated to risk. To help distinguish between the two explanations, I examine the predictive power of B/M in competition with the Fama and French (1993) three-factor model.

The multifactor regressions employ the conditional time-series methodology of Shanken (1990). Roughly speaking, these regressions combine the three-factor model with the simple regressions above. Fama and French estimate the unconditional model

$$R_i(t) = a_i + b_i\, R_\mathrm{M}(t) + s_i\, \mathrm{SMB}(t) + h_i\, \mathrm{HML}(t) + e_i(t), \tag{2}$$

where R_M is the excess market return, SMB (small minus big) is the size factor, and HML (high minus low) is the book-to-market factor. Unconditional, here, refers to the implicit assumption that the coefficients of the model are constant over time. If this assumption is not satisfied, the estimates from Eq. (2) can be misleading. The unconditional intercepts and factor loadings could be close to zero, but might vary considerably over time.

The conditional regressions allow both expected returns and factor loadings to vary with B/M. Suppose, for simplicity, that the coefficients of the three-factor model are linearly related to the firm's B/M ratio, or

$$a_{it} = a_{i0} + a_{i1}B/M_i(t-1), \quad b_{it} = b_{i0} + b_{i1}B/M_i(t-1),$$
$$s_{it} = s_{i0} + s_{i1}B/M_i(t-1), \quad h_{it} = h_{i0} + h_{i1}B/M_i(t-1). \tag{3}$$

Substituting these equations into the unconditional regression yields a conditional version of the three-factor model:

$$R_i = a_{i0} + a_{i1}B/M_i + (b_{i0} + b_{i1}B/M_i)R_{\mathrm{M}} + (s_{i0} + s_{i1}B/M_i)\mathrm{SMB} + (h_{i0} + h_{i1}B/M_i)\mathrm{HML} + e_i, \tag{4}$$

where the time subscripts have been dropped to reduce clutter. Multiplying the factors through gives the regression equation for each portfolio. Thus, the conditional regressions contain not only an intercept and the three factors, but also four interactive terms with the portfolio's lagged B/M.[2]

Basically, Eq. (4) breaks the predictive power of B/M into risk and non-risk components. The coefficient a_{i1}, the interactive term with the intercept, measures the predictive ability of B/M that is incremental to its association with risk in the three-factor model. A non-zero coefficient says that changes in the factor loadings, captured by the coefficients b_{i1}, s_{i1}, and h_{i1}, do not fully explain the time-series relation between B/M and expected return. Thus, rational asset-pricing theory predicts that a_{i1} will be zero for all stocks, assuming that the factors are adequate proxies for priced risk. The mispricing, or characteristics-based, view implies that B/M will forecast returns after controlling for risk and, consequently, a_{i1} should be positive.

2.2. Discussion

The conditional regressions directly test whether the three-factor model or the characteristic-based model better explains changes in expected returns. To interpret the regressions as a test of rational pricing, we must assume, of course, that the Fama and French factors capture priced risk in the economy. This assumption could be violated in two important ways (see Roll, 1977). First, an equilibrium multifactor model might describe stock returns, but the Fama and French factors are not adequate proxies for the unknown risks. In this case, B/M can predict time-variation in expected returns missed by the three-factor model if it relates to the true factor loadings. Fortunately, this problem will not be

[2] Similar regressions appear in previous studies. Fama and French (1997) estimate regressions in which only the factor loadings on HML vary with B/M. He et al. (1996) estimate a model in the spirit of Eq. (4), but they constrain the intercepts and book-to-market coefficients to be the same across portfolios. Given previous cross-sectional evidence, the B/M coefficient will be non-zero in the absence of time-varying expected returns.

a concern for the current paper because the three-factor model will, in fact, explain the predictability associated with B/M.

Unfortunately, the assumption can also be violated in the opposite way: mispricing might explain deviations from the CAPM, but the size and book-to-market factors happen to absorb the predictive power of B/M. This possibility is a concern particularly because the factors are empirically motivated. Daniel and Titman (1997), for example, argue that the construction of HML, which is designed to mimic an underlying risk factor in returns related to B/M, could induce 'spurious' correlation between a portfolio's B/M ratio and its factor loading. HML is weighted, by design, towards firms with high B/M. If similar types of firms become mispriced at the same time, then we should expect that a firm will covary more strongly with HML when its B/M is high. As a result, apparent changes in risk might help explain B/M's predictive ability even under the mispricing story.

In defense of the time-series regressions, it seems unlikely that changes in the factor loadings would completely absorb mispricing associated with B/M. More importantly, Daniel and Titman's argument cannot fully account for the relation between B/M and risk. The argument suggests that the loadings on HML will tend to vary with B/M, but it does not say anything about the loadings on the market and size factors. We will see below, however, that B/M captures significant time variation in market betas and the loadings on SMB. Further, I provide evidence in Section 5.3 that the time-series relation between B/M and the factor loadings on HML is not driven by changes in the industry composition of the factor. I estimate the conditional regressions with an 'industry neutral' factor, which prevents HML from becoming weighted towards particular industries. When this factor is used in place of HML, we will continue to see a strong time-series relation between B/M and the factor loadings.

Finally, it is useful to note that many industries have large *unconditional* factor loadings on HML, which suggests that HML does not simply capture mispricing in returns. Intuitively, Daniel and Titman's argument suggests that a given stock will sometimes vary positively and sometimes negatively with HML. Depending on the type of firms that are currently under- and overpriced, HML will be related to constantly changing micro- and macroeconomic factors. For example, HML will be sensitive to interest rate and inflation risk when it is weighted towards underpriced financial firms, but will be negatively related to these risks when financial firms are overpriced. Corresponding to the changes in HML, a stock will tend to covary positively with HML when similar firms are underpriced, but negatively when similar firms are overpriced. Over time, however, a firm's average factor loading on HML should be close to zero under the mispricing story, unless firms are persistently under- and overpriced (which seems unreasonable).

This intuition can be formalized. Suppose that temporary overreaction explains deviations from the CAPM, and that HML, because of its construction, absorbs this mispricing (ignore the size factor for simplicity). To be more specific, assume that the proxy for the market portfolio, M, is not mean-variance efficient conditional on firms' B/M ratios. However, HML is constructed to explain the deviations from the CAPM, and R_M and HML together span the conditional tangency portfolio. The appendix proves that, in the time-series regression

$$R_i(t) = a_i + b_i R_M(t) + h_i \,\mathrm{HML}(t) + e_i(t), \tag{5}$$

the unconditional factor loading on HML, h_i, will equal zero if assets are correctly priced on average over time.[3] This result reflects the idea that temporary mispricing should not explain unconditional deviations from the CAPM. As noted above, however, many industries have large unconditional loadings on both SMB and HML, which therefore suggests that the factors do not simply capture mispricing in returns.

In summary, the multifactor regressions test whether the three-factor model or the characteristic-based model explains time-variation in expected returns. The interpretation of the regressions, like the results for any asset-pricing test, is limited by our need to use a proxy for the unobservable equilibrium model of returns. Nevertheless, the regressions should help us understand whether the risk or mispricing story is a better description of asset prices.

3. Data and descriptive statistics

The empirical analysis focuses on industry portfolios. These portfolios should exhibit cross-sectional variation in expected returns and risk, so the tests can examine a diverse group of portfolios. Industry portfolios are believed a priori to provide variation in expected returns and factor loadings, while sorting by other criteria is often motivated by previous empirical evidence. Hence, industry portfolios are less susceptible to the data-snooping issues discussed by Lo and MacKinlay (1990).

As a robustness check, I also examine portfolios sorted by size and B/M. In cross-sectional studies, different sets of portfolios often produce vastly different estimates of risk premia. Of course, the time-series regressions in this paper might also be sensitive to the way portfolios are formed. Size portfolios have the advantage that they control for changes in market value, which has been shown to be associated with risk and expected returns, yet should be relatively stable

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[3] The result also requires that time-variation in b_i and h_i is uncorrelated with the factors' expected returns. This assumption seems reasonable since I am interested in the factor loadings changing over time with firm-specific variables, like B/M, not with macroeconomic variables. It is also consistent with the empirical evidence presented in Section 5.

over time. The book-to-market portfolios allow us to examine how the expected returns and risk of distressed, or high-B/M, firms change over time.

The portfolios are formed monthly from May 1964 through December 1994, for a time series of 368 observations. The industry and size portfolios consist of all NYSE, Amex, and Nasdaq stocks on the Center for Research in Security Prices (CRSP) tapes, while the book-to-market portfolios consist of the subset of stocks with Compustat data. Stocks are sorted into 13 industry portfolios based on two-digit Standard Industrial Classification (SIC) codes as reported by CRSP. For the most part, the industries consist of consecutive two-digit codes, although some exceptions were made when deemed appropriate.[4] The size portfolios are formed based on the market value of equity in the previous month, with breakpoints determined by NYSE deciles. To reduce the fraction of market value in any single portfolio, the largest two portfolios are further divided based on the 85th and 95th percentiles of NYSE stocks, for a total of 12 portfolios. Finally, the book-to-market portfolios are formed based on the ratio of book equity in the previous fiscal year to market equity in the previous month. Again, the breakpoints for these portfolios are determined by NYSE deciles. The lowest and highest deciles are further divided using the 5th and 95th percentiles of NYSE stocks, for a total of 12 portfolios.

For all three sets of portfolios, value-weighted returns are calculated using all stocks with CRSP data, and value-weighted B/M ratios are calculated from the subset of stocks with Compustat data.[5] To ensure that the explanatory power of B/M is predictive, I do not assume that book data become known until five months after the end of the fiscal year. Also, to reduce the effect of potential selection biases in the way Compustat adds firms to the database (see the discussion by Kothari et al., 1995), a firm must have three years of data before it is included in any calculation requiring book data. The time-series regressions use excess returns, calculated as returns minus the one-month T-bill rate, and the natural logarithm of B/M.

Table 1 reports summary statistics for the portfolios. The average monthly returns for the industry portfolios range from 0.83% for utilities and telecommunications firms to 1.28% for the service industry (which includes entertainment, recreation, and services), for an annualized spread of 6.1%. Coincidentally, these industries also have the lowest (3.67%) and highest (6.78%) standard deviations, respectively. The size and book-to-market portfolios also exhibit wide variation in average returns and volatility. Average returns for the size portfolios vary

[4] Details available on request.

[5] The stocks included in the calculation of B/M are a subset of those included in the calculation of returns, and we can interpret the estimate of B/M as a proxy for the entire portfolio. The inferences in this paper are unchanged when portfolio returns are based only on those stocks with Compustat data.

from 0.80% for the largest stocks to 1.24% for the smallest stocks, and the standard deviations of returns decrease monotonically with size, from 6.68% to 4.17%. Average returns for the book-to-market portfolios range from 0.76% for the second decile through 1.46% for the stocks with the highest B/M. Interestingly, the standard deviation of returns are U-shaped; they decrease monotonically with B/M until the sixth decile, which has a standard deviation of 4.42%, and increase thereafter, to 6.86% for portfolio 10b.

The statistics for B/M, like those for returns, reveal considerable cross-sectional differences in portfolio characteristics. Average B/M doubles from 0.40 for chemical firms to 0.82 for the transportation industry. A similar spread is shown for size portfolios, with B/M ranging from 0.51 for the largest stocks to 1.03 for the smallest stocks. The book-to-market portfolios, of course, have the greatest cross-sectional variation, with average B/M ranging from 0.15 for the low-B/M portfolio to 2.66 for the high-B/M portfolio. The standard deviations over time are also reasonably high, reflecting the volatility of stock returns. The time-series standard deviation of B/M is, on average, 0.20 for the industries, 0.24 for the size portfolios, and 0.29 for the book-to-market portfolios. Variation in B/M will be necessary for the time-series regressions to have power distinguishing between the competing hypotheses.

Table 2 reports summary statistics for the Fama and French (1993) factors, which are described fully in the appendix. The market factor, R_M, is the excess return on the CRSP value-weighted index, and the size and book-to-market factors, SMB and HML, are zero-investment portfolios designed to mimic underlying risk factors in returns. The average monthly return of R_M is 0.39%, of SMB is 0.30%, and of HML is 0.38%. The risk premium for each factor is measured by its mean return, so these averages imply positive compensation for bearing factor risk. As noted by Fama and French, the procedure used to construct SMB and HML appears to successfully control each factor for the influence of the other, as demonstrated by the low correlation between the factors, equal to -0.06. Also, SMB is positively correlated with R_M (correlation of 0.36), while HML is negatively correlated with R_M (-0.35). Thus, the returns on the size and B/M factors are not independent of the market return, reflecting the fact that their construction did not control for differences in the betas of the underlying stocks.

The CAPM and most empirical studies examine the relation between simple-regression market betas and expected returns. To enhance comparison with cross-sectional studies, I use size and B/M factors that are orthogonal to R_M. These factors, SMBO and HMLO, are constructed by adding the intercepts to the residuals when SMB and HML are regressed on a constant and the excess market return. From regression analysis (e.g., Johnston, 1984, p. 238), the coefficients in the three-factor model will be unaffected by the change in variables, except that market betas will now be the simple-regression betas of the CAPM. Table 2 shows that the average return on the book-to-market factor

Table 1
Summary statistics for industry, size, and book-to-market portfolios, 5/64–12/94

Each month from May 1964 through December 1994, value-weighted portfolios are formed from all NYSE, Amex, and Nasdaq stocks on CRSP. Firms must also have Compustat data for the book-to-market portfolios. Book-to-market (B/M) is calculated as the ratio of book equity in the previous fiscal year to market equity in the previous month for all stocks with Compustat data. The industry portfolios are based on two-digit SIC codes. The size portfolios are based on the market value of equity in the previous month, with breakpoints determined by NYSE deciles; portfolios 9 and 10 are further divided using the 85 and 95 percentiles of NYSE stocks. The book-to-market portfolios are based on B/M in the previous month, with breakpoints determined by NYSE deciles; portfolios 1 and 10 are further divided using the 5 and 95 percentiles of NYSE stocks

Portfolio	Return (%)		Book-to-market				Number of firms	
	Mean	Std. dev.	Mean	Std. dev.	Autocorr.	Adj. R^2 [a]	May 1964	Dec. 1994
Panel A: Industry portfolios								
Nat. resources	0.84	5.69	0.57	0.14	0.97	0.28	90	360
Construction	0.86	5.45	0.78	0.26	0.99	0.69	237	409
Food, tobacco	1.21	4.57	0.51	0.18	0.99	0.36	106	134
Consumer products	1.05	6.02	0.75	0.36	0.99	0.81	108	257
Logging, paper	0.98	5.35	0.54	0.15	0.98	0.54	74	190
Chemicals	0.96	4.78	0.40	0.13	0.99	0.28	102	392
Petroleum	1.08	5.23	0.74	0.20	0.98	0.38	30	32
Machinery, equipment	0.88	5.35	0.42	0.13	0.99	0.40	290	1222
Transportation	0.87	5.39	0.82	0.27	0.98	0.71	162	260
Utilities, telecom.	0.83	3.67	0.77	0.25	0.99	0.57	122	384
Trade	1.04	5.65	0.49	0.18	0.98	0.55	167	785
Financial	0.95	4.75	0.75	0.19	0.97	0.68	117	1747
Services and other	1.28	6.78	0.47	0.20	0.98	0.55	61	981

Panel B: Size portfolios								
Smallest	1.24	6.68	1.03	0.41	0.98	0.88	409	3338
2	1.16	6.17	0.90	0.32	0.97	0.79	175	932
3	1.15	6.08	0.85	0.30	0.97	0.77	154	634
4	1.16	5.91	0.84	0.31	0.97	0.80	149	463
5	1.21	5.70	0.76	0.26	0.96	0.80	136	426
6	1.22	5.41	0.72	0.23	0.97	0.88	130	333
7	1.07	5.19	0.68	0.19	0.97	0.88	132	310
8	1.09	5.13	0.67	0.19	0.98	0.86	130	274
9a	1.02	4.89	0.67	0.18	0.97	0.78	62	122
9b	0.97	4.71	0.66	0.20	0.97	0.78	64	111
10a	0.88	4.50	0.62	0.17	0.98	0.70	63	109
Largest	0.80	4.17	0.51	0.15	0.99	0.41	62	109
Panel C: Book-to-market portfolios								
Lowest	0.98	5.69	0.15	0.05	0.97	0.59	21	559
1b	0.83	5.15	0.24	0.07	0.97	0.64	19	328
2	0.76	5.04	0.34	0.10	0.97	0.82	40	493
3	0.79	4.78	0.46	0.14	0.98	0.93	39	470
4	0.83	4.63	0.57	0.18	0.98	0.94	39	469
5	0.82	4.47	0.67	0.21	0.98	0.94	42	492
6	0.98	4.42	0.78	0.24	0.98	0.94	40	467
7	1.17	4.54	0.89	0.28	0.98	0.94	42	461
8	1.25	4.72	1.04	0.32	0.98	0.95	43	460
9	1.43	5.20	1.28	0.40	0.98	0.96	43	574
10a	1.46	6.12	1.65	0.53	0.97	0.93	24	378
Highest	1.46	6.86	2.66	0.95	0.96	0.84	25	482

[a] Adjusted R^2 from regressing the portfolio's B/M ratio on the value-weighted B/M ratio of all stocks that meet both CRSP and Compustat data requirements.

Table 2
Summary statistics for factors, 5/64–12/94

The factors are calculated monthly from May 1964 through December 1994. R_M is the return on the CRSP value-weighted index minus the one-month T-bill rate. SMB is the return on a portfolio of small stocks minus the return on a portfolio of big stocks. HML is the return on portfolio of high-B/M stocks minus the return on a portfolio of low-B/M stocks. SMBO and HMLO are orthogonalized versions of SMB and HML, constructed by adding the intercepts to the residuals in regressions of SMB and HML on a constant and R_M. All returns are reported in percent

Factor	Mean	Std. dev.	Autocorr.	Correlation				
				R_M	SMB	HML	SMBO	HMLO
R_M	0.39	4.45	0.06	1.00	0.36	− 0.35	0.00	0.00
SMB	0.30	2.91	0.19		1.00	− 0.06	0.93	0.07
HML	0.38	3.00	0.14			1.00	0.07	0.94
SMBO	0.21	2.71	0.06				1.00	0.07
HMLO	0.47	2.81	0.14					1.00

increases from 0.38% to 0.47%, but the return on the size factor decreases from 0.30% to 0.21%. The correlation between the size and book-to-market factors, 0.07, remains close to zero.

4. The predictability of portfolio returns

This section investigates the simple time-series relation between expected returns and B/M. The simple regressions help evaluate the economic importance of B/M, without regard to changes in risk or mispricing, and provide a convenient benchmark for the conditional three-factor model. In addition, the analysis complements recent studies which find that B/M forecasts aggregate stock returns (Kothari and Shanken, 1997; Pontiff and Schall, 1998).

As discussed above, the risk and mispricing views both suggest that B/M will predict portfolio returns. For each portfolio, I estimate the time-series regression

$$R_i(t) = \gamma_{i0} + \gamma_{i1} B/M_i(t-1) + e_i(t), \tag{6}$$

where R_i is the portfolio's excess return and B/M_i is the natural log of its lagged book-to-market ratio. The slope coefficient in this regression is expected to be positive.

Several complications arise in estimating Eq. (6). First, the appropriate definition of B/M is unclear. Cross-sectional studies suggest that a portfolio's B/M relative to other firms could be important. Thus, $B/M_i(t-1)$ might be defined as either the portfolio's actual B/M ratio or its B/M ratio minus an aggregate index. The latter varies primarily with market-adjusted stock returns, and would be a better measure if common variation in B/M is unrelated to mispricing.[6] Asset-pricing theory provides little guidance. The conclusions in this paper are not sensitive to the definition of B/M, and for simplicity I report only results for raw B/M. Also, to ease the interpretation of the results, B/M is measured as deviations from its time-series mean for the remainder of the paper. As a consequence, when B/M_i equals zero in the regressions, B/M is actually at its long-run average for the portfolio.

Second, Stambaugh (1986) shows that contemporaneous correlation between returns and B/M will bias upward the slope coefficient in Eq. (6). Suppose that B/M follows the AR(1) process

$$B/M_i(t) = c_i + p_i B/M_i(t-1) + u_i(t). \tag{7}$$

The bias in the estimate of γ_{i1} is approximately

$$E[\hat{\gamma}_{i1} - \gamma_{i1}] \approx [\mathrm{cov}(e_i, u_i)/\mathrm{var}(u_i)][-(1 + 3p_i)/T], \tag{8}$$

where T is the length of the time series. The residuals in (6) and (7), e_i and u_i, are negatively related because a positive stock return decreases the portfolio's B/M. Also, Table 1 shows that B/M is highly persistent over time, with autocorrelations ranging from 0.96 to 0.99 at the first lag. Together, the correlation between e_i and u_i and the persistence in B/M impart a strong upward bias in the estimate of γ_{i1}. In a related context, for market returns regressed on aggregate B/M, Kothari and Shanken (1997) bootstrap the distribution of the slope and find that Stambaugh's formula is empirically valid. The tests below adjust for this bias.

4.1. Industry portfolios

Table 3 reports results for the industry portfolios. The evidence provides some support for a positive association between expected returns and lagged B/M, but the high volatility of stock returns reduces the power of the tests. The bias-adjusted slopes range from -0.53 for food and tobacco firms to 1.75 for the natural resources industry, and 10 of the 13 coefficients are greater than zero. The average estimate is positive, 0.58, although it is only about one standard error, 0.62, from zero (the standard error reflects cross-sectional correlation in the estimates). Stronger evidence of predictive ability is provided by the χ^2 test of the slope coefficients. This test rejects at the 5% level the hypothesis that B/M does not capture any variation in expected returns.

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[6] Kothari and Shanken (1997) and Pontiff and Schall (1998) show that aggregate B/M predicts market returns during the period 1926 through 1992, which could reflect aggregate mispricing. Their results for the period 1963 through 1992 are much weaker. For the current paper, preliminary tests indicate that aggregate B/M has little power to forecast the market, size, and book-to-market factors.

Table 3
Predictability of industry returns, 5/64–12/94

$$R_i(t) = \gamma_{i0} + \gamma_{i1} B/M_i(t-1) + e_i(t)$$

The industry portfolios are described in Table 1. R_i is the portfolio's monthly excess return (in percent) and B/M_i is the natural log of the portfolio's book-to-market ratio at the end of the previous month, measured as a deviation from its time-series mean. The table reports both ordinary least squares (OLS) and seemingly unrelated regression (SUR) estimates of the slope coefficients. The OLS bias-adjusted slopes correct for small-sample biases using Eq. (8) in the text. The bias correction for the SURs, as well as the covariance matrix of the bias-adjusted estimates, is obtained from bootstrap simulations

Portfolio	OLS				SUR			
	γ_{i1}	Bias-adj γ_{i1}	Std. err.	Adj. R^2	γ_{i1}	Std. err.	Bias-adj γ_{i1}	Std. err.
Nat. resources	2.56[b]	1.75	1.19	0.01	0.67	0.69	0.07	0.77
Construction	1.10	0.15	0.83	0.00	0.13	0.29	−0.30	0.44
Food, tobacco	0.35	−0.53	0.64	0.00	0.50	0.31	0.17	0.43
Consumer products	0.88	−0.06	0.72	0.00	0.71[b]	0.31	0.33	0.45
Logging, paper	2.07	1.20	1.07	0.01	0.20	0.43	−0.30	0.55
Chemicals	1.01	0.09	0.78	0.00	0.06	0.35	−0.41	0.51
Petroleum	2.33[b]	1.46	1.00	0.01	1.56[b]	0.67	0.96	0.80
Mach., equipment	0.77	−0.19	0.80	0.00	−0.25	0.31	−0.69	0.50
Transportation	1.19	0.37	0.80	0.00	0.41	0.35	−0.02	0.47
Utilities, telecom.	1.06	0.40	0.57	0.01	1.11	0.36	0.77	0.52
Trade	1.69	0.97	0.88	0.01	0.70	0.37	0.35	0.45
Financial	1.93[b]	1.18	0.96	0.01	1.14[b]	0.42	0.74	0.47
Services, other	1.69	0.79	0.93	0.01	0.86[b]	0.36	0.51	0.46
Average	1.43[b]	0.58			0.60[b]		0.17	
(Std. err.)	(0.62)	(0.62)			(0.20)		(0.23)	
χ^2 [a]	18.44	26.42[b]			22.48[b]		9.83	
(p-value)	(0.142)	(0.015)			(0.048)		(0.707)	

[a] $\chi^2 = c'\Sigma^{-1}c$, where c is the vector of coefficient estimates and Σ is the estimate of the covariance matrix of c. Under the null that all coefficients are zero, this statistic is asymptotically distributed as χ^2 (d.f. 13).

[b] Denotes coefficients that are greater than two standard errors from zero or χ^2 statistics with a p-value less than 0.050.

The average coefficient, 0.58, is similar to the cross-sectional slope, 0.50, estimated by Fama and French (1992). Economically, the average coefficient is reasonably large. Consider, for example, the effect that a change in B/M equal to two standard deviations would have on expected returns. For the average industry portfolio, the time-series standard deviation of B/M is 0.33. An increase in B/M twice this large maps into a 0.38% change (0.66×0.58) in expected return for the typical portfolio, or 4.67% annually. On the other hand, the predictive power of B/M is low as measured by the adjusted R^2s. Lagged B/M explains at most 1% of the total variation in portfolio returns. This result is consistent with previous studies at the market level, which generally find that pre-determined variables explain only a small fraction of monthly returns (e.g., Fama and French, 1989).

In addition to the ordinary least squares (OLS) estimates just described, Table 3 reports seemingly unrelated regression (SUR) estimates of the equations. OLS treats the regression for each portfolio separately, and ignores interactions among the equations. The residuals across portfolios are correlated, however, because industries' excess returns are driven by many of the same macroeconomic factors. SUR uses this information to estimate the system of equations more efficiently (Zellner, 1962). Although SUR requires an estimate of the residual covariance matrix, the efficiency gain is likely to be large because (1) the error terms are highly correlated across portfolios (see Greene, 1993, p. 489), and (2) the dimension of the covariance matrix (13×13) is small relative to the length of the time series (368 months). Indeed, Table 3 shows that the average standard deviation of the SUR slopes is 0.40, compared with 0.86 for OLS. While the standard deviations are estimated with error, the large decrease suggests that SUR is substantially more efficient.

It was noted above that OLS slope estimates are biased upward. I am not aware of any research that explores the bias in SUR estimates, and there is little reason to believe that it is identical to that of OLS. Without an analytical estimate, I rely on bootstrap simulations to assess the sampling distribution of the SUR slopes. The simulation procedure, described in the appendix, randomly generates time series of returns and B/M, imposing the restriction that expected returns and B/M are unrelated. Since the true coefficient in the simulation equals zero, the mean of the distribution represents the bias in SUR estimates. Further, the standard deviation of the distribution provides an estimate of the SUR standard error.[7]

[7] I also simulate the distribution of the OLS slope estimates and find that the analytical estimate of the bias is reasonably accurate. The average bias from the simulations is 0.92 compared with 0.85 from Eq. (8). The standard errors from the simulation, however, tend to be larger than the OLS estimates. For example, the standard deviation of the average coefficient is 0.76, compared with the OLS standard error of 0.62.

Table 3 shows that the bias-adjusted SUR estimates tend to be smaller than their OLS counterparts. The coefficients range from -0.69 for the machinery and equipment industry to 0.96 for petroleum firms, and eight of the 13 estimates are positive. The average coefficient on B/M, 0.17, is positive, although it is under one standard error, 0.23, from zero. In addition, the χ^2 statistic cannot reject the hypothesis that all slope coefficients are zero. The simulations indicate that the average bias in the SUR estimates, 0.43, is about half the bias in the OLS regressions, 0.85. The magnitude remains significant, however, and the average SUR coefficient decreases by two-thirds, from 0.60 to 0.17, after correcting for bias.

In sum, the evidence in Table 3 is consistent with a positive relation between B/M and expected returns, but B/M explains at most a small fraction of returns. After adjusting for bias in the regressions, only the χ^2 statistic for the OLS slope coefficients is significant at conventional levels. We will see below that the power of the tests is much greater in the conditional three-factor regressions, because the factors absorb much of the volatility of returns. In addition, the size and book-to-market portfolios reveal a considerably stronger relation between B/M and future returns.

As a final observation, it is useful to keep in mind that the regressions cannot reject economically meaningful coefficients on B/M. A typical confidence interval around the average estimate, for either OLS or SUR, would include reasonably large coefficients. Moreover, low explanatory power does not imply that B/M is necessarily unimportant. For example, Kandel and Stambaugh (1996) show that predictive variables with low explanatory power can have a large impact on asset allocation decisions. I suspect a similar result would hold at the portfolio level: the optimal portfolio held by a risk-averse, Bayesian investor is probably sensitive to predictive variables which have low statistical significance.

4.2. Size and book-to-market portfolios

Table 4 shows results for the size and book-to-market portfolios. For simplicity, I report only the SUR estimates, along with the bias-adjusted estimates, since the evidence above indicates that SUR increases the precision of the slope estimates. The table shows that B/M predicts statistically reliable variation in returns for both the size and book-to-market portfolios. After correcting for bias, four coefficients for the size portfolios and nine coefficients for the book-to-market portfolios are more than two standard errors above zero. All 12 estimates are positive for the size portfolios, and the average coefficient, 0.27, is greater than three standard errors from zero. Similarly, ten of the 12 coefficients for the book-to-market portfolios are positive, and the average coefficient, 1.02, is more than three standard errors above zero. The estimates generally increase from the low-B/M deciles to the high-B/M deciles.

Table 4
Predictability of returns: Size and book-to-market portfolios, 5/64–12/94

$$R_i(t) = \gamma_{i0} + \gamma_{i1} B/M_i(t-1) + e_i(t)$$

The size and book-to-market portfolios are described in Table 1. R_i is the portfolio's monthly excess return (in percent) and B/M_i is the natural log of the portfolio's book-to-market ratio at the end of the previous month, measured as a deviation from its time-series mean. The table reports seemingly unrelated regression (SUR) estimates of the slope coefficients, together with bias-adjusted slope estimates. The bias correction for the SURs, as well as the covariance matrix of the bias-adjusted estimates, is obtained from bootstrap simulations

Size portfolios					Book-to-market portfolios				
Portfolio	SUR γ_{i1}	Std. err.	Bias-adj γ_{i1}	Std. err.	Portfolio	SUR γ_{i1}	Std. err.	Bias-adj γ_{i1}	Std. err.
Smallest	0.07	0.33	0.00	0.28	Lowest	− 0.22	0.57	− 0.45	0.54
2	0.32	0.23	0.31[b]	0.15	1b	− 0.22	0.55	− 0.46	0.50
3	0.30	0.21	0.28[b]	0.13	2	0.57	0.55	0.31	0.45
4	0.31	0.19	0.29	0.15	3	1.21[b]	0.51	0.96[b]	0.44
5	0.18	0.20	0.15	0.15	4	1.32[b]	0.50	1.09[b]	0.42
6	0.19	0.20	0.16	0.15	5	1.32[b]	0.51	1.06[b]	0.45
7	0.38	0.22	0.34[b]	0.17	6	1.19[b]	0.52	0.93[b]	0.45
8	0.45[b]	0.22	0.40[b]	0.18	7	1.80[b]	0.53	1.51[b]	0.46
9a	0.46	0.26	0.42	0.21	8	1.85[b]	0.56	1.53[b]	0.49
9b	0.44	0.24	0.38	0.21	9	2.09[b]	0.60	1.77[b]	0.49
10a	0.54	0.28	0.45	0.24	10a	2.27[b]	0.74	1.88[b]	0.61
Largest	0.18	0.33	0.03	0.39	Highest	2.52[b]	0.79	2.14[b]	0.68
Average	0.32[b]		0.27[b]		Average	1.31[b]		1.02[b]	
(Std. err.)	(0.16)		(0.08)		(Std. err.)	(0.46)		(0.29)	
χ^2 [a]	10.84		20.71		χ^2 [a]	25.12[b]		28.21[b]	
(p-value)	(0.543)		(0.055)		(p-value)	(0.014)		(0.005)	

[a] $\chi^2 = c'\Sigma^{-1}c$, where c is the vector of coefficient estimates and Σ is the estimate of the covariance matrix of c. Under the null that all coefficients are zero, this statistic is asymptotically distributed as χ^2 (d.f. 12).

[b] Denotes coefficients that are greater than two standard errors from zero or χ^2 statistics with a p-value less than 0.050.

Interestingly, the bias in the regressions is significantly smaller for the size and book-to-market portfolios than for the industry portfolios. The bootstrap estimate of the bias is 0.05 for the size portfolios and 0.29 for the book-to-market portfolios, compared with 0.43 for the industries (see Table 3). Also, the standard errors from the simulated distribution are less than the actual SUR estimates, while the opposite is true for industry portfolios. From the bootstrap distribution, the standard error of the average coefficient is only 0.08 for the size portfolios and 0.29 for the book-to-market portfolios.

Economically, the individual estimates and the average coefficient are quite large for the book-to-market portfolios. A two-standard-deviation increase in B/M for the typical portfolio predicts a 0.61% monthly increase in expected return, or 7.6% annually. The implied change in expected return is greater than 11% annually for the five portfolios with the highest B/M. The conclusions from the OLS regressions (not reported) are qualitatively similar, but the estimates are less precise. The average bias-adjusted OLS slope is 1.13 (standard error of 0.82) for the size portfolios and 1.30 (standard error of 0.77) for the book-to-market portfolios. The strong relation between expected returns and B/M documented in Table 4 should provide a challenging test of the three-factor model.

5. Expected returns, characteristics, and risk: empirical results

The evidence above indicates the B/M predicts significant time-variation in expected returns. In this section, I examine the explanatory power of B/M in competition with the Fama and French (1993) three-factor model. As discussed above, the conditional regressions directly test whether the three-factor model or the characteristic-based model better explains changes in expected returns over time.

Fama and French estimate the unconditional model

$$R_i(t) = a_i + b_i R_M(t) + s_i \,\mathrm{SMBO}(t) + h_i \,\mathrm{HMLO}(t) + e_i(t), \tag{9}$$

where SMB and HML have been replaced here by the orthogonalized factors SMBO and HMLO (see Section 3). The conditional version of the three-factor model allows the intercepts and factor loadings to vary linearly with lagged B/M. Repeating Eq. (4), the conditional model is specified as

$$\begin{aligned} R_i = {} & a_{i0} + a_{i1} B/M_i + (b_{i0} + b_{i1} B/M_i) R_M \\ & + (s_{i0} + s_{i1} B/M_i)\mathrm{SMBO} + (h_{i0} + h_{i1} B/M_i)\mathrm{HMLO} + e_i, \end{aligned} \tag{10}$$

where B/M is lagged one month relative to returns and time subscripts have been dropped for simplicity. Multiplying the factors through gives the equation to be estimated for each portfolio. The B/M interactive term with the intercept,

a_{i1}, is analogous to the slope coefficient in the simple regressions above, except that the multifactor regressions control for changes in risk. Consequently, a_{i1} measures the predictive ability of B/M that cannot be explained by the Fama and French three-factor model.

5.1. Industry portfolios

Before continuing to the conditional model, Table 5 reports unconditional three-factor regressions for the industry portfolios.[8] Consistent with the results of Fama and French (1997), the size and book-to-market factors explain significant co-movement in industry returns not captured by the market. For both SMBO and HMLO, ten of the 13 coefficients deviate from zero by more than two standard errors. In fact, nine coefficients on the size factor and eight coefficients on the book-to-market factor are greater than four standard errors from zero. If the loadings change over time and are uncorrelated with the factors, the unconditional estimates can be interpreted as the average factor sensitivities of the industries. Therefore, unless some industries were 'distressed' throughout the sample period, the significant explanatory power of SMBO and HMLO suggests that they proxy for more than just distress factors. Instead, the mimicking portfolios appear to reflect information relevant to a broad cross section of firms (see also Section 5.3).

The factors, however, cannot completely explain cross-sectional variation in average returns. Under the hypothesis that the three-factor model explains average returns, the intercepts in the time-series regressions should be zero. Table 5 shows that several intercepts are individually significant, and the Gibbons et al. (1989) F-statistic rejects at the 1% level the restriction that all are zero. Economically, the intercepts are generally small, but two deviate from zero by over 3% annually. In sum, SMBO and HMLO proxy for pervasive risk factors in industry portfolios, and the three-factor model provides a reasonable, though not perfect, description of average returns.[9]

Table 6 reports SUR estimates of the conditional model. For simplicity, I do not report the constant terms of the intercepts and factor loadings (a_{i0}, b_{i0}, s_{i0}, and h_{i0}). Since the industries' B/M ratios are measured as deviations from their time-series means, the constant terms are simply estimates of the average coefficients, and they are nearly identical to the unconditional results in Table 5.

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[8] For these regressions, OLS and SUR are identical because the regressors are the same for all portfolios (Greene, 1993, p. 488).

[9] As a robustness check, I also estimate heteroskedastic-consistent standard errors and an asymptotically valid χ^2 statistic for the hypothesis that all intercepts are zero (based on the covariance estimates of White (1984); see also Shanken (1990)). The results are not sensitive to heteroskedasticity adjustments.

Table 5
Unconditional three-factor regressions: Industry portfolios, 5/64–12/94

$$R_i(t) = a_i + b_i R_M(t) + s_i\,\mathrm{SMBO}(t) + h_i\,\mathrm{HMLO}(t) + e_i(t)$$

The industry portfolios and factors are described in Tables 1 and 2. R_i is the portfolio's monthly excess return (in percent). R_M is the return on the CRSP value-weighted index minus the one-month T-bill rate. SMBO is the return on a portfolio of small stocks minus the return on a portfolio of big stocks, orthogonalized with respect to R_M. HMLO is the return on portfolio of high-B/M stocks minus the return on a portfolio of low-B/M stocks, again orthogonalized with respect to R_M. The table reports ordinary least squares estimates of the equations and the Gibbons et al. (1989) F-test of the intercepts

Portfolio	a		b		s		h		Adj R^2
	Coeff.	Std. err.	Coeff.	Std. err.	Coeff.	Std. err.	Coeff.	Std. err.	
Nat. resources	− 0.05	0.20	0.97[b]	0.04	0.03	0.07	− 0.02	0.07	0.57
Construction	− 0.23[b]	0.10	1.14[b]	0.02	0.31[b]	0.04	0.17[b]	0.03	0.89
Food, tobacco	0.38[b]	0.12	0.90[b]	0.03	− 0.12[b]	0.04	− 0.01	0.04	0.77
Consumer products	− 0.15	0.12	1.18[b]	0.03	0.68[b]	0.04	0.19[b]	0.04	0.86
Logging, paper	0.01	0.11	1.11[b]	0.02	0.05	0.04	0.05	0.04	0.85
Chemicals	0.21[b]	0.10	0.98[b]	0.02	− 0.21[b]	0.04	− 0.20[b]	0.03	0.85
Petroleum	0.29	0.19	0.81[b]	0.04	− 0.45[b]	0.07	0.12[b]	0.07	0.53
Mach., equipment	0.04	0.10	1.11[b]	0.02	0.14[b]	0.04	− 0.28[b]	0.04	0.87
Transportation	− 0.24	0.12	1.08[b]	0.03	0.20[b]	0.04	0.28[b]	0.04	0.83
Utilities, telecom.	− 0.06	0.10	0.65[b]	0.02	− 0.26[b]	0.04	0.38[b]	0.04	0.74
Trade	0.03	0.14	1.13[b]	0.03	0.26[b]	0.05	0.01	0.05	0.80
Financial	− 0.04	0.08	1.00[b]	0.02	− 0.04	0.03	0.21[b]	0.03	0.89
Services, other	0.16	0.11	1.38[b]	0.03	0.74[b]	0.04	0.17[b]	0.04	0.90
GRS F[a]	2.63								
(p-value)	(0.003)								

[a]The GRS F-statistic equals $(T - N - K + 1)/[N(T - K)]a'\Sigma^{-1}a$, where a is the vector of intercept estimates, Σ is the estimate of the covariance matrix of a, T is 368 (months), N is 13 (portfolios), and K is 4 (independent variables). Under the null hypothesis that all intercepts are zero, and assuming that returns are multivariate normal, this statistic is distributed as F (d.f. 13, 352).
[b]Denotes coefficients that are greater than two standard errors from zero.

Table 6
Conditional three-factor regressions: Industry portfolios, 5/64–12/94

$$R_i = a_{i0} + a_{i1}B/M_i + (b_{i0} + b_{i1}B/M_i)R_M + (s_{i0} + s_{i1}B/M_i)\mathrm{SMBO} + (h_{i0} + h_{i1}B/M_i)\mathrm{HMLO} + e_i$$

The industry portfolios and factors are described in Tables 1 and 2. R_i is the portfolio's monthly excess return (in percent) and B/M_i is the natural log of the portfolio's book-to-market ratio at the end of the previous month, measured as a deviation from its time-series mean. R_M is the return on the CRSP value-weighted index minus the one-month T-bill rate. SMBO is the return on a portfolio of small stocks minus the return on a portfolio of big stocks, orthogonalized with respect to R_M. HMLO is the return on portfolio of high-B/M stocks minus the return on a portfolio of low-B/M stocks, again orthogonalized with respect to R_M. The table reports seemingly unrelated regression estimates of the interactive terms, a_{i1}, b_{i1}, s_{i1}, and h_{i1}, which measure time-variation in the intercepts and factor loadings

Portfolio	a_1		b_1		s_1		h_1	
	Coeff.	Std. err.	Coeff.	Std. err.	Coeff.	Std. err.	Coeff.	Std. err.
Nat. resources	− 0.13	0.62	− 0.01	0.12	− 0.28	0.23	− 0.22	0.20
Construction	− 0.36	0.24	− 0.16[b]	0.05	0.05	0.09	0.14	0.09
Food, tobacco	− 0.12	0.26	0.02	0.05	0.23[b]	0.09	0.40[b]	0.09
Consumer products	0.03	0.23	− 0.17[b]	0.04	0.12	0.08	0.27[b]	0.07
Logging, paper	− 0.28	0.38	− 0.06	0.07	− 0.11	0.14	0.34[b]	0.13
Chemicals	− 0.30	0.28	− 0.05	0.06	0.06	0.10	0.28[b]	0.10
Petroleum	0.62	0.54	− 0.05	0.12	− 0.32	0.20	− 0.16	0.19
Mach., equipment	− 0.72[b]	0.22	0.03	0.05	0.18[b]	0.08	0.29[b]	0.08
Transportation	0.07	0.30	− 0.24[b]	0.07	0.00	0.12	0.02	0.10
Utilities, telecom.	0.33	0.26	0.01	0.06	0.12	0.10	0.04	0.09
Trade	− 0.05	0.32	− 0.02	0.07	0.27[b]	0.12	0.55[b]	0.10
Financial	0.43	0.31	0.07	0.07	− 0.17	0.12	− 0.33[b]	0.11
Services, other	− 0.08	0.27	0.00	0.05	0.23[b]	0.10	0.35[b]	0.08
Average	− 0.04		− 0.05[b]		0.03		0.15[b]	
(Std. err.)	(0.09)		(0.02)		(0.03)		(0.03)	
χ^2 [a]	14.27		38.94[b]		24.72[b]		95.76[b]	
(p-value)	(0.355)		(0.000)		(0.025)		(0.000)	

[a] $\chi^2 = c'\Sigma^{-1}c$, where c is the vector of coefficient estimates and Σ is the estimate of the covariance matrix of c. Under the null that all coefficients are zero, this statistic is asymptotically distributed as χ^2 (d.f. 13).
[b] Denotes coefficients that are greater than two standard errors from zero or χ^2 statistics with a p-value less than 0.050.

Across all parameters, the mean absolute difference between the constant terms and the unconditional estimates in Table 5 is 0.017; for the intercepts only, it is 0.006. The similarity between the two sets of regressions indicates that changes in the loadings are largely uncorrelated with the factors.

The interactive terms with B/M are more interesting for our purposes. The table shows that B/M captures time-variation in risk, but does not appear to directly predict expected returns. The χ^2 statistics easily reject the hypotheses that B/M is unrelated to the loadings on R_M, SMBO, and HMLO. The B/M interactive terms with R_M, SMBO, and HMLO are over two standard errors from zero for 3 portfolios, 4 portfolios, and 8 portfolios, respectively. B/M tends to be positively related to the loadings on the size and book-to-market factors (financial firms are the exception), but negatively related to market betas. Interpreting increases in B/M as evidence of distress, it appears that market risk becomes relatively less important for distressed industries. While somewhat surprising, a similar result has been documented previously for firms near bankruptcy (e.g., McEnally and Todd, 1993).

In contrast, there is no evidence that B/M explains economically or statistically significant variation in the intercepts. None of the interactive terms with the intercepts is significantly positive, eight of the 13 estimates are negative, and the average coefficient, -0.04, is insignificantly different from zero (standard error of 0.09).[10] In fact, the only significant coefficient is actually negative (for the machinery and equipment industry), which is inconsistent with the overreaction story. In addition, the χ^2 statistic cannot reject the hypothesis that all coefficients on B/M are zero, with a p-value of 0.355. Thus, variation in risk appears to explain any association between B/M and expected returns.

Importantly, the lack of statistical significance is not driven by low power. The standard error of the average coefficient is relatively low, 0.09, and allows rejection of economically significant slopes. For example, suppose that the actual coefficient is two standard errors above the sample estimate, or 0.13. This coefficient maps into less than a 0.09% change in the monthly intercept when B/M varies by 0.66, twice its standard deviation for the typical portfolio. The OLS estimates (not reported) of the conditional regressions support these conclusions. Individually, the B/M coefficients are not significant, with an average estimate equal to -0.07 (standard error of 0.11), and the χ^2 statistic does not reject the joint restriction that all are zero (p-value of 0.370). The

[10] There is no mechanical reason that the average coefficient is zero. Conditional asset-pricing tests typically use the same conditioning variables for all portfolios, and some linear combination of the coefficients must be zero. However, no linear constraint is imposed on the coefficients here because B/M differs across portfolios. For example, aggregate B/M explains, on average, half of the variation in an industry's B/M ratio. In fact, when B/M is measured net of an aggregate index, the average correlation across portfolios is necessarily close to zero.

evidence is inconsistent with the argument that B/M proxies for mispricing in stock returns.

We saw earlier that the slope estimate is biased upward in a simple regression of returns on lagged B/M. The B/M term in the three-factor regression is likely to be biased upward as well, which would strengthen the conclusions above. An ad hoc estimate of the bias can be obtained by substituting the residuals from the three-factor regressions for the simple-regression error terms in Eq. (8). The average bias estimated this way, 0.17, is much smaller than the bias in the simple regressions, 0.85. Bootstrap simulations like those described in Section 4 produce a similar estimate, 0.18.

5.2. Size and book-to-market portfolios

Tables 7 and 8 report similar findings for the size and book-to-market portfolios. In the unconditional regressions in Table 7, SMBO and HMLO capture significant co-movement in stock returns. For the size portfolios, the loadings on all factors are greatest for the smallest portfolios and decrease almost monotonically with size. They range from 0.91 to 1.22 on the market factor, −0.31 to 1.39 on SMBO, and −0.08 to 0.30 on HMLO. For the book-to-market portfolios, the loadings on SMBO and HMLO increase almost monotonically from the lowest to the highest deciles. The coefficients vary widely across portfolios. The cross-sectional spread is −0.09–0.87 for the loadings on SMBO and −0.77–0.97 for the loadings on HMLO. Market betas are generally close to one, ranging from 0.91 to 1.13, but are highest for the extreme portfolios (portfolios 1a and 10b). Consistent with the evidence in Fama and French (1993), the multivariate F-statistic rejects the asset-pricing restriction that all intercepts are zero. However, the deviations from zero are small (with the exception of low-B/M portfolio), and the three-factor model provides a fairly accurate description of average stock returns.

The conditional three-factor regressions are more important for the current paper. Table 8 reports SUR estimates for the conditional model, in which intercepts and factor loadings vary linearly with lagged B/M. As before, the constant terms in the regressions are similar to the unconditional coefficients in Table 7 and I report only the interactive terms with B/M.

The evidence supports the conclusion that B/M captures significant variation in risk, but has little power to directly predict expected returns. For both sets of portfolios, the χ^2 statistics strongly reject, at the 0.001 level, the hypothesis that B/M is unrelated to the factor loadings. B/M displays a consistently positive relation to the loadings on the size and book-to-market factors. For the 24 portfolios shown in Table 8, 15 of the interactive terms with SMBO are greater than two standard errors above zero, and only one is significantly negative. Similarly, 16 of the coefficients on HMLO are significantly positive, and only one is significantly negative. The relation between B/M and markets betas is

Table 7
Unconditional three-factor regressions: Size and book-to-market portfolios, 5/64–12/94

$$R_i(t) = a_i + b_i R_M(t) + s_i\,\mathrm{SMBO}(t) + h_i\,\mathrm{HMLO}(t) + e_i(t)$$

The portfolios and factors are described in Tables 1 and 2. R_i is the portfolio's monthly excess return (in percent). R_M is the return on the CRSP value-weighted index minus the one-month T-bill rate. SMBO is the return on a portfolio of small stocks minus the return on a portfolio of big stocks, orthogonalized with respect to R_M. HMLO is the return on portfolio of high-B/M stocks minus the return on a portfolio of low-B/M stocks, again orthogonalized with respect to R_M. The table reports ordinary least squares estimates of the equations and the Gibbons et al. (1989) F-test of the intercepts

Portfolio	*a*		*b*		*s*		*h*		Adj R^2
	Coeff.	Std. err.	Coeff.	Std. err.	Coeff.	Std. err.	Coeff.	Std. err.	
Panel A: Size portfolios									
Smallest	– 0.15	0.09	1.16[b]	0.02	1.39[b]	0.03	0.30[b]	0.03	0.93
2	– 0.13[b]	0.05	1.19[b]	0.01	1.09[b]	0.02	0.19[b]	0.02	0.97
3	– 0.11[b]	0.04	1.22[b]	0.01	0.96[b]	0.02	0.15[b]	0.01	0.98
4	– 0.05	0.05	1.21[b]	0.01	0.84[b]	0.02	0.12[b]	0.02	0.98
5	0.03	0.05	1.19[b]	0.01	0.74[b]	0.02	0.11[b]	0.02	0.98
6	0.09	0.05	1.15[b]	0.01	0.59[b]	0.02	0.11[b]	0.02	0.97
7	– 0.01	0.05	1.12[b]	0.01	0.43[b]	0.02	0.10[b]	0.02	0.97
8	0.02	0.05	1.12[b]	0.01	0.27[b]	0.02	0.13[b]	0.02	0.97
9a	0.01	0.06	1.07[b]	0.01	0.09[b]	0.02	0.14[b]	0.02	0.95
9b	– 0.01	0.05	1.04[b]	0.01	0.05[b]	0.02	0.11[b]	0.02	0.96
10a	0.00	0.05	0.99[b]	0.01	– 0.12[b]	0.02	0.03	0.02	0.96
Largest	0.04	0.04	0.91[b]	0.01	– 0.31[b]	0.01	– 0.08[b]	0.01	0.97
GRS F[a]	2.43								
(p-value)	(0.005)								

Panel B: Book-to-market portfolios

Lowest	0.40[b]	0.09	1.12[b]	0.02	– 0.02	0.03	– 0.77[b]	0.03	0.91
1a	0.11	0.09	1.07[b]	0.02	– 0.09[b]	0.03	– 0.42[b]	0.03	0.90
2	– 0.04	0.07	1.09[b]	0.01	– 0.07[b]	0.02	– 0.25[b]	0.02	0.94
3	– 0.06	0.07	1.03[b]	0.02	– 0.06[b]	0.03	– 0.10[b]	0.02	0.92
4	– 0.10	0.08	0.99[b]	0.02	– 0.04	0.03	0.09[b]	0.03	0.90
5	– 0.14	0.08	0.95[b]	0.02	– 0.01	0.03	0.19[b]	0.03	0.89
6	– 0.05	0.08	0.91[b]	0.02	– 0.06[b]	0.03	0.39[b]	0.03	0.90
7	0.08	0.07	0.93[b]	0.02	– 0.01[b]	0.03	0.48[b]	0.03	0.91
8	0.06	0.07	0.93[b]	0.02	0.10[b]	0.03	0.65[b]	0.03	0.91
9	0.14	0.08	1.01[b]	0.02	0.25[b]	0.03	0.71[b]	0.03	0.92
10a	0.02	0.12	1.12[b]	0.03	0.52[b]	0.04	0.81[b]	0.04	0.87
Highest	– 0.12	0.15	1.13[b]	0.03	0.87[b]	0.06	0.97[b]	0.05	0.82
GRS F[a]	2.24								
(p-value)	(0.010)								

[a] The GRS F-statistic equals $(T-N-K+1)/[N(T-K)]a'\Sigma^{-1}a$, where a is the vector of intercept estimates, Σ is the estimate of the covariance matrix of a, T is 368 (months), N is 12 (portfolios), and K is 4 (independent variables). Under the null hypothesis that all intercepts are zero, and assuming that returns are multivariate normal, this statistic is distributed as F (d.f. 12, 353).

[b] Denotes coefficients that are greater than two standard errors from zero.

Table 8
Conditional three-factor regressions: Size and book-to-market portfolios, 5/64–12/94

$$R_i = a_{i0} + a_{i1}B/M_i + (b_{i0} + b_{i1}B/M_i)R_{\mathrm{M}} + (s_{i0} + s_{i1}B/M_i)\mathrm{SMBO} + (h_{i0} + h_{i1}B/M_i)\mathrm{HMLO} + e_i$$

The portfolios and factors are described in Tables 1 and 2. R_i is the portfolio's monthly excess return (in percent) and B/M_i is the natural log of the portfolio's book-to-market ratio at the end of the previous month, measured as a deviation from its time-series mean. R_M is the return on the CRSP value-weighted index minus the one-month T-bill rate. SMBO is the return on a portfolio of small stocks minus the return on a portfolio of big stocks, orthogonalized with respect to R_M. HMLO is the return on portfolio of high-B/M stocks minus the return on a portfolio of low-B/M stocks, again orthogonalized with respect to R_M. The table reports seemingly unrelated regression estimates of the interactive terms, a_{i1}, b_{i1}, s_{i1}, and h_{i1}, which measure time-variation in the intercepts and factor loadings

Portfolio	a_1		b_1		s_1		h_1	
	Coeff.	Std. err.	Coeff.	Std. err.	Coeff.	Std. err.	Coeff.	Std. err.
Panel A: Size portfolios								
Smallest	−0.10	0.24	−0.10[b]	0.04	−0.08	0.09	0.17[b]	0.07
2	0.09	0.15	−0.10[b]	0.03	0.05	0.05	0.25[b]	0.04
3	0.09	0.12	−0.06[b]	0.02	0.07	0.04	0.17[b]	0.04
4	0.06	0.12	−0.06[b]	0.02	0.11[b]	0.04	0.22[b]	0.04
5	−0.09	0.12	−0.09[b]	0.02	0.08[b]	0.04	0.21[b]	0.04
6	−0.10	0.13	−0.05[b]	0.02	0.19[b]	0.05	0.17[b]	0.04
7	−0.01	0.15	0.02	0.03	0.33[b]	0.05	0.16[b]	0.04
8	0.03	0.14	0.09[b]	0.03	0.19[b]	0.05	0.18[b]	0.04
9a	−0.16	0.17	0.10[b]	0.03	0.23[b]	0.06	0.18[b]	0.05
9b	0.07	0.15	0.08[b]	0.03	0.14[b]	0.05	0.07	0.05
10a	0.18	0.15	0.09[b]	0.03	0.07	0.06	−0.06	0.06
Largest	−0.07	0.08	−0.08[b]	0.02	−0.21[b]	0.03	−0.02	0.03
Average	0.00		−0.01		0.10[b]		0.14[b]	
(Std. err.)	(0.05)		(0.01)		(0.02)		(0.01)	
χ^2 [a]	7.67		78.67[b]		81.49[b]		126.28[b]	
(p-value)	(0.810)		(0.000)		(0.000)		(0.000)	

Panel B: Book-to-market portfolios

Lowest	– 0.70[b]	0.25	0.21[b]	0.05	0.24[b]	0.09	– 0.18[b]	0.09
1b	– 0.79[b]	0.27	0.10	0.06	– 0.01	0.10	0.17	0.09
2	– 0.04	0.23	– 0.03	0.05	0.21[b]	0.08	0.05	0.07
3	0.67[b]	0.24	– 0.08	0.04	0.06	0.09	0.09	0.07
4	0.43	0.25	– 0.11[b]	0.05	0.19[b]	0.09	0.19[b]	0.08
5	0.24	0.25	– 0.13[b]	0.05	0.30[b]	0.09	0.25[b]	0.08
6	– 0.07	0.25	– 0.13[b]	0.05	0.05	0.09	0.43[b]	0.07
7	0.35	0.25	0.00	0.04	0.12	0.09	0.32[b]	0.07
8	0.17	0.25	– 0.07	0.05	0.18[b]	0.09	0.33[b]	0.07
9	0.34	0.26	0.13[b]	0.05	0.35[b]	0.10	– 0.02	0.08
10a	0.05	0.39	0.18[b]	0.07	0.33[b]	0.14	0.27[b]	0.11
Highest	– 0.26	0.43	0.16[b]	0.08	0.68[b]	0.16	0.51[b]	0.12
Average	0.03		0.02		0.23[b]		0.20[b]	
(Std. err.)	(0.07)		(0.01)		(0.03)		(0.02)	
χ^2 [a]	24.32[b]		42.08[b]		103.26[b]		146.74[b]	
(p-value)	(0.018)		(0.000)		(0.000)		(0.000)	

[a] $\chi^2 = c'\Sigma^{-1}c$, where c is the vector of coefficient estimates and Σ is the estimate of the covariance matrix of c. Under the null that all coefficients are zero, this statistic is asymptotically distributed as χ^2 (d.f. 12).

[b] Denotes coefficients that are greater than two standard errors from zero or χ^2 statistics with a p-value less than 0.050.

mixed. An increase in B/M predicts smaller betas for ten portfolios and larger betas for eight portfolios. Together with Table 6, the conditional regressions provide considerable evidence that B/M explains variation in risk.

Changes in risk absorb nearly all of B/M's predictive ability. The interactive terms with the intercepts are generally small and statistically insignificant. The average coefficient for the size portfolios is 0.00 (standard error of 0.05) and for the book-to-market portfolios is 0.03 (standard error of 0.07). Neither estimate is statistically different from zero, and we can reject economically significant coefficients. For example, true coefficients of 0.10 and 0.17 are two standard errors above the averages reported in Table 8. These coefficients map into 0.06% and 0.10% changes in monthly expected returns, respectively, when B/M varies by twice its standard error for the typical portfolio. The findings are striking given the significant explanatory power of B/M in simple regressions (see Table 4). By controlling for changes in risk, the average slopes on B/M decrease from 0.27 to 0.00 for the size portfolios and 1.02 to 0.03 for the book-to-market portfolios. B/M does not appear to have incremental explanatory power in predicting returns.

Individually, the estimates for the size portfolios are small, and the χ^2 statistic cannot reject the hypothesis that all coefficients are zero, with a p-value of 0.810. The results for the book-to-market portfolios, however, provide some evidence of predictability: two coefficients are significantly negative (-0.70 and -0.79 for portfolios 1a and 1b) and one is significantly positive (0.67 for the portfolio 3). I discount the significance of the negative coefficients since they are inconsistent with both the efficient-market and overreaction stories. Also, the positive coefficient is the maximum estimate observed after searching over many coefficients, which provides an upward-biased estimate of the true maximum.[11] Overall, the picture that emerges from Tables 6 and 8 is that B/M contains substantial information about the riskiness of stock portfolios, but does not directly predict expected returns. There is virtually no support for the overreaction hypothesis.

5.3. Industry-neutral HML

Daniel and Titman (1997) argue that HML does not proxy for a separate risk factor in returns, but explains return covariation only because similar types of firms become mispriced at the same time. Their argument suggests that an industry's B/M ratio and its loading on HML will be related even under the

[11] Bonferroni confidence intervals provide a straightforward way to incorporate searching into statistical significance. Viewed in isolation, the estimate for decile 3 has a one-sided p-value of 0.002. Recognizing that the estimate is the maximum over 37 total portfolios, the Bonferroni upper bound on the p-value is 0.002×37, or 0.083. See Johnson and Wichern (1982, p. 197).

mispricing story. By construction, HML invests in stocks with high B/M ratios. When an industry's B/M increases, HML becomes weighted toward firms in that industry and will, therefore, tend to covary more strongly with the industry return. In this case, time-varying factor loadings on HML might help explain mispricing related to B/M. To check whether the results for industry portfolios are driven by changes in the industry composition of HML, I replicate the three-factor regressions using an 'industry-neutral' book-to-market factor.

As detailed in the Appendix, HML equals the return on a portfolio of high-B/M stocks minus the return on a portfolio of low-B/M stocks. I construct an industry-neutral factor, HML-N, in exactly the same way, except that stocks are sorted by their industry-adjusted B/M ratios, defined as the firm's B/M ratio minus the value-weighted average for all firms in their industry. The industries are defined for this purpose using the same classifications as the industry portfolios. By construction, then, the adjusted B/M ratios for firms in each industry are distributed around zero, so every industry should be represented approximately equally in the high- and low-B/M portfolios used to obtain HML-N.[12]

Empirically, the sorting procedure does not dramatically alter the book-to-market factor. HML-N has an average monthly return of 0.44% and a standard deviation of 2.42%, compared with 0.38% and 3.00%, respectively, for HML. The correlation between the two book-to-market factors, 0.87, is fairly high, which suggests that much of the variation in HML is unrelated to industry factors. In fact, part of the difference between HML and HML-N is caused by the difference in their market betas. The market beta of HML-N equals -0.03, significantly closer to zero than the -0.23 beta of HML. I also note that the sorting procedure affects SMB, since the size factor controls for differences in stocks' B/M ratios. The new size factor, which I continue to call SMB, has a mean return of 0.24% and a standard deviation of 2.64%, compared with 0.30% and 2.91% for Fama and French's (1993) size factor. The two size factors are almost perfectly correlated, with a sample correlation of 0.99. As before, I orthogonalize these factors with respect to the market return for the three-factor regressions.

Table 9 reports conditional regressions for the industry portfolios. For simplicity, the table reports only the coefficient estimates because the standard errors are close to those in Tables 5 and 6 (most differ by less than 0.01). The results are surprisingly similar to the findings for the Fama and French factors. Like HML, HML-N explains significant co-movement in returns: ten of the 13 unconditional factor loadings are greater than two standard errors from zero, and the χ^2 statistic strongly rejects the hypothesis that all are zero. In addition, B/M

[12] As an alternative, I also divided the industry-adjusted B/M ratios by the standard deviation across firms in the industry. This modification does not affect the qualitative results.

Table 9
Three-factor regressions with industry-neutral HML: Industry portfolios, 5/64–12/94

$$R_i = a_{i0} + a_{i1}B/M_i + (b_{i0} + b_{i1}B/M_i)R_M + (s_{i0} + s_{i1}B/M_i)\text{SMBO} + (h_{i0} + h_{i1}B/M_i)\text{HML-N} + e_i$$

The industry portfolios are described in Table 1. R_i is the portfolio's monthly excess return (in percent) and B/M_i is the natural log of the portfolio's book-to-market ratio at the end of the previous month, measured as a deviation from its time-series mean. R_M is the return on the CRSP value-weighted index minus the one-month T-bill rate. SMBO is the return on a portfolio of small stocks minus the return on a portfolio of big stocks. HML-N is the return on a portfolio of high-B/M stocks minus the return on a portfolio of low-B/M stocks. HML-N is 'industry neutral', constructed by sorting stocks based on their industry-adjusted B/M ratios, defined as the firm's B/M ratio minus its industry average. The table reports coefficient estimates from seemingly unrelated regressions. The standard errors of the coefficients are similar to those reported in Tables 5 and 6

Portfolio	Intercept		R_M		SMBO		HML-N	
	a_0	a_1	b_0	b_1	s_0	s_1	h_0	h_1
Nat. resources	− 0.06	− 0.19	0.98[b]	0.00	0.00	− 0.28	0.05	− 0.39
Construction	− 0.27[b]	− 0.42	1.15[b]	− 0.15[b]	0.24[b]	− 0.01	0.32[b]	0.15
Food, tobacco	0.38[b]	− 0.06	0.90[b]	0.02	− 0.10[b]	0.29[b]	− 0.13[b]	0.29[b]
Consumer products	− 0.16	− 0.02	1.20[b]	− 0.12[b]	0.67[b]	0.12	0.18[b]	0.26[b]
Logging, paper	− 0.02	− 0.32	1.12[b]	− 0.04	0.01	− 0.17	0.11[b]	0.41[b]
Chemicals	0.20[b]	− 0.23	0.99[b]	− 0.05	− 0.19[b]	0.06	− 0.22[b]	0.20
Petroleum	0.32	0.71	0.81[b]	− 0.05	− 0.50[b]	− 0.36	0.10	− 0.36
Mach., equipment	− 0.01	− 0.70[b]	1.13[b]	0.03	0.15[b]	0.13	− 0.23[b]	0.38[b]
Transportation	− 0.24[b]	− 0.01	1.12[b]	− 0.21[b]	0.14[b]	0.07	0.39[b]	− 0.04
Utilities, telecom.	0.00	0.33	0.65[b]	− 0.01	− 0.27[b]	0.19	0.24[b]	0.08
Trade	0.01	− 0.07	1.14[b]	0.02	0.26[b]	0.29[b]	− 0.06	0.53[b]
Financial	− 0.01	0.38	0.99[b]	0.07	− 0.02	− 0.12	0.18[b]	− 0.34[b]
Services, other	0.16	− 0.07	1.37[b]	0.04	0.78[b]	0.23[b]	− 0.27[b]	0.41[b]
Average	0.02	− 0.05	1.04[b]	− 0.03[b]	0.09[b]	0.03	0.05[b]	0.12[b]
(Std. err.)	(0.02)	(0.08)	(0.01)	(0.02)	(0.01)	(0.03)	(0.01)	(0.03)
χ^2 [a]	36.42[b]	13.52	59841.86[b]	30.37[b]	727.70[b]	23.76[b]	288.46[b]	77.23[b]
(p-value)	(0.001)	(0.408)	(0.000)	(0.004)	(0.000)	(0.033)	(0.000)	(0.000)

[a] $\chi^2 = c'\Sigma^{-1}c$, where c is the vector of coefficient estimates and Σ is the estimate of the covariance matrix of c. Under the null that all coefficients are zero, this statistic is asymptotically distributed as χ^2 (d.f. 13).
[b] Denotes coefficients that are greater than two standard errors from zero or χ^2 statistics with a p-value less than 0.050.

captures significant time-variation in the factor loadings. Focusing on HML-N, seven of the 13 interactive terms are more than two standard errors from zero, and both the average coefficient (0.12, standard error of 0.03) and the χ^2 statistic (p-value less than 0.001) reject the hypothesis of constant risk. Again, B/M does not predict returns after controlling for changes in risk. None of the interactive terms with the intercept, a_{i1}, is significantly positive, and more than half of the estimates are negative. The average coefficient is also negative, and the χ^2 statistic cannot reject that all coefficients are zero.

These results say several interesting things about the book-to-market factor. First, HML (or HML-N) appears to capture a risk factor in returns that is unrelated to industry, contrary to the arguments of Daniel and Titman (1997). Neither the variation in HML, nor its covariation with industry returns, changes substantially when I control for changes in HML's industry composition. Second, HML appears to proxy for more than a distress factor in returns, unless some industries were distressed throughout the sample period. The cross-sectional spread of the unconditional factor loadings on HML is large (0.66 compared with 0.73 for market betas), and the variation across individual stocks is undoubtedly greater. Thus, HML contains information about a broad cross section of firms regardless of whether they are currently distressed. Finally, changes in the industry composition of HML do not drive changes in the industry portfolios' factor loadings. B/M continues to explain significant time-variation in risk after controlling for changes in HML's industry composition. Taken as a whole, the evidence supports the argument that B/M relates to a priced risk factor in returns.

6. Summary and conclusions

Previous studies find that B/M explains significant cross-sectional variation in average returns. That finding implies that, at a fixed point in time, B/M conveys information about the firm's expected return relative to other stocks. This paper addresses a related question: For a given portfolio, does B/M contain information about the portfolio's expected return over time? The time-series analysis complements research on the predictability of stock returns at the aggregate level, and provides an alternative to cross-sectional tests of the risk- and characteristic-based asset-pricing stories.

The main empirical tests focus on industry portfolios. I find some evidence that an industry's B/M ratio predicts changes in its expected return, but the high variance of monthly returns reduces the precision of the estimates. The average, bias-adjusted coefficient on B/M, 0.58, is similar to the cross-sectional slope, 0.50, estimated by Fama and French (1992). The size and book-to-market portfolios produce more reliable evidence that B/M predicts returns. The results suggest that B/M tracks economically large changes in expected returns.

The conditional multifactor regressions indicate that B/M captures time-variation in risk, as measured by the Fama and French (1993) three-factor model. B/M tends to be positively related to the loadings on the size and book-to-market factors, but its relation to market betas is more difficult to characterize. The general impression conveyed by the conditional regressions is that market risk becomes relatively less important as a portfolio's B/M ratio increases. While it is beyond the scope of the current paper, understanding the economic reasons for the pattern of coefficients would provide additional insights into the connection between B/M and risk. I simply note here that the positive association between B/M and the loadings on HML does not seem to be driven by industry-related variation in the book-to-market factor.

After controlling for changes in risk, B/M contains little additional information about expected returns. Time-variation in the intercepts of the three-factor model measures the incremental explanatory power of B/M. For the industry portfolios, the average estimate has the opposite sign predicted by the overreaction story, and it is not significantly different from zero. Across the 13 portfolios, eight coefficients are negative and none are significantly positive at conventional levels. Results for the size and book-to-market portfolios support these inferences: the average coefficients are indistinguishable from zero and roughly half the estimates are negative. The evidence for these portfolios is especially striking given B/M's strong predictive power when it is used alone in simple regressions. I have also replicated the tests in this paper using a firm's size in place of its B/M ratio, and find results qualitatively similar to those for B/M. In short, the three-factor model appears to explain time-varying expected returns better than a characteristic-based model.

To interpret the results, it is important to remember that we can always find some factor model to describe expected returns under both the efficient-market and mispricing stories (see, e.g., Roll, 1977; Shanken, 1987). The tests obtain economic meaning only when restrictions are imposed on the model. According to asset-pricing theory, the factors should capture pervasive risk in the economy related to investment opportunities or consumption. Under the mispricing view, it seems unlikely that the factors would explain, unconditionally, substantial covariation in returns. Many industries have large unconditional loadings on both the size and book-to-market factors, which provides some evidence that the factors proxy for priced risk in the economy.

Unfortunately, the case for rational pricing is not entirely satisfactory. This paper has been concerned primarily with changes in expected returns over time, not with their average levels. Consistent with the results of Fama and French (1993,1997) and Daniel and Titman (1997), I find that the unconditional intercepts in the three-factor model are not zero. Thus, the model does not explain average returns. Just as important, the risk factors captured by the size and B/M mimicking portfolios have not been identified. The rational-pricing story will remain incomplete, and perhaps unconvincing, until we know more about the underlying risks.

Appendix A

This appendix proves that h_i equals zero in Eq. (5), describes the Fama and French (1993) factors, and summarizes the bootstrap simulations in Section 4.

A.1. Proof that $h_i = 0$

Let M be the proxy for the market portfolio, and assume that HML is constructed so that M and HML span the conditional tangency portfolio. The portfolio weights of HML can change over time, but I suppress the time subscript for simplicity. Without lack of generality, assume that $\mathrm{cov}(R_{\mathrm{M}}, \mathrm{HML}) = 0$. We need to show that, under the mispricing story, the factor loading on HML must be zero in the unconditional time-series regression

$$R_i(t) = a_i + b_i R_{\mathrm{M}}(t) + h_i \,\mathrm{HML}(t) + e_i(t). \tag{A.1}$$

I assume that mispricing is temporary, by which I mean that conditional deviations from the CAPM have expectation zero. Also, assume that time-variation in b_i and h_i is unrelated to time-variation in the factor expected returns. These assumptions imply that the CAPM holds unconditionally:

$$\mathrm{E}[R_i] = b_i' \mathrm{E}[R_{\mathrm{M}}], \tag{A.2}$$

where b_i' is the unconditional market beta. Also, taking expectations in Eq. (A.1) yields

$$\mathrm{E}[R_i] = a_i + b_i \mathrm{E}[R_{\mathrm{M}}] + h_i \mathrm{E}[\mathrm{HML}]. \tag{A.3}$$

If $a_i = 0$ and $b_i = b_i'$, then it follows from Eqs. (A.2) and (A.3) that h_i must be zero. Otherwise, the expected returns in the two equations cannot be equal.[13] The orthogonality between R_{M} and HML establishes that $b_i = b_i'$. Also, M and HML span the tangency portfolio, so a_i'' is zero in the conditional regression (e.g., Shanken, 1987)

$$R_i(t) = a_i'' + b_{i,t}'' R_{\mathrm{M}}(t) + h_{i,t}'' \,\mathrm{HML}(t) + e_i''(t), \tag{A.4}$$

where the conditional market beta and loading on HML are given by $b_{i,t}''$ and $h_{i,t}''$, respectively. Because changes in the parameters are uncorrelated with the

[13] I assume here that $\mathrm{E}[\mathrm{HML}] \neq 0$. It is straightforward to show that the conditional expectation of HML cannot be zero, and there is no reason that the unconditional expectation should be zero.

factor expected returns, the conditional intercept equals the unconditional intercept in Eq. (A.3). This result establishes that $a_i = a_i'' = 0$. It follows that h_i must be zero.

A.2. Factors

The factors used in this study are similar to those of Fama and French (1993), with a few minor differences. The three-factor model consists of market, size, and book-to-market factors. The market factor equals the return on the CRSP value-weighted index minus the T-bill rate at the beginning of the month. This factor differs somewhat from the market factor used by Fama and French, since they used only stocks with Compustat data to calculate the market return. However, there is little reason to limit the regression to stocks on Compustat, so all firms on CRSP are used for both the dependent portfolios and the market factor.

The size and book-to-market factors are calculated as follows. Each month, all stocks with market value data on CRSP for the previous month and book value data on Compustat for the previous fiscal year are sorted independently on size and B/M. I do not assume that book data become known until five months after fiscal year end. Following Fama and French, I define book equity as the book value of stockholder's equity minus the book value of preferred stock plus balance-sheet deferred taxes and investment tax credits, where the book value of preferred stock is given by redemption, liquidation, or par value, in that order of availability. Only firms with non-negative book equity and stock classified as common equity by CRSP are included.

Stocks are sorted into two size portfolios and three book-to-marketportfolios, using as breakpoints the median market value and the 30th and 70th book-to-market percentiles of NYSE stocks, respectively. I calculate value-weighted returns for each of the six portfolios formed by the intersection of the two size and three book-to-market portfolios. In other words, returns are calculated for three portfolios of small stocks, with low, medium, and high B/M ratios, and for three portfolios of 'big' stocks, also with low, medium, and high B/M ratios. The size factor, SMB, equals the average return on the three small portfolios minus the average return on the three big portfolios. The book-to-market factor, HML, equals the average return on the two high-B/M portfolios minus the average return on the two low-B/M portfolios. Hence, SMB and HML are returns on zero-investment portfolios designed to capture risk factors related to size and B/M, respectively.

A.3. Bootstrap simulations

The OLS slope estimate is biased upward in a regression of stock returns on lagged B/M (see Stambaugh, 1986). Since the bias in SUR estimates is unknown, I rely on bootstrap simulations to assess their sampling distribution.

The return regression can be thought of as part of the system

$$R_i(t) = \gamma_{i0} + \gamma_{i1} B/M_i(t-1) + e_i(t), \tag{A.5}$$

$$B/M_i(t) = c_i + p_i B/M_i(t-1) + u_i(t). \tag{A.6}$$

The bias in the OLS estimate of γ_{i1} is a function of p_i and cov(e_i, u_i). Therefore, to estimate the bias in the SUR estimates, the simulation maintains the strong autocorrelation in B/M and the negative covariance between e_i and u_i that are observed in the data. Also, since SUR jointly estimates the system of equations for all portfolios, the simulation incorporates cross-sectional correlation among the residuals.

The bootstrap generates artificial time series of excess returns and B/M from Eqs. (A.5) and (A.6). To construct returns, γ_{i0} is set equal to portfolio i's average return and γ_{i1} is set equal to zero. Notice that the OLS bias is not a function of γ_{i1} (see Eq. (8) in the text), so the value of γ_{i1} that is chosen should not be important. To construct B/M, the beginning value is given by the historical starting value and c_i and p_i are set equal to the sample estimates. The artificial time series, for 368 months, are then generated by sampling from the OLS residuals of the system, obtained after adjusting for the OLS bias in γ_{i1}. Each month of the sample, OLS produces a vector of residuals from both equations, where the vectors are made up of the error terms for all portfolios. I randomly select, with replacement, pairs of residual vectors from this population.

Given these series, I estimate the return equations using the SUR methodology. The process is repeated 1500 times to construct an empirical distribution of SUR estimates. Since γ_{i1} equals zero by construction, the mean of the distribution estimates the bias in the SUR estimates. The covariance matrix provides an estimate of the SUR standard errors and covariances.

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