NBER WORKING PAPER SERIES

THE VALUE SPREAD

Randolph B. Cohen
Christopher Polk
Tuomo Vuolteenaho

Working Paper 8242
http://www.nber.org/papers/w8242

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
April 2001

Correspondence: Christopher Polk, Kellogg Graduate School of Management, Northwestern University, 2001 Sheridan Rd., Evanston IL 60208-2001, USA; phone 847.467.1191; fax 847.491.5719; email: c-polk@nwu.edu. This paper subsumes the 3/15/1996 version of an earlier draft of this paper titled "Will the scaled-price effect in stock returns continue?" The most recent version of this paper is available at http://www.kellogg.nwu.edu/faculty/polk/research/work.htm. We would like to thank Kenneth French and Grantham, Mayo, Van Otterloo & Co. for providing us with some of the data used in this study. We are grateful to Cliff Asness, Ron Bird, John Campbell, John Cochrane, Mike Cooper, Kent Daniel, Gene Fama, Steve Kaplan, Owen Lamont, Rafael Laporta, Andy Lutz, Andrei Shleifer, Jeremy Stein, Maria Vassalou, and seminar participants at the NBER 2000 Summer Institute, the GMO Research Conference, and Purdue University for their comments. We thank Qianqiu Liu for excellent research assistance. The views expressed herein are those of the authors and not necessarily those of the National Bureau of Economic Research.

The Value Spread
Randolph B. Cohen, Christopher Polk and Tuomo Vuolteenaho
NBER Working Paper No. 8242
April 2001
JEL No. G120, G140

ABSTRACT

We decompose the cross-sectional variance of firms' book-to-market ratios using both a long U.S. panel and a shorter international panel. In contrast to typical aggregate time-series results, transitory cross-sectional variation in expected 15-year stock returns causes only a relatively small fraction (20%) of the total cross-sectional variance. The remaining dispersion can be explained by expected 15-year profitability and persistence of valuation levels. Furthermore, this fraction appears stable across time and across types of stocks. We also show that the expected return on value-minus-growth strategies is atypically high at times when the value spread (the difference between the book-to-market ratio of a typical value stock and a typical growth stock) is wide.

Randolph B. Cohen
Harvard Business School
Boston, MA 02163, USA

Christopher Polk
Kellogg Graduate School of Management
Northwestern University
2001 Sheridan Road
Evanston, IL 60208, USA

Tuomo Vuolteenaho
Department of Economics
Harvard University
Cambridge, MA 02138, USA
and NBER

THE VALUE SPREAD

The ratio of book value to market value of common equity (i.e., the book-to-market ratio) is an important determinant of the cross-section of average equity returns. Firms with high book-to-market ratios have higher average returns than firms with low book-to-market ratios [Rosenberg, Reid, and Lanstein (1985), Fama and French (1992), and others]. Thus the book-to-market ratios have information concerning subsequent expected returns. Simultaneously, differences in firms' book-to-market ratios are also related to differences in future expected cash-flow and earnings growth as well as future profitability. Low-book-to-market firms grow faster and are persistently more profitable than high-book-to-market firms. Intuitively, both expected returns and expected growth play a role in determining the market price and thus the book-to-market ratio.

We decompose the cross-sectional variance of firms' book-to-market ratios using a long (1937-1997) U.S. panel and a shorter (1982-1998) international panel. Our variance decomposition shows what fraction of the cross-sectional dispersion in the book-to-market ratios is caused by variation in expected returns and what fraction by variation in expected cash flows. Provided that book-to-market does not behave explosively, an approximate identity equates the current book-to-market ratio with an infinite discounted sum of future stock returns and profitability. This identity implies that a low current book-to-market ratio has to be justified by either high expected future profitability or low expected future returns. Therefore, to a very accurate approximation, all cross-sectional variation in the book-to-market ratios must necessarily be accounted for by cross-sectional variation in expected long-horizon stock returns and/or profitability.

The observation that the cross-sectional variation in the book-to-market ratios is related to cross-sectional variation in future profitability is not new. For example, Fama and French (1995) show that a high book-to-market ratio signals persistent poor earnings and profitability and a low book-to-market ratio signals strong earnings and profitability. The novel part of our analysis is that by using a present-value model we are able to measure exactly how much the cross-sectional variation in expected profitability contributes to the cross-sectional variation in firms' book-to-market ratios. Therefore, our analysis is able to quantitatively, not just qualitatively, comment on the source of the heterogeneity in valuation ratios across firms.

Our first and most basic finding is easily summarized. We find that transitory variation in 15-year expected returns is responsible for only a small fraction of the cross-sectional book-to-market variance. In the long U.S. panel, approximately 80% of the unconditional cross-sectional variance of the book-to-market ratios can be explained by expected future 15-year profitability and persistence of valuation levels, while just 20% can be explained by transitory variation in expected returns. This fraction appears stable across time and across types of stocks.

It is interesting to relate our basic cross-sectional result to aggregate time-series results in the previous literature. Earlier studies [Campbell and Shiller (1988), Cochrane (1992), Vuolteenaho (2000), and others] examine the time series of aggregate scaled-price measures to quantify the nature of the information they contain. These papers find that the substantial majority of the information in the time series of scaled prices is about expected returns, and relatively little is about cash flows. For example, Vuolteenaho (2000) finds that almost all of the time-series variation in the aggregate book-to-market ratio is due to expected stock returns and approximately none due to expected profitability. Our observation that the cross-section of individual stocks looks very different from aggregate indices in this regard is interesting in its own right but may also be relevant for the interpretation of the previous aggregate studies. If the cross-section of valuation ratios is largely driven by rational cash-flow expectations, the conclusion that the aggregate valuation ratios are exclusively driven by irrational sentiment is perhaps less plausible.

Our results also suggest that most of a growth stock's atypical valuation is simply due to high expected profitability rather than due to that stock having a low expected return. For example, Cisco Systems and General Motors have approximately the same book value (Cisco $29.7 vs. GM $31.5 billion) but Cisco has a far greater market value (Cisco $175.6 vs. GM $31.3 billion). According to our results, most of the difference is because equity on Cisco's books is expected to be more productive than that on GM's.[1] However, some reversion toward book value in the form of higher relative stock returns for GM is to be expected.

Note that our basic decomposition is silent as to whether the information we measure in a firm's book-to-market ratio concerning subsequent returns is due to risk or mispricing. In the above example, for example, the higher expected equity returns for GM relative to Cisco may or may not be due to mispricing of either stock; the difference may be risk-related. However, even if one takes the extreme stand and characterizes the expected-return component of book-to-market as a market-inefficiency phenomenon, our evidence suggests that at most about 20% of the variation in valuation ratios across firms can be linked to capital-market inefficiencies. Most of that variation represents differences in expected future profitability, heterogeneity that is considerably less controversial.

We refine our basic result by extending our analysis of the cross-sectional heterogeneity of valuation ratios. First, we replicate our measurements using a shorter international panel (1982-98, 23 countries excluding the United States). While the short time dimension of our international sample reduces the statistical precision of our estimates, the international point estimates support the conclusions drawn from the U.S. sample. At the five-year horizon, approximately 41% of the variation in the country-adjusted book-to-market ratios can be allocated to expected country-adjusted profitability, 14% to expected country-adjusted stock returns, and the remaining 47% to persistence of the country-adjusted book-to-market ratios. The fact that we obtain similar point estimates from a largely independent sample lends credibility to our basic result.

Second, in order to continue to study the relation between the results at different levels of aggregation, we further split the information in book-to-market concerning future returns and future profitability into intra- and inter-industry components. We find that the book-to-market effect in returns is mostly an intra-industry effect. This confirms evidence at the monthly horizon presented by Cohen and Polk (1999), Lewellen (1999), Asness, Porter, and Stevens (2000). More importantly, these results show that controlling for industry effects does not alter our variance decomposition results.

Third, we document statistically strong results concerning the predictability of returns on strategies that go long value stocks and short growth stocks. The above variance-decomposition results suggest that the difference in average returns between value and growth stocks may vary through time with the value spread (i.e., the book-to-market ratio of a typical value stock minus that of a typical growth stock). In other words, if the variance decomposition is constant over time with a non-trivial portion of the variance allocated to expected returns, the level of the value spread should predict returns on value minus growth strategies. Stocks whose book equity is cheap should have especially high expected returns at times when their book equity is especially cheap.

We test this hypothesis on the Fama-French (1993) HML portfolio and find that the HML value spread indeed has strong predictive power for HML returns, evidence that the expected return on the HML portfolio varies over time. Our expected-return estimates suggest that the expected return on HML was zero or negative in the periods 1948-53 and 1977-1979. Point estimates obtained from an international analysis are consistent with the U.S. HML-predictability results. Our findings are also consistent with those of Asness, Friedman, Krail, and Liew (2000) who examine the cross-section of scaled-price measures and returns on scaled-price portfolios. Using data from a relatively recent period (1982-1999) and a sample of U.S. stocks listed on I/B/E/S, they find that value spreads and spreads in projected earnings growth have predictive power for the time-series of monthly returns on value versus growth strategies.

The remainder of the paper is organized as follows. Section I describes the data. Section II presents the variance-decomposition framework and results. Section III concentrates on predicting value-minus-growth returns. Section IV concludes.

I. Data

A. U.S. panel data set

The basic U.S. data come from the merger of three databases. The first one of these, the Center for Research in Securities Prices (CRSP) monthly stock file, contains monthly prices, shares outstanding, dividends and returns for NYSE, AMEX, and NASDAQ stocks. The second database, the COMPUSTAT annual research file, contains the relevant accounting information for most publicly traded US stocks. The COMPUSTAT accounting information is supplemented by the third database, Moody's book equity information collected by Davis, Fama, and French (2000).[2] The basic merged data covers the period 1928-1997, but we only include the period 1937-1997 in our long U.S. panel. (We also obtain our main stated results in the data set that includes the early years.) In the final sample, all variables are of annual frequency and the panel contains 192,661 firm-years. Appendix 1 contains detailed data definitions.

Although the basic data set has some data as early as year 1928, we begin our long U.S. panel data set at the end of year 1937 in order to ensure a meaningful quantitative interpretation of the book-to-market and profitability series. The logic behind this choice is based on disclosure regulation. Before the Securities Exchange Act of 1934, there was essentially no regulation to ensure the flow of accurate and systematic accounting information. Among other things, the act prescribes specific annual and periodic reporting and record-keeping requirements for these companies. The companies required to file reports with the SEC must also "make and keep books, records, and accounts, which, in reasonable detail, accurately and fairly reflect the transactions and disposition of the assets of the issuer." In addition, the legislation introduces the concept of “an independent public or certified accountant” to certify financial statements and imposes statutory liabilities on accountants.

While the value-relevant information may have been disclosed via other channels, it is clear that interpreting the pre-1934 and post-1934 book-to-market ratios as having similar information content would be unrealistic. After studying the implementation of the act, we also decided to exclude the 1934-37 data segment. This period could reasonably be characterized as an initial enforcement period, after which reporting conventions have converged to their steady states.[3]

B. International panel data set

In addition to the long U.S. panel, we also construct a shorter international panel. The annual international panel is constructed from a monthly data set created by Grantham, Mayo, Van Otterloo & Co. (GMO). GMO’s monthly data set is in turn constructed from the Morgan Stanley Capital International data and various real-time data sources. The international panel spans the period 1982-98. The number of countries in the data set begins at 19 and ends at 22, and 23 different countries are included in the panel at various points of time. U.S. data are not included. The international panel contains 27,913 firm-years.

II. Decomposing the cross-sectional variance of firms’ book-to-market ratios

It is well known that firms’ book-to-market (BE/ME) ratios describe cross-sectional variation in returns and profitability. For example, Fama and French (1995) show that value stocks typically have higher stock returns and lower profitability than growth stocks. However, calculating how each of these two effects contribute to the cross-sectional spread in firms' BE/ME ratios requires a quantitative framework. We employ Vuolteenaho’s (2000) return-profitability model to decompose the cross-sectional variance of BE/ME ratios into three components: 1) covariance of future market-adjusted stock returns with past market-adjusted BE/ME ratios, 2) covariance of future market-adjusted profitability (i.e., accounting return on equity – ROE) with past market-adjusted BE/ME ratios, and 3) persistence of market-adjusted BE/ME ratios.

The following intuition underlies the decomposition. Suppose two firms (neither one of which pays dividends or issues equity) have different BE/ME ratios. Over time, this value spread can close by either high BE/ME firms experiencing higher stock returns than low BE/ME firms or by high BE/ME firms being less profitable and growing their book equity slower than the low BE/ME firms. On the one hand, if the spread closes via stock returns, the covariance of past relative BE/ME ratios and future relative returns is positive. On the other hand, if the spread closes via profitability, the covariance of past relative BE/ME ratios and future relative profitability is negative. There is also a third possibility – the spread may not close completely. In this case, the difference in BE/ME ratios persists, and the covariance of past and future relative BE/ME ratios is high.

A. Approximate model of the book-to-market ratio

To derive Vuolteenaho's (2000) return-profitability model necessitates three specific assumptions. First, because the model is stated in terms of logarithms, one must assume book value, *BE*, market value, *ME*, and dividends, *D*, are strictly positive. Although this assumption is not necessarily satisfied for all individual firms, it is almost surely satisfied for the BE/ME-sorted portfolios we use in our tests. Second, one must assume firms' log BE/ME ratios to be stationary, even though both log book and market equity series have an integrated component. Third, we assume that earnings, dividends, and book equity series satisfy the clean-surplus relation.[4] The clean-surplus relation ties the income statement and balance sheet dynamics together. In that relation, earnings, dividends, and book equity satisfy:

$$BE_t - BE_{t-1} = X_t - D_t \tag{1}$$

– book value today equals book value last year plus earnings (X_t) less (net) dividends.

The reported earnings, dividends, and book values do not always strictly adhere to the above clean-surplus relation. In order to exactly satisfy this assumption in our sample, we define our earnings series as the sum of dividends and the change in book equity. This approach is partly dictated by necessity (the early data consists of book-equity series but does not contain earnings).[5]

Accounting and stock returns remain to be defined. Let r_t denote the log stock return and e_t the log clean-surplus accounting return on equity, defined as

$$r_t \equiv \log\left(1 + \frac{\Delta ME_t + D_t}{ME_{t-1}}\right) \tag{2}$$

$$e_t \equiv \log\left(1 + \frac{\Delta BE_t + D_t}{BE_{t-1}}\right) \tag{3}$$

Substituting the log dividend-growth rate, Δd_t, the log dividend-price ratio, δ_t, and the log dividend-to-book-equity ratio, $\gamma_t \equiv d_t - b_t$, to the return definitions (2) and (3) yields

$$r_t = \log(\exp(-\delta_t)+1) + \Delta d_t + \delta_{t-1} \tag{4}$$

$$e_t = \log(\exp(-\gamma_t)+1) + \Delta d_t + \gamma_{t-1} . \tag{5}$$

Finally, we denote the log BE/ME ratio by θ_t :

$$\theta_t = \log\left(BE_t / ME_t\right) \tag{6}$$

An inconvenient nonlinear law describes the evolution of a firm's BE/ME ratio if that firm pays dividends. However, a linear model can do a good job of approximating the nonlinear evolution of $\theta_t = \log\left(BE_t / ME_t\right)$

$$e_t - r_t = \rho\theta_t - \theta_{t-1} + \kappa_t \tag{7}$$

where ρ is a parameter, κ_t approximation error, and $\rho < 1$ if the firms pay any dividends and $\rho = 1$ if the firms do not. This approximation can be justified by the following logic. We approximate both stock and accounting returns by a first order Taylor series approximation, choosing the same expansion point:

$$r_t = \log(\exp(-\delta_t)+1) + \Delta d_t + \delta_{t-1} \approx \alpha - \rho\delta_t + \Delta d_t + \delta_{t-1} \tag{8}$$

$$e_t = \log(\exp(-\gamma_t)+1) + \Delta d_t + \gamma_{t-1} \approx \alpha - \rho\gamma_t + \Delta d_t + \gamma_{t-1} \tag{9}$$

Subtracting (9) from (8) yields the linearized accounting identity (7).

Iterating (7) forward yields the first result.[6] Using the convenient linear form of equation (7) it is possible to express the BE/ME ratio as an infinite discounted sum of future profitability and stock returns:

$$\theta_{t-1} = \sum_{j=0}^{N} \rho^j r_{t+j} - \sum_{j=0}^{N} \rho^j e_{t+j} + \sum_{j=0}^{N} \rho^j \kappa_{t+j} + \rho^{N+1}\theta_{t+N} , \tag{10}$$

If the BE/ME ratio is well behaved and $\rho < 1$, the last term of (10) converges to zero as $N \to \infty$:

$$\theta_{t-1} = \sum_{j=0}^{\infty} \rho^j r_{t+i} - \sum_{j=0}^{\infty} \rho^j e_{t+j} + \sum_{j=0}^{\infty} \rho^j \kappa_{t+j} . \tag{11}$$

This approximate model for a firm's BE/ME provides the foundation for our variance decomposition.

B. Cross-sectional variance decomposition

If all firms have stationary BE/ME ratios with the same unconditional mean, the cross-sectional variance of firms' log BE/ME ratios can be decomposed into two parts: predictability of market-adjusted stock returns and predictability of market-adjusted returns on equity. In other words, if there is cross-sectional spread in log BE/ME ratios, current relative log BE/ME ratios must covary with future relative log stock returns and/or future relative log profitability. In the sections that follow, we will typically refer to these variables without the relative, market-adjusted, or log modifier for ease of description. Similarly, we will use "unconditional variance" of BE/MEs to refer to the unconditional variance of cross-sectionally demeaned BE/MEs; the true unconditional variance would include time variation in the cross-sectional mean of BE/MEs.

To derive the variance decomposition, we multiply both sides of (12) by $\tilde{\theta}_{t-1}$, drop the approximation error, and take unconditional expectations:

$$\mathrm{var}(\tilde{\theta}) \approx \sum_{j=0}^{\infty} \rho^j \,\mathrm{cov}\left[\tilde{r}_{t+j}, \tilde{\theta}_{t-1}\right] - \sum_{j=0}^{\infty} \rho^j \,\mathrm{cov}\left[\tilde{e}_{t+j}, \tilde{\theta}_{t-1}\right] \tag{13}$$

Since all firms are assumed to have stationary BE/ME ratios with equal unconditional expectations, the third term, corresponding to the BE/ME ratio far into the future, drops out, even if $\rho = 1$. Equation (13) shows that (under the maintained assumptions) the unconditional cross-sectional variance of firms' BE/ME ratios is due to cross-sectional covariance of future stock and/or accounting relative returns with past BE/ME ratios. Above, market-adjusted quantities are denoted by tildes. It is important to note that $\mathrm{var}(\tilde{\theta})$ in equation (13) corresponds to the average squared market-adjusted BE/ME ratio, and that this variance metric is thus best interpreted as the typical cross-sectional dispersion in BE/MEs.

Due to the infinite sums, implementing the above variance decomposition (13) requires an assumed auxiliary statistical model and the assumption of equal long-run BE/ME ratios for all firms. If one is unwilling to make such assumptions, a different variance decomposition can be used. The infinite sums in (13) can be replaced with finite sums if an additional term is included. Working with equation (10) without taking the limit $N \to \infty$ and repeating the above steps yields

$$\mathrm{var}(\tilde{\theta}) \approx \sum_{j=0}^{N} \rho^j \,\mathrm{cov}\left[\tilde{r}_{t+j}, \tilde{\theta}_{t-1}\right] - \sum_{j=0}^{N} \rho^j \,\mathrm{cov}\left[\tilde{e}_{t+j}, \tilde{\theta}_{t-1}\right] + \rho^{N+1} \,\mathrm{cov}\left[\tilde{\theta}_{t+N}, \tilde{\theta}_{t-1}\right] \tag{14}$$

Compared to equation (13), equation (14) has an additional term: The last term of (14) is a catchall predictability term that captures the profitability and stock-return predictability beyond horizon *N*, as well as cross-sectional heterogeneity of the mean BE/ME ratios.

A relative variance decomposition may be easier to interpret. Assuming that the cross-sectional variance of the BE/ME ratios is not zero, one can divide both sides of equation (14) by the unconditional BE/ME variance:

$$1 \approx \frac{\sum_{j=0}^{N} \rho^j \,\mathrm{cov}\left[\tilde{r}_{t+j}, \tilde{\theta}_{t-1}\right]}{\mathrm{var}(\tilde{\theta})} - \frac{\sum_{j=0}^{N} \rho^j \,\mathrm{cov}\left[\tilde{e}_{t+j}, \tilde{\theta}_{t-1}\right]}{\mathrm{var}(\tilde{\theta})} + \rho^{N+1} \frac{\mathrm{cov}\left[\tilde{\theta}_{t+N}, \tilde{\theta}_{t-1}\right]}{\mathrm{var}(\tilde{\theta})} \tag{15}$$

The three terms in (15) represent the fraction of variance attributable to the three sources. The relative variance decomposition is particularly easy to interpret – each component in (15) corresponds to a simple regression coefficient. The predictive regression coefficient of long-horizon returns less the predictive regression coefficient of long-horizon profitability plus a measure of the persistence of BE/ME spread must be equal to one.

Past research that decomposes the time-series variance of aggregate portfolios often uses vector autoregressions (VARs) instead of long-horizon regressions. In our cross-sectional application, the long-horizon regression methodology is preferable to the more common VAR methodology. The difficulty with the VAR methodology arises from rebalancing effects. Appendix 2 discusses this problem in more detail.

C. Cross-sectional variance-decomposition results using the U.S. panel

To implement the cross-sectional variance decomposition, each year we create 40 value-weight portfolios of stocks by sorting on BE/ME and track the subsequent stock returns, profitability, and book-to-market ratios of these portfolios. For example, in 1997 (the last year of the U.S. sample) the low BE/ME portfolio has a value-weight average BE/ME of .04, while the highest portfolio is at 2.82. The mean portfolio BE/ME is .62, while the standard deviation across portfolios is .54. Dispersion in BE/ME has risen and fallen many times over the years. For 1987 the standard deviation (.55) is almost identical to the 1997 value, but for 1991 it is more than twice as high (1.18).

Equation (15) implies that the coefficients in the following three separate, forward-looking regressions measure the percentage of information in a firm’s BE/ME ratio concerning aspects of the firm's future:

$$\begin{aligned}
&\sum_{j=0}^{N-1} \rho^j \tilde{r}_{t+j,i} = b(\tilde{r}, N)\, \tilde{\theta}_{t-1,i} + \varepsilon(\tilde{r}, N, i) \\
&\sum_{j=0}^{N-1} \rho^j \tilde{e}_{t+j} = b(\tilde{e}, N)\, \tilde{\theta}_{t-1,i} + \varepsilon(\tilde{e}, N, i) \\
&\rho^N \tilde{\theta}_{t+N-1} = b(\tilde{r}, N)\, \tilde{\theta}_{t-1,i} + \varepsilon(\tilde{\theta}, N, i)
\end{aligned} \tag{16}$$

We estimate these coefficients using the 40 BE/ME-sorted portfolios and report the combined results in Table 1 Panel A. Thus, we regress the future returns, profitabilities, and book-to-market ratios for the 40 buy-and-hold portfolios on the portfolios’ current book-to-market ratios. As we are interested in a cross-sectional variance decomposition, all variables are cross-sectionally demeaned. For example, $\tilde{\theta}_{t,i}$ is the aggregate book equity of the stocks in portfolio i in the end of year t divided by the portfolio’s aggregate market value less the average of these ratios across the 40 portfolios in the end of year *t*. In the system of regressions described in equation (16), $b(\tilde{r}, N) - b(\tilde{e}, N) + b(\tilde{\theta}, N) \approx 1$.

The N=1 row of the table breaks the BE/ME ratio into information about future 1-year returns, about future 1-year ROE, and about the future 1-year-ahead BE/ME ratios. The split is 3% for future returns, 15% for future profitability, and 83% for persistence in BE/ME ratios. At one-year horizon, the BE/ME ratio predicts all three variables with the expected signs. Because BE/ME ratios are quite persistent, the largest component of the unconditional variance of BE/ME ratios is due to covariance with next year's BE/ME ratio.

Of course, next year's BE/ME ratio also has information about future returns and ROEs beyond one year. Subsequent rows of the table exploit this by looking further ahead, to 2, 3, 5, 10 and 15 years. Figure 1 graphs these coefficients as a function of the forecast horizon. 20% of BE/ME information is about 15-year returns, 58% about 15-year profitabilities. The remaining 26% of the information is about 15-year-forward BE/ME ratios, a residual component we will refer to as the persistent component of the BE/ME ratios. The stationarity and homogeneity assumptions would guarantee that even the persistent component is informative about future returns and profitability beyond 15 years. Given the facts about the first 15 years (i.e., the return coefficients level at 20% while profitability coefficients continue to increase as a function of N), it seems safe to assume that most of the remaining information in the persistent component of BE/ME ratios concerns cash flows and not returns.

Our general interpretation of these regression results in Table 1 Panel A is thus as follows. Most of the information in the BE/ME ratios of individual firms is about future profitability. About 20% of cross-sectional differences in BE/ME ratios can be attributed to differences in expected returns. Differences in expectations of future profitability explain the other 80%.

Our procedure imposes the discount coefficient rho (ρ) to be constant across firms. Because long-run dividend yields and pay-out ratios may vary systematically with BE/ME ratios, the assumption of a constant discount coefficient may lead to a poor approximation. Fortunately, our regressions provide a natural way to evaluate the effect of the approximation error on the variance-decomposition results. Repeating the derivations in equations (10)-(15) and carrying the approximation error along shows that the variance component due to the approximation error equals $1 - b(\tilde{r}, N) + b(\tilde{e}, N) - b(\tilde{\theta}, N)$. The approximation error's share of the unconditional variance is thus 0.01% at the one-year horizon and -4.74% at the 15-year horizon. These computations indicate that the error in the constant-rho linear approximation does not materially affect our results.

Table 1 Panel A also reports the standard errors for the variance decomposition. Although we use regression coefficient point estimates obtained using pooled OLS, the usual OLS standard errors are likely to be significantly understated. The problem with OLS standard errors arises from two well-known sources. First, the regression residuals may be correlated in the cross-section. If this correlation is related to the explanatory variables, the standard errors are not valid. Second, because we use overlapping dependent variables, the regression residuals are likely to be autocorrelated. A more general and precise statement of these problems is that the covariance matrix of the pooled regression errors is not proportional to an identity matrix. In order to calculate appropriate standard errors that account for correlation of the residuals both over time and in the cross-section, we adapt Rogers's (1983, 1993) standard-error formulas to our regressions. Appendix 3 contains the details of these calculations.

Not surprisingly, the statistical evidence that the past BE/ME ratios predict future BE/MEs is overwhelming, as t-statistics in the last column are uniformly high. Predictions of future BE/MEs start out at t-statistics above 70 and remain above 2.0 even 15 years out. There is a high degree of persistence in firms' BE/ME ratios.

The ability of BE/ME to predict profitability at longer horizons is also very convincing. The t-statistics in the early years range from 3 to 11, and even toward the 15-year mark stay above 2.0. The reduction in statistical significance results from an increase in the standard errors as we look farther into the future. We suspect that this is mainly due to the longer prediction horizon generating a smaller number of independent observations in our sample.

This problem is particularly severe in the prediction of returns, especially for horizons longer than three years. Although the coefficients on future expected returns grow with the horizon, the standard errors grow even faster and as a consequence the t-statistics fall below 2.0 in the later years. Because we use long-horizon regressions and compute corrected standard errors, we cannot reject the hypothesis that none of the BE/ME variance is due to expected returns at conventional levels for the 15-year horizon specification (the associated t-statistic is 1.82). This is consistent with our conclusion that, in the cross-section, firms' BE/ME ratios are mainly driven by expected profitability, not expected returns.

D. Cross-sectional variance-decomposition results using the international panel

Table 2 Panel A estimates the system of regression equations (16) using the international panel. Again, the N=1 row of the table breaks the BE/ME ratio into information concerning the future 1-year returns, future 1-year ROE, and future 1-year-ahead BE/ME ratios. The split is again close to 3% for future returns. In the international panel, the remaining portion contains less information about future profitability (11%) and more about persistence in BE/MEs (85%).

As before, we look further ahead. However, data availability limits our long-horizon estimates to 2, 3, and 5 years. After 5 years, the precision of the variance-decomposition estimates and the accuracy of the asymptotic standard errors decrease dramatically. 18% of BE/ME information is about 5-year returns, 33% about 5-year profitabilities. The remaining 49% of the information is about the 5-year-forward BE/ME ratios.

One might argue that a portion of the cross-sectional variance of the unadjusted BE/ME ratios is due to permanent differences in accounting measures across countries. This argument suggests that once this noise due to accounting standards is removed, the country-adjusted BE/ME should contain a higher percentage of information concerning returns and/or transitory profitability. Therefore, we refine our variance decomposition of Panel A by adjusting each variable (BE/ME, return, and profitability) by subtracting the appropriate value-weight country measure.

However, the results (reported in Panel B) are quite similar to the unadjusted decomposition. In fact, for the adjusted data, only 14% of the cross-sectional variance of country-adjusted BE/ME is due to cross-sectional differences in expected returns. As with the unadjusted results, virtually half of the cross-sectional variance is due to persistence in country-adjusted BE/ME.

As mentioned before, given the stationarity and homogeneity assumptions, the persistent component should be informative about future returns and profitability beyond 5 years. This fact combined with our data limitations in the international panel make measurement of the percentage of cross-sectional differences in the BE/ME ratios attributable to differences in expected returns more difficult. Still, it seems safe to say that, as in the domestic results, most of the information in the BE/ME ratios of individual firms is about future profitability. While these international results are noisier, we interpret them as supporting our main results obtained from the U.S. data.

E. U.S. intra-industry results

This section examines the role of industry in the pieces of information contained in the BE/ME ratios. We are interested in two industry-related phenomena. First, we decompose the cross-sectional variance of the industry-adjusted BE/ME ratios. This decomposition answers the question: to what extent is within-industry variation of the BE/ME ratios driven by within-industry variation in expected profitability and/or returns? Second, we decompose the variance of raw (i.e., not industry-adjusted) BE/MEs into six components by further separating the profitability, return, and BE/ME-persistence components of Table 1 Panel A into inter- and intra-industry parts. This decomposition shows whether inter-industry or intra-industry phenomena are the main drivers of the cross-section of raw BE/MEs.

Table 1 Panel B decomposes the variance of intra-industry BE/MEs using Fama-French (1996) industry classifications. Just as persistent differences in accounting standards across countries might introduce noise to comparisons of BE/ME among stocks of different nations, similarly persistent differences in accounting standards across U.S. industries could cause persistent BE/ME differences. Such differences in industry BE/ME would be unrelated to near-term predictability of either profitability or returns. In section II.C's decomposition, (Table 1 Panel A) we sort firms into 40 portfolios based on their raw BE/ME ratio. But in Panel B we sort stocks into portfolios based on intra-industry BE/ME. Intra-industry BE/ME is defined as the difference between a firm's BE/ME and the value-weight average BE/ME of the industry the firm is in. Thus the test assets for Table 1 Panel B are portfolios that are more industry-balanced than those in Table 1 Panel A as every industry is likely to have firms that are high, medium, and low in their industry-relative BE/ME ratio.

We find that the importance of future return, ROE, and BE/ME in explaining current BE/ME relative to a firm's industry, is quite comparable to their importance in explaining overall BE/ME. Over 15 years, returns explain 19% of cross-sectional variation, ROEs 58%, and future BE/ME 27%, similar to the corresponding numbers in Table 1 Panel A.

Table 3 examines the relative importance of industry and intra-industry variation to the BE/ME cross-section. The test portfolios are created by sorting on the raw BE/ME ratios, and the only difference between the portfolios used in Table 1 Panel A and Table 3 is that portfolios used in Table 3 exclude stocks that cannot be assigned to an industry of at least ten firms. In an extension of the concept of intra-industry BE/ME, each of the three variance components – future returns, future ROEs, and future BE/ME – are subdivided into two pieces. The first pieces, labeled *intra-industry* in the table, are computed for each firm as the excess of its return, ROE or future BE/ME over the return, ROE or future BE/ME for the industry the firm is in. The second component, labeled *industry* in the Table, is simply the value-weight return, ROE, or future BE/ME for the relevant industry as a whole. Since a firm's return in any given year is the sum of the return on the firm's industry for that year and the excess return of the firm *over* that industry return; and since the same can be said for ROE or future BE/ME, it is clear that we can replace our 3-component decomposition with a new 6-component decomposition, while preserving the original identity.

The coefficients in Table 3 show that regardless of horizon roughly 80% of the information in the raw BE/ME ratio concerns the firm's behavior relative to its industry, while the remaining percentage is informative about the industry as a whole. Looking a single year ahead, the coefficient on intra-industry return is .021, while that on industry return is .0055. The ROE coefficients are -.132 and -.014, respectively, while the BE/ME coefficients are .634 and .194, respectively. This suggests that while the majority of the return information in the BE/ME ratio is about intra-industry return, a non-trivial portion concerns the return on the industry as a whole. Fifteen years out, the intra-industry return explains 16.4% of firm BE/ME, while industry return explains 4.5%. These results are similar in spirit to Lewellen (1999). His analysis documents that controlling for industry does not significantly reduce the degree of cross-sectional spread in sensitivity to the HML factor of Fama and French (1993).

The dominance of intra-industry information is even greater in the profitability series. The coefficient on intra-industry ROE is nine times larger than that on industry ROE after one year, and is nineteen times larger (-.503 vs. -.026) after fifteen years. It is no surprise that most of the information in the BE/ME ratios is about intra-industry performance rather than industry performance – after all, if this were not the case, BE/ME would essentially just be a proxy for industry. But it is interesting to observe that as regards the relation between BE/ME and returns, both intra-industry and industry components are important, while the relation between the BE/ME ratio and future ROE is primarily based on industry-relative information.

F. Does the variance-decomposition vary as a function of firm characteristics

The relative importance of the three elements of the decomposition -- transitory variation in expected returns, transitory variation in profitability and persistant differences in the BE/ME ratios -- may be different for different firms. Such variation can be examined via a conditional variance decomposition. We analyze this possibility by initially sorting firms each year into three groups based on a particular firm characteristic.

We then sort firms into five portfolios based on BE/ME and estimate the variance decomposition separately within each of the three groups. This conditional variance decomposition is simply the best estimate of equation (15) for a particular type of firm.

Natural firm characteristics to examine are size and the BE/ME ratio itself, which have the advantage that conditioning on them does not reduce the size of the sample. Size (i.e. market capitalization) may proxy for liquidity or speed of information dispersion, factors which may influence the amount of transitory variation in returns. Similarly, a variance decomposition conditional on the BE/ME ratio may highlight asymmetries in the amount of transitory variation due to expected returns, perhaps as a result of short sale constraints that prevent liquidity providers from selling stocks with very low expected returns. Therefore, we sort firms into three size groups based on NYSE breakpoints to examine how the variance decomposition varies with market capitalization (Table 4 Panel A) and we sort firms into three groups based on firm BE/ME (Table 4 Panel B) to examine how the decomposition depends on BE/ME.

The decomposition conditional on size indicates that the book-to-market ratios have less information concerning differences in expected returns among large firms than small or medium-sized firms. However the differences do not seem economically large and are not statistically significant. For large firms, approximately 16% of the information in the BE/ME ratios is due to differences in expected returns while for small firms this number is 18%. One might initially be surprised by this result, as previous literature, for example Fama and French (1993), has generally indicated that the value effect is stronger among small stocks. These two potentially conflicting pieces of evidence are reconcilable. First, the split is quite different at short horizons (4.5% due to expected 1-year returns for small firms and only 2.3% for large). However, this difference is counterbalanced by the fact that at short horizons, large stocks have more persistent BE/ME. The regression coefficient of future 1-year BE/ME on current BE.ME is .8757 for large stocks but only .8141 for small stocks. Small stock BE/MEs have more return information in the short run, but also more profitability information. In the long run these effectively cancel, leaving the total split between return and profitability information similar for small and large stocks. Second, note that since N-year returns in the first equation in the system of regressions in (16) are given by the product, $b(\tilde{r}, N)\tilde{\theta}_{t-1}$, a large cross-sectional variation in expected returns can generated by *either* a large $b(\tilde{r}, N)$ *or* a large spread in $\tilde{\theta}_{t-1}$. This observation is central to our ability to forecast the returns on value versus growth strategies in section III and applies here as well. Small stocks do have a stronger value effect, even at long horizons, not because their BE/ME ratios have more information concerning future returns but rather because their BE/ME's are more dispersed. This difference in dispersion is substantial: For the smallest third, the average cross-sectional variance of log BE/ME for the five BE/ME quintiles was 0.53; higher than the corresponding value of 0.39 for the largest third of the sample.

Panel B of Table 4 allows the decomposition to vary with BE/ME. Largely by construction, the medium-BE/ME third has an average cross-sectional variance of log BE/ME of just 0.03, while both the high-BE/ME (0.14) and low-BE/ME (0.22) stocks exhibit far more spread. At the 1-year horizon, high-BE/ME firms' BE/MEs have more information concerning expected returns. As the horizon increases, the percentage of information in the BE/ME ratios concerning differences in future returns remains relatively low for low BE/ME firms. It is only at the 15-year horizon that the information content becomes roughly equal.

In general, the differences we document in the decomposition as a function of size and BE/ME are not economically large. Moreover, our general conclusion that most of the cross-sectional dispersion in the BE/ME ratios is due to differences in cash flows is consistently true across the subsets of firms we study.

G. Does the variance decomposition vary as a function of market-wide instruments?

The relative importance of the three drivers of the value spread may also vary over time. This time variation can also be examined via a conditional variance decomposition. In this case, the conditional variance decomposition is simply the best estimate of equation (15) at any point in time. While there are many ways to estimate a conditional version of (15), we begin with perhaps the simplest approach. We write the three regression coefficients in (15) as linear functions of variables with intuitive predictive content.

We limit ourselves to simple market-wide instruments including the median firm's BE/ME ratio, the cross-sectional variance of firms' BE/ME ratios, the cross-sectional variance of firms' profitability, the cross-sectional covariance of firms' BE/ME ratios and profitability, and bond-yield variables. Our choice of market-wide instruments attempts to use information in a particular cross-section of the BE/ME ratios to draw inferences about the time-series properties of the information in a typical firm's BE/ME ratio. For example, if the correlation between the BE/ME ratios and firm profitability is higher than normal, then one might expect that the typical firm's BE/ME ratio probably contains more information concerning future expected cash flows than future expected returns. Similarly, if the typical firm is cheap as represented by a higher than normal median BE/ME, one might expect the typical firm's BE/ME ratio to contain more information concerning expected returns. This conclusion follows from the results of Vuolteenaho (2000) who finds that most of the time variation in the aggregate BE/ME ratio is due to changes in future expected returns.

We do not show the results of these conditional variance decompositions because, in general, we do not find any periods in time where BE/ME ratios contain more information about expected returns. Thus the percentage of information in the BE/ME ratio is relatively constant, perhaps surprisingly so. Of course, as we emphasized earlier, the value spread does move quite a lot through time. If the information content in the value spread is constant, then expected returns to a value strategy should exhibit rich, time-varying patterns as the value spread moves around. We analyze this possibility in the next section.

III. Predicting value versus growth returns

Consider a portfolio that is long high-BE/ME stocks and short low-BE/ME stocks. Fama and French (1993,1996) popularize such a zero-investment portfolio (HML) in numerous applications. First, Fama and French construct six value-weight portfolios from the intersections of the two size and the three BE/ME groups. The HML portfolio is then formed by buying both the small and the large high-BE/ME portfolios (combined position denoted by H) and selling short both the small and the large low-BE/ME portfolios (combined position denoted by L). The two components of HML are thus high- and low-BE/ME portfolios with about the same weighted-average size.

The conditional variance decomposition above can be used to motivate a forecasting model for the return on the HML portfolio. Apply (12) to both the H and L portfolio, difference, and reorganize:

$$\sum_{j=0}^{\infty} \rho^j E_{t-1} r_{t+j}^{HML} = (\theta_{t-1}^H - \theta_{t-1}^L) + \left[\sum_{j=0}^{\infty} \rho^j E_{t-1} e_{t+j}^H - \sum_{j=0}^{\infty} \rho^j E_{t-1} e_{t+j}^L \right] \tag{17}$$

This motivates a predictive regression:

$$R_t^{HML} = a + b\,(\theta_{t-1}^H - \theta_{t-1}^L) + c\,(e_{t-1}^H - e_{t-1}^L) + \varepsilon_t\,, \tag{18}$$

where the past profitability spread is used as a proxy for the spread in discounted future expected profitability. Since most of the empirical work that relies on the time-series of returns on the HML portfolio uses simple (not log) returns, we use annual simple returns as the dependent variable in our regression.

We present OLS estimates of the coefficients in HML forecasting regressions similar to equation (18). Furthermore, as one might expect an increase in the expected return on HML to be associated with an increase in the volatility of the HML return, we also produce maximum-likelihood GLS estimates based on an accompanying model (using the same instruments) of the log variance of the HML portfolio:

$$R_t^{HML} = Z_{t-1}\beta + \varepsilon_t, \quad \varepsilon_t \sim N[0, \exp(Z_{t-1}\gamma)], \tag{19}$$

where Z_{t-1} are the lagged predictor variables (including the value spread) and β, γ are parameters. Since the above specification produces conditional variance estimates, it enables us to compute a time-series of estimated Sharpe ratios as well as estimated expected returns. For a detailed exposition of the iterative estimation procedure and the standard-error formulas, see Greene (1997, p. 557-569).

Figure 2 displays the log BE/ME of the high-, medium-, and low-BE/ME portfolios created by Fama and French (1993). One can see from the figure that the log BE/MEs of the three size-balanced portfolios move around quite a bit over the 61-year period. While the level of BE/MEs appears volatile and persistent, the value spread (the difference between H and L portfolios' BE/MEs) appears to be following a mean reverting process.

Table 5 Panel A shows the regression results. In that table, we report the coefficients in an OLS regression, the GLS counterpart, and the coefficients (γ) in the exponential-linear conditional-variance model. In the discussion, we focus on the GLS estimates of the conditional mean. As expected, we find that the difference between BE/MEs of the low- and high-BE/ME portfolios, the value spread, is a significant predictor of the return on the HML portfolio. The simple regression coefficient of the value spread is 0.287; the t-statistic is 3.14. This result indicates that the annual expected return on HML is time-varying. As the annual standard deviation of the value spread is 8.75 percentage points, this predictive regression implies substantial time variation in the HML premium: the standard deviation of the fitted values of HML is 1.3 times the unconditional mean HML return.

Figure 3 graphs the expected return on the HML portfolio using this specification. As a measure of the economic significance of our finding, Figure 3 also graphs the associated conditional Sharpe ratio. As specified in equation (19), we generate these estimates each year by using the value spread to predict the return and log variance of HML. In general, we find that the point estimates of the HML Sharpe ratio vary over time considerably.

In order to examine the robustness of our results to data-snooping concerns, we re-estimate this simple forecasting model using the international panel. We hope that the international sample provides an out-of-sample test of our finding of time-variation in the expected return on value-versus-growth strategies in the US sample. As with the US value spread, our forecasting variable seems well-behaved. As the international sample is only 17 years long, we estimate the predictability using country-adjusted variables in the hope of increasing the precision of our regression coefficients. The results, reported in Table 5 Panel B, are imprecise but the coefficients are consistent with the domestic estimates.

Table 5 Panel A also contains multiple regressions with additional predictor variables. In the multiple regression specified by equation (18), the value spread's coefficient and t-statistic are 0.2915 and 3.14, respectively. However, the recent difference in ROE's between value and growth stocks does not provide additional predictive power (coefficient of 0.0030, t-statistic 0.5913). We also report a specification with the value spread interacted with the median BE/ME ratio of the market. In the conditional variance decompositions discussed in section II.F, this variable, though statistically insignificant, was the most successful in tracking time-variation in the information content of firms' BE/ME ratio. As with the conditional variance decompositions, this variable is only marginally significant.

We complete our analysis of time-variation in the return on value-versus-growth strategies by investigating what macroeconomic variables are correlated with the value spread. In particular, we regress the value spread on several variables that intuitively might explain movements in the value spread. These regressions are shown in Table 6. We initially regress the value spread on the median BE/ME ratio. This variable has no explanatory power by itself (t-statistic of –0.12). We turn to the default spread (the difference in yields between BAA and AAA long-term corporate bonds) that, like the median BE/ME ratio is an indicator of low frequency movements in business conditions. We find that the value spread has a positive and statistically significant coefficient on the default yield spread. The coefficient is 0.153 with an associated t-statistic of 2.0. Almost a quarter of the variation in the value spread can be linked to movements in this variable alone. We also include the median BE/ME ratio and the lagged profitability spread: The median BE/ME ratio is now statistically and economically significant and the lagged profitability spread is marginally so. The full model now explains over 42% of the movements in the value spread.

When we add both the median BE/ME ratio and the default spread to the return-predictive regressions in Table 4, we find that the value spread remains significant (coefficient of .394, t-statistic of 3.1) while the median BE/ME ratio is now statistically significant (coefficient of .128, t-statistic of 1.8) at the 10% level. Unreported orthogonalized regressions show that the component of the value spread that is correlated with the market's BE/ME ratio or default yield spread does not predict HML returns. The predictive ability of the value spread is entirely due to the component that is orthogonal to these market-wide instruments.

IV. Conclusions

The present-value formula allows us to decompose the cross-sectional variance of firms' book-to-market ratios into three components: 1) covariance of future stock returns with the past book-to-market ratios, 2) covariance of future profitability (i.e., accounting return on equity) with the past book-to-market ratios, and 3) persistence of the book-to-market ratios. We estimate this decomposition from a large (1937-1997) panel with three simple long-horizon regressions.

Our results suggest that approximately 20% of the cross-sectional dispersion of book-to-market ratios can be explained with expected 15-year stock returns, 58% with expected 15-year profitability, and 26% with 15-year persistence of book-to-market ratios. Intuition and the time-series behavior of returns and profitability suggest that the persistence of the book-to-market ratios is mostly due to cross-sectional variation in expected profitability beyond the 15-year horizon. Hence, we aggressively interpret our regressions as suggesting that approximately 20% of the dispersion in the book-to-market ratios is due to dispersion in expected stock returns and 80% due to dispersion in expected profitability.

We document similar results for an international panel covering 23 countries (excluding the US) over the 1982-1998 period. As with the domestic panel, most of the variation in the book-to-market ratios, even after adjusting for differences in accounting practices across countries, is due to information concerning expected future profitability.

One could conjecture from the above variance decomposition result that the expected annual premium on Fama and French's (1993) HML portfolio is time-varying. Our empirical evidence confirms that supposition: the expected return on a value-minus-growth strategy is atypically high at times when the value spread is wide and the market is cheap.

Appendix 1: U.S. data

In order to be included in our U.S. sample, a firm-year must satisfy the following data requirements. When using COMPUSTAT as our source of accounting information, we require that the firm must be on COMPUSTAT for two years. This requirement avoids potential survivor bias due to COMPUSTAT backfilling data. Also, due to data-quality concerns, all predictive tests require the dependent variable to correspond to year 1937 or later.

Book equity is defined as the stockholders' equity, plus balance sheet deferred taxes (data item 74) and investment tax credit (data item 208) (if available), plus post-retirement benefit liabilities (data item 330) (if available) minus the book value of preferred stock. Depending on availability, we use redemption (data item 56), liquidation (data item 10), or par value (data tiem 130) (in that order) for the book value of preferred stock. Stockholders' equity used in the above formula is calculated as follows. We prefer the stockholders' equity number reported by Moody's, or COMPUSTAT (data item 216). If neither one is available, we measure stockholders' equity as the book value of common equity (data item 60) plus the par value of preferred stock. (Note that the preferred stock is added at this stage because it is later subtracted in the book equity formula.) If common equity is not available, we compute stockholders' equity as the book value of assets (data item 6) minus total liabilities (data item 181), all from COMPUSTAT.

The BE/ME ratio used to form portfolios in May of year t is book common equity for the fiscal year ending in calendar year t-1, divided by market equity at the end of May of year t.[7] We require the firm to have a valid past BE/ME. Moreover, in order to eliminate likely data errors, we discard those firms with BE/ME ratios less than .01 and greater than 100.

When computing stock returns, we include delisting data when available on the CRSP tapes. In some cases, CRSP records delisting prices several months after the security ceases trading and thus after a period of missing returns. In these cases, we calculate the total return from the last available price to the delisting price and pro-rate this return over the intervening months.

The clean-surplus ROE is calculated as follows. We compute the firm's annual earnings using the assumption of clean surplus accounting and the firm's dividends from CRSP. The formula used for computing log ROE is

$$e_t = \log\left(\left[\frac{(1+R_t)M_{t-1} - D_t}{M_t}\right]\left[\frac{B_t}{B_{t-1}}\right] - \left[1 - \frac{D_t}{B_{t-1}}\right]\right), \tag{A2.1}$$

where M denotes market and B book equity, D dividends, and R the stock return. This relation is simply that earnings this year equals the change in book equity plus dividends with an appropriate adjustment for equity offerings.

Appendix 2: Why not VARs with managed portfolios?

At first, it may seem that a VAR model would be a simpler and more elegant alternative to our long-horizon regressions. It is tempting to include, for example, HML return, HML value spread, and HML profitability spread into a VAR model state vector and compute the variance decomposition along the lines of Campbell and Shiller (1988) and Vuolteenaho (2000). It turns out, however, that the economic interpretation of the VAR-based variance decomposition may be materially different from the long-horizon regression variance decomposition we advocate. The difference between the two methods originates from the fact that the HML portfolio's weights are managed.

To illustrate this point, consider a general managed portfolio series and a VAR model. Let r_t^{t-1}, θ_t^{t-1}, and e_t^{t-1} denote the log return, log book-to-market, and log profitability on a buy-and-hold portfolio. The superscript in the above variables denotes the time when the buy-and-hold portfolio was formed. Adapting the basic linearized book-to-market law (7) to this notation yields:

$$e_t^{t-1} - r_t^{t-1} \approx \rho\theta_t^{t-1} - \theta_{t-1}^{t-1} \qquad \text{(A1.1)}$$

As one can see, the basic identity describes the evolution of a buy-and-hold portfolio's book-to-market.

An equation describing the book-to-market evolution of a managed portfolio must include an additional term due to rebalancing. Adding $\rho(\theta_t^t - \theta_t^{t-1})$ to both sides of (A1.1) results:

$$e_t^{t-1} - r_t^{t-1} + \rho(\theta_t^t - \theta_t^{t-1}) \approx \rho\theta_t^t - \theta_{t-1}^{t-1} \qquad \text{(A1.2)}$$

Equation (A1.2) describes the evolution of a managed portfolio series. The change in managed portfolio book-to-market is explained by three terms: managed portfolio profitability, managed portfolio return, and a rebalancing term.

Comparison of equations (A1.1) and (A1.2) highlights the difference between a VAR variance decomposition and a long-horizon regression variance decomposition. A long-horizon regression is based on iteration of (A1.1). A VAR-model maps a vector [r_{t-1}^{t-2}, θ_{t-1}^{t-1}, e_{t-1}^{t-2}] to [r_t^{t-1}, θ_t^t, e_t^{t-1}] and, thus, can only implement a variance decomposition based on iterating equation (A1.2). The more aggressively the portfolio is rebalanced, the larger the difference between the two.

Experiments with a first-order VAR specification indicate that the covariance term,

$$\frac{\operatorname{cov}\left[\sum_{i=0}^{\infty} \rho^{i+1} (\theta_{t+i}^{t+i} - \theta_{t+i}^{t+i-1}), \theta_{t-1}^{t-1}\right]}{\operatorname{var} \theta_{t-1}^{t-1}} , \tag{A1.3}$$

is economically quite large (contributing approximately 30% of the total cross-sectional variance). Thus, interpretation of a VAR-based variance decomposition with managed portfolios is difficult.

Appendix 3: Regression standard errors

In many finance applications, the available data set contains perhaps seventy overlapping cross-sections, each with hundreds or even thousands of data points. In such cases, incorrectly assuming that the errors covariance matrix is proportional to an identity matrix can yield standard errors that are severely biased downwards. This bias is due to the fact that error correlations are often systematically related to the explanatory variables. Fortunately, the statistics literature has proposed a solution for a similar problem frequently arising with complex surveys: Rogers's (1983, 1993) robust standard errors. Compared to the popular Fama-MacBeth (1973) procedure, this method has the practical advantage of giving the standard errors for pooled-OLS/WLS coefficients – allowing for, among other things, the use of common time-series variables in the regressions.

A simple exposition of Rogers's (1983, 1993) standard errors starts from the familiar formula for OLS standard errors. Let X denote the panel of explanatory variables, Ω the covariance matrix of the panel of errors, and $X_{t-N+1,t+N-1}$ and $\Omega_{t-N+1,t+N-1}$ a single cluster of explanatory variables and the corresponding error covariance matrix. A cluster is defined as the set of cross-sections whose errors are correlated with the errors of the year-*t* cross-section. Assuming that the errors may be dependent within a cluster but are independent across clusters allows writing

$$(X'X)^{-1} X'\Omega X (X'X)^{-1} = (X'X)^{-1} \sum_{t=1}^{T} \left[X'_{t-N+1,t+N-1} \Omega_{t-N+1,t+N-1} X_{t-N+1,t+N-1}\right] (X'X)^{-1} . \tag{A3.1}$$

We denote regression errors by ε, and notation for fitted values is modified with a hat. As $X'_{t-N+1,t+N-1} \Omega_{t-N+1,t+N11} X_{t-N+1,t+N-1} = E(X'_{t-N+1,t+N-1} \varepsilon_{t-N+1,t+N-1} \varepsilon'_{t-N+1,t+N-1} X_{t-N+1,t+N-1})$, Rogers's standard errors are computed by substituting in-sample estimates of the errors for true errors to get an in-sample variance estimator of regression coefficients:

$$(X'X)^{-1} \sum_{t=1}^{T} \left[X'_{t-N+1,t+N-1} \hat{\varepsilon}_{t-N+1,t+N-1} \hat{\varepsilon}'_{t-N+1,t+N-1} X_{t-N+1,t+N-1}\right] (X'X)^{-1} \tag{A3.2}$$

Under plausible assumptions, these standard errors are consistent in T, i.e., they converge as the time dimension of the panel grows. In order to ensure that the effect of a single cluster on the coefficient estimates vanishes as more and more clusters are included, Rogers's assumptions include that the time-series of $X'_{t-N+1,t+N-1}\varepsilon_{t-N+1,t+N-1}\varepsilon'_{t-N+1,t+N-1}X_{t-N+1,t+N-1}$ is well behaved.

The above standard-error formula can be interpreted as generalized White's standard errors; in the special case of only one observation per cluster (e.g., a univariate time series with serially uncorrelated errors), the standard errors are equivalent to White (1980) heteroscedasticity consistent standard errors. The method can also be interpreted as an application of Hansen's (1982) Generalized Method of Moments or as a multivariate generalization of Hansen-Hodrick (1980) standard errors.

[1] The Cisco Systems' and General Motors' data are from finance.yahoo.com as of 3/7/2001.

[2] We thank Kenneth French for providing us with the data.

[3] Merino and Mayper (1999) provide statistics on the enforcement of the 1934 Securities Exchange Act. In the first 10 years of the enforcement of the 1934 act, the SEC began 279 proceedings. Of these proceedings, 272 were begun in the 1933-37 period and only seven began in the latter five years. In these proceedings, the SEC identified numerous types of accounting and non-accounting violations by publicly traded firms. The above indicates that enforcement was broad and active in the first five years, whereas in the 1938-42 period, few enforcement proceedings were initiated. While the total number of identified problems in firms' statements was similar during both the 1933-37 (101 accounting violations) and 1938-42 (83 accounting violations) period, it appears that in the latter period, only the worst violators were examined, in which many errors per registration statement were uncovered. This decline in proceedings may signal increasing compliance by registrants or declining interest by the SEC in regulatory enforcement. We believe the former cause was the driving force behind the reduced number of new proceedings. It is thus reasonable to characterize the 1933-37 period as the initial and strict enforcement period and the 1938-42 as the beginning of a steady-state level of enforcement.

[4] The clean-surplus relation has also been used in equity valuation by Ohlson (1995), Feltham and Ohlson (1999), and others.

[5] In their Appendix, Frankel and Lee (1999) list the accounting standards that violate clean-surplus accounting. They argue that these violations of the clean-surplus accounting are largely unpredictable. Thus, using reported earnings instead imputed clean-surplus earning would probably not materially affect our variance-decomposition results.

[6] The accounting identity, which holds for every sample path, can be iterated forward or backward. In a previous version of this paper, we also iterated (7) backwards in order to calculate a backward-looking cross-sectional variance decomposition.

[7] Some earlier research [see, for example, Fama and French (1992)] uses ME at the end of year t-1 to compute BE/ME. In order that our decomposition of BE/ME hold, however, we use the May of year-t market equity as the denominator in BE/ME.

References

Asness, C., J. Friedman, R. Krail, and J. Lieu, 2000, Style timing: Value versus growth, *Jounal of Portfolio Management*, Spring.

Asness, C., R. B. Porter, and R. Stevens, 2000, Predicting stock returns using industry relative firm characteristics, University of Florida working paper.

Campbell, J. Y. and R. J. Shiller, 1988, The dividend-price ratio and expectations of future dividends and discount factors, *Review of Financial Studies* 1, 195-228.

Cochrane, J. H., 1992. Explaining the variance of price-dividend ratios, *Review of Financial Studies* 5, 243-280.

Davis, J. L., E. F. Fama, and K. R. French, 2000. Characteristics, covariances, and average returns: 1929 to 1997, *Journal of Finance*, 55, 389-406.

Fama, E. F. and K. R. French, 1992. The cross-section of expected stock returns, *Journal of Finance* 47, 427-465.

Fama, E. F. and K. R. French, 1993, Common risk factors in the returns on stocks and bonds, *Journal of Financial Economics* 33, 3-56.

Fama, E. F. and K. R. French, 1995, Size and book-to-market factors in earnings and returns, *Journal of Finance* 50, 131-155.

Fama, E. F. and K. R. French, 1996. Multifactor explanations of asset pricing anomalies, *Journal of Finance* 51, 55-84.

Fama, E. F. and K. R. French, 1997, Industry costs of equity, *Journal of Financial Economics* 43, 153-193.

Fama, E. F. and J. MacBeth, 1973, Risk, return, and equilibrium: empirical tests, *Journal of Political Economy* 81, 607-636.

Feltham, G. A. and J. A. Ohlson, 1999, Residual earnings valuation with risk and stochastic interest rates, *Accounting Review* 74, 2-23.

Frankel, R., and C. M. C. Lee, 1999, Accounting diversity and international valuation, working paper, Johnson Graduate School of Management.

Green, W. H., 1997, *Econometric Analysis* (Prentice Hall, Upper Saddle River, NY).

Hansen, L. P., 1982, Large sample properties of generalized methods of moments estimators, *Econometrica* 50, 1029-1054.

Hansen, L. P., and R. J. Hodrick, 1980, Forward exchange rates as optimal predictors of future spot rates: An econometric analysis, *Journal of Political Economy* 88, 829-853.

Lewellen, Jonathan, 1999, The time-series relations among expected return, risk, and book-to-market, *Journal of Financial Economics* 54, 5-44.

Merino, B. and A. Mayper, 1999, The rhetoric and reality of American dream: Securities legislation and the accounting profession in the 1930s, working paper, University of North Texas.

Ohlson, J. A., 1995, Earnings, book values, and dividends in equity valuation, *Contemporary Accounting Research* 11, 661-87.

Rogers, W. H., 1983, Analyzing complex survey data, Rand Corporation memorandum. Santa Monica, CA.

Rogers, W. H., 1993, Regression standard errors in clustered samples, Stata Technical Bulletin Reprints STB-13 – STB-18, 88-94.

Rosenberg, B., K. Reid, and R. Lanstein, 1985, Persuasive evidence of market inefficiency, *Journal of Portfolio Management* 11, 9-17.

Vuolteenaho, T., 2000, Understanding the aggregate book-to-market ratio, working paper, Harvard University Department of Economics.

White, H., 1980, A heteroscedasticity-consistent covariance matrix estimator and a direct test of heteroscedasticity, *Econometrica* 48, 817-838.

Table 1: Decomposition of the unconditional book-to-market variance (U.S. data)

This table reports the unconditional variance decomposition of firms' log book-to-market ratios (BE/ME) computed from the U.S. data sample (1937-1997, 192,661 firm-years). Panel A uses basic data and Panel B industry-adjusted data. We use Fama and French's (1997) industry classifications. The first column shows the horizon N. The second column shows the simple predictive regression coefficient of cross-sectionally demeaned, N-period discounted future stock return on cross-sectionally demeaned BE/ME. The third column shows the simple predictive regression coefficient of cross-sectionally demeaned, N-period discounted future profitability (ROE) on cross-sectionally demeaned BE/ME. The fourth column shows the simple predictive regression coefficient of cross-sectionally demeaned, N-period-in-the-future discounted BE/ME on cross-sectionally demeaned BE/ME.

$$\sum_{j=0}^{N-1}\rho^j \tilde{r}_{t+j,i} = b(\tilde{r},N)\,\tilde{\theta}_{t-1,i} + \varepsilon(\tilde{r},N,i);$$

$$\sum_{j=0}^{N-1}\rho^j \tilde{e}_{t+j,i} = b(\tilde{e},N)\,\tilde{\theta}_{t-1,i} + \varepsilon(\tilde{e},N,i);$$

$$\rho^N \tilde{\theta}_{t+N-1,i} = b(\tilde{\theta},N)\,\tilde{\theta}_{t-1,i} + \varepsilon(\tilde{\theta},N,i)$$

$$b(\tilde{r},N) - b(\tilde{e},N) + b(\tilde{\theta},N) \approx 1$$

Each data point consists of the value-weight BE/ME (θ), return (r), and ROE (e) for one of 40 portfolios we form each year by sorting firms on BE/ME. The identity derived in the paper guarantees that the expected-return column minus the expected-profitability column plus the future-BE/ME column equals approximately one. Reversing the sign of the profitability column provides a %-variance decomposition of the cross-sectional variance of firms' log BE/ME ratios. All variables are log transformed before demeaning, as specified by the identity. The discount coefficient rho (ρ) equals 0.96. The point estimates are produced by pooled OLS and the standard errors (in parentheses) are produced using GMM. The applicable standard-error formulas account for cross-sectional and serial correlation of the errors.

Panel A: Basic U.S. data (ρ=0.96)

N	Expected returns	Expected profitability	Future BE/ME
1	0.0272 (0.0083)	-0.1469 (0.0097)	0.8258 (0.0127)
2	0.0559 (0.0242)	-0.2386 (0.0360)	0.7055 (0.0378)
3	0.0809 (0.0441)	-0.3006 (0.0613)	0.6194 (0.0607)
5	0.1198 (0.0834)	-0.3826 (0.0895)	0.5012 (0.0954)
10	0.1734 (0.0951)	-0.4938 (0.1185)	0.3399 (0.1441)
15	0.1996 (0.1097)	-0.5832 (0.1754)	0.2646 (0.0967)

Panel B: Industry-adjusted U.S. data (ρ=0.96)

N	Expected returns	Expected profitability	Future BE/ME
1	0.0236 (0.0078)	-0.1209 (0.0080)	0.8590 (0.0086)
2	0.0510 (0.0262)	-0.2103 (0.0300)	0.7459 (0.0267)
3	0.0763 (0.0464)	-0.2765 (0.0547)	0.6584 (0.0451)
5	0.1163 (0.0840)	-0.3679 (0.0857)	0.5359 (0.0786)
10	0.1677 (0.0999)	-0.4853 (0.1445)	0.3596 (0.1153)
15	0.1859 (0.1092)	-0.5784 (0.1549)	0.2743 (0.0909)

Table 2: Decomposition of the unconditional book-to-market variance (international data)

This table reports the unconditional decomposition of firms' log book-to-market equity ratios (BE/ME) computed from the international data sample (1982-1998, 27,913 firm-years). Panel A uses basic data and Panel B country-adjusted data. The first column shows the horizon N. The second column shows the simple predictive regression coefficient of cross-sectionally demeaned, N-period discounted future stock return on cross-sectionally demeaned BE/ME. The third column in shows the simple predictive regression coefficient of cross-sectionally demeaned, N-period discounted future profitability (ROE) on cross-sectionally demeaned BE/ME. The fourth column shows the simple predictive regression coefficient of cross-sectionally demeaned, N-period-in-the-future discounted BE/ME on cross-sectionally demeaned BE/ME.

$$\sum_{j=0}^{N-1} \rho^j \tilde{r}_{t+j,i} = b(\tilde{r}, N)\, \tilde{\theta}_{t-1,i} + \varepsilon(\tilde{r}, N, i);$$

$$\sum_{j=0}^{N-1} \rho^j \tilde{e}_{t+j,i} = b(\tilde{e}, N)\, \tilde{\theta}_{t-1,i} + \varepsilon(\tilde{e}, N, i);$$

$$\rho^N \tilde{\theta}_{t+N-1,i} = b(\tilde{\theta}, N)\, \tilde{\theta}_{t-1,i} + \varepsilon(\tilde{\theta}, N, i)$$

$$b(\tilde{r}, N) - b(\tilde{e}, N) + b(\tilde{\theta}, N) \approx 1$$

Each data point consists of the value-weight BE/ME (θ), return (r), and ROE (e) for one of 40 portfolios we form each year by sorting firms on BE/ME. The identity derived in the paper guarantees that the first column minus the second column plus the third column equals approximately one. Reversing the sign of the second column provides a %-variance decomposition of the cross-sectional variance of firms' log book-to-market ratios. All variables are log transformed before demeaning, as specified by the identity. The discount coefficient rho (ρ) equals 0.96. The point estimates are produced by pooled OLS and the standard errors (in parentheses) are produced using GMM. The applicable standard-error formulas account for cross-sectional and serial correlation of the errors.

Panel A: Basic international data (ρ=0.97)

N	Expected returns	Expected profitability	Future BE/ME
1	0.0348 (0.0155)	-0.1114 (0.0102)	0.8546 (0.0156)
2	0.0849 (0.0471)	-0.1978 (0.0326)	0.7199 (0.0390)
3	0.1192 (0.0812)	-0.2516 (0.0422)	0.6312 (0.0629)
5	0.1775 (0.1181)	-0.3288 (0.0466)	0.4899 (0.0834)

Panel B: Country-adjusted international data (ρ=0.97)

N	Expected returns	Expected profitability	Future BE/ME
1	0.0317 (0.0131)	-0.1188 (0.0077)	0.8546 (0.0139)
2	0.0664 (0.0311)	-0.2225 (0.0268)	0.7228 (0.0305)
3	0.0921 (0.0310)	-0.2967 (0.0344)	0.6277 (0.0346)
5	0.1401 (0.0410)	-0.4110 (0.0274)	0.4726 (0.0339)

Table 3: Decomposition into inter-industry and intra-industry components (U.S. data)

This table reports the unconditional decomposition of firms' log book-to-market ratios (BE/ME) computed from the U.S. data sample (1937-1997, 192,661 firm-years). We use Fama and French's (1997) industry classifications. The first column shows the horizon N. The second and third columns show the simple predictive regression coefficients of cross-sectionally demeaned, N-period discounted future industry stock return on cross-sectionally demeaned BE/ME and the simple predictive regression coefficient of cross-sectionally demeaned, N-period discounted industry-adjusted future stock return on cross-sectionally demeaned BE/ME. The fourth and fifth columns shows the simple predictive regression coefficient of cross-sectionally demeaned, N-period discounted future industry profitability (ROE) on cross-sectionally demeaned BE/ME and the simple predictive regression coefficient of cross-sectionally demeaned, N-period discounted industry-adjusted future ROE on cross-sectionally demeaned BE/ME. The sixth and seventh columns show the simple predictive regression coefficient of cross-sectionally demeaned, N-period-in-the-future discounted industry BE/ME on cross-sectionally demeaned BE/ME and the simple predictive regression coefficient of cross-sectionally demeaned, N-period-in-the-future discounted industry-adjusted BE/ME on cross-sectionally demeaned BE/ME. Each data point consists of the value-weight variables for one of 40 portfolios we form each year by sorting firms on BE/ME. Because of the identity, a particular linear combination of the coefficients equals one:

$$\sum_{j=0}^{N-1}\rho^j\tilde{r}_{t+j,ii}=b(\tilde{r}_{ii},N)\,\tilde{\theta}_{t-1,i}+\varepsilon(\tilde{r}_{ii},N,i);\sum_{j=0}^{N-1}\rho^j\tilde{e}_{t+j,ii}=b(\tilde{e}_{ii},N)\,\tilde{\theta}_{t-1,i}+\varepsilon(\tilde{e}_{ii},N,i);\,\rho^N\tilde{\theta}_{t+N-1,ii}=b(\tilde{\theta}_{ii},N)\,\tilde{\theta}_{t-1,i}+\varepsilon(\tilde{\theta}_{ii},N,i);$$

$$\sum_{j=0}^{N-1}\rho^j\tilde{r}_{t+j,I}=b(\tilde{r}_{I},N)\,\tilde{\theta}_{t-1,i}+\varepsilon(\tilde{r}_{I},N,i);\sum_{j=0}^{N-1}\rho^j\tilde{e}_{t+j,I}=b(\tilde{e}_{I},N)\,\tilde{\theta}_{t-1,i}+\varepsilon(\tilde{e}_{I},N,i);\,\rho^N\tilde{\theta}_{t+N-1,I}=b(\tilde{\theta}_{I},N)\,\tilde{\theta}_{t-1,i}+\varepsilon(\tilde{\theta}_{I},N,i)$$

$$b(\tilde{r}_{ii},N)-b(\tilde{e}_{ii},N)+b(\tilde{\theta}_{ii},N)+b(\tilde{r}_{I},N)-b(\tilde{e}_{I},N)+b(\tilde{\theta}_{I},N)\approx 1$$

Reversing the signs of the fourth and fifth columns provides a %-variance decomposition of the cross-sectional variance of firms' log book-to-market ratios. All variables are log transformed before demeaning, as specified by the identity. The discount coefficient rho (ρ) equals 0.96. The point estimates are produced by pooled OLS and the standard errors (in parentheses) are produced using GMM. The applicable standard-error formulas account for cross-sectional and serial correlation of the errors.

N	Industry's expected returns	Expected industry-adjusted returns	Industry's expected profitability	Expected industry-adjusted profitability	Industry's expected future BE/ME	Expected industry-adjusted BE/ME
1	0.0055 (0.0031)	0.0214 (0.0058)	-0.0141 (0.0021)	-0.1318 (0.0097)	0.1935 (0.0094)	0.6336 (0.0156)
2	0.0102 (0.0092)	0.0449 (0.0162)	-0.0225 (0.0068)	-0.2142 (0.0351)	0.1765 (0.0235)	0.5318 (0.0472)
3	0.0141 (0.0158)	0.0654 (0.0301)	-0.0280 (0.0105)	-0.2713 (0.0598)	0.1639 (0.0347)	0.4587 (0.0758)
5	0.0230 (0.0269)	0.0971 (0.0588)	-0.0336 (0.0186)	-0.3471 (0.0870)	0.1463 (0.0447)	0.3576 (0.118)
10	0.0442 (0.0444)	0.1382 (0.0683)	-0.0376 (0.0168)	-0.4416 (0.1015)	0.1064 (0.0406)	0.2279 (0.1609)
15	0.0450 (0.0315)	0.1639 (0.1067)	-0.0258 (0.0797)	-0.5027 (0.1009)	0.0855 (0.0444)	0.1733 (0.1174)

Table 4: Decomposition of the unconditional book-to-market (U.S. data)

This table reports the unconditional variance decomposition of firms' log book-to-market ratios (BE/ME) computed from the U.S. data sample (1937-1997, 192,661 firm-years) for three groupings based on either firm size (Panel A) or firm BE/ME (Panel B). We calculate yearly market capitalization breakpoints for the size groupings in Panel A using only NYSE stocks. The first column shows the horizon N. Within each grouping, the first column shows the simple predictive regression coefficient of cross-sectionally demeaned, N-period discounted future stock return on cross-sectionally demeaned BE/ME. The second column shows the simple predictive regression coefficient of cross-sectionally demeaned, N-period discounted future profitability (ROE) on cross-sectionally demeaned BE/ME. The third column shows the simple predictive regression coefficient of cross-sectionally demeaned, N-period-in-the-future discounted BE/ME on cross-sectionally demeaned BE/ME.

$$\sum_{j=0}^{N-1} \rho^j \tilde{r}_{t+j,i} = b(\tilde{r}, N)\, \tilde{\theta}_{t-1,i} + \varepsilon(\tilde{r}, N, i);$$

$$\sum_{j=0}^{N-1} \rho^j \tilde{e}_{t+j,i} = b(\tilde{e}, N)\, \tilde{\theta}_{t-1,i} + \varepsilon(\tilde{e}, N, i);$$

$$\rho^N \tilde{\theta}_{t+N-1,i} = b(\tilde{\theta}, N)\, \tilde{\theta}_{t-1,i} + \varepsilon(\tilde{\theta}, N, i)$$

$$b(\tilde{r}, N) - b(\tilde{e}, N) + b(\tilde{\theta}, N) \approx 1$$

Each data point consists of the value-weight BE/ME (θ), return (r), and ROE (e) for one of 5 portfolios we form each year by sorting firms on BE/ME within each group. The identity derived in the paper guarantees that the expected-return column minus the expected-profitability column plus the future-BE/ME column equals approximately one. Reversing the sign of the profitability column provides a %-variance decomposition of the cross-sectional variance of firms' log BE/ME ratios. All variables are log transformed before demeaning, as specified by the identity. The table displays the appropriate discount coefficient rho (ρ) for each group. The point estimates are produced by pooled OLS and the standard errors (in parentheses) are produced using GMM. The applicable standard-error formulas account for cross-sectional and serial correlation of the errors.

Panel A: %-variance decomposition conditional on firm size

	Small (ρ=0.99) var($\tilde{\theta}$) = 0.53			Medium (ρ=0.98) var($\tilde{\theta}$) = 0.46			Big (ρ=0.95) var($\tilde{\theta}$) = 0.39		
N	Expected returns	Expected profitability	Future BE/ME	Expected returns	Expected profitability	Future BE/ME	Expected returns	Expected profitability	Future BE/ME
1	0.0449	-0.1404	0.8141	0.0466	-0.1636	0.7916	0.0231	-0.1036	0.8757
	(0.0107)	(0.0085)	(0.0147	(0.0124)	(0.0090)	(0.0186)	(0.0094)	(0.0039)	(0.0100)
2	0.0946	-0.2614	0.6441	0.0940	-0.2653	0.6443	0.0442	-0.1832	0.7770
	(0.0351)	(0.0391)	(0.0580)	(0.0264)	(0.0246)	(0.0497)	(0.0274)	(0.0152)	(0.0251)
3	0.1350	-0.3204	0.5454	0.1259	-0.3313	0.5483	0.0640	-0.2458	0.6966
	(0.0583)	(0.0455)	(0.0619)	(0.0409)	(0.0379)	(0.0777)	(0.0484)	(0.0304)	(0.0410)
5	0.1899	-0.4239	0.3912	0.1830	-0.4013	0.4273	0.0920	-0.3425	0.5763
	(0.0959)	(0.0748)	(0.0791)	(0.0754)	(0.0628)	(0.1132)	(0.0842)	(0.0691)	(0.0702)
10	0.2030	-0.5587	0.3139	0.2310	-0.5027	0.2918	0.1326	-0.5007	0.3772
	(0.1924)	(0.2140)	(0.0596)	(0.1633)	(0.2271)	(0.1216)	(0.1458)	(0.2090)	(0.1116)
15	0.1787	-0.6923	0.2788	0.2568	-0.5845	0.2440	0.1574	-0.6149	0.2689
	(0.1918)	(0.2919)	(0.1476)	(0.2322)	(0.3638)	(1186)	(0.1611)	(0.3045)	(0.0689)

Panel B: %-variance decomposition conditional on firm book-to-market

	Low (ρ=0.95) var($\tilde{\theta}$) = 0.22			Medium (ρ=0.96) var($\tilde{\theta}$) = 0.03			High (ρ=0.97) var($\tilde{\theta}$) = 0.14		
N	Expected returns	Expected profitability	Future BE/ME	Expected returns	Expected profitability	Future BE/ME	Expected returns	Expected profitability	Future BE/ME
1	0.0102	-0.1638	0.8283	0.0375	-0.0873	0.8792	0.0240	-0.1479	0.8176
	(0.0155)	(0.0117)	(0.0225)	(0.0184)	(0.0069)	(0.0177)	(0.0180)	(0.0179)	(0.0244)
2	0.0234	-0.2730	0.7072	0.0568	-0.1568	0.7930	0.0541	-0.2507	0.6761
	(0.0419)	(0.0473)	(0.0686)	(0.0466)	(0.0291)	(0.0476)	(0.0435)	(0.0613)	(0.0627)
3	0.0362	-0.3388	0.6321	0.0805	-0.1959	0.7318	0.1022	-0.3223	0.5502
	(0.0760)	(0.0822)	(0.1184)	(0.0881)	(0.0558)	(0.0819)	(0.0611)	(0.1033)	(0.0916)
5	0.0573	-0.4344	0.5208	0.0890	-0.2966	0.6261	0.1614	-0.3841	0.4242
	(0.1634)	(0.1268)	(0.2033)	(0.1760)	(0.1105)	(0.1250)	(0.0986)	(0.1275)	(0.1200)
10	0.0985	-0.5790	0.3477	0.1222	-0.4834	0.4527	0.1427	-0.4789	0.3764
	(0.2853)	(0.2744)	(0.3745)	(0.2989)	(0.2958)	(0.1773)	(0.1147)	(0.1715)	(0.2274)
15	0.1349	-0.6763	0.2712	0.1476	-0.6193	0.3652	0.0943	-0.6949	0.2948
	(0.4153)	(0.5269)	(0.3090)	(0.3565)	(0.4163)	(0.1384)	(0.1315)	(0.1767)	(0.2667)

Table 5: HML-return predictability

The table reports regressions predicting the simple return on the HML portfolio. Each regression contains a constant and the HML value spread. In addition, some of the regressions contain combinations of the following variables: the lagged ROE of the HML portfolio, market BE/ME, default yield spread (Moody's BAA less AAA corporate-bond yield), and an interaction term between the value spread and the median BE/ME of the market.

The HML value spread is defined as the difference between the log BE/ME of the H portfolio and the log BE/ME of the L portfolio. The HML ROE is defined as the difference between the log ROE of the H portfolio and the log ROE of the L portfolio. These portfolios are constructed following Fama and French's (1993) methodology. The international HML portfolio is country balanced, i.e., for each country, the stocks are first sorted into the six elementary portfolios based on country-specific break points and all stocks in each elementary portfolio are value weighted.

For each specification, we report three rows. The first row reports the OLS estimates of linear-regression coefficients of HML return on predictor variables. OLS R^2 on the first row is adjusted for degrees of freedom. The second row reports the maximum-likelihood GLS estimates of linear-regression coefficients of HML return on predictor variables. GLS R^2 on the second row is the variance of fitted values (computed using GLS parameter estimates) divided by the sample variance of HML return. The third row shows the maximum-likelihood GLS coefficients in an exponential-linear conditional-variance model, shown in equation (19) of the text. T-statistics are in parentheses.

Panel A: U.S. HML return (1938-1997)

Parameter estimate (t-statistic)	**Constant**	**Value spread**	**Lagged ROE**	**Market BE/ME**	**Default yield spread**	**Value spread * market BE/ME**	**R^2**	**St. dev. $E_{t-1}(R_t)$**
OLS return coeff.	-0.323 (-2.4)	0.246 (2.8)					0.108	0.040
GLS return coeff.	-0.376 (-2.8)	0.287 (3.1)					0.160	0.047
GLS variance coeffi.	-7.239 (-4.2)	1.830 (1.6)						
OLS return coeff.	-0.322 (-2.4)	0.256 (2.8)	0.001 (0.2)				0.093	0.040
GLS return coeff.	-0.360 (-2.7)	0.292 (3.1)	0.003 (0.6)				0.156	0.045
GLS variance coeffi.	-7.491 (-4.4)	1.907 (1.6)	-0.017 (-0.3)					
OLS return coeff.	-0.317 (-2.4)	0.263 (3.0)				0.035 (1.1)	0.111	0.043
GLS return coeff.	-0.414 (2.9)	0.334 (3.2)				0.044 (1.3)	0.226	0.054
GLS variance coeffi.	-6.971 (-4.0)	1.957 (1.7)				0.758 (1.8)		
OLS return coeff.	-0.311 (-2.4)	0.285 (3.0)	0.004 (0.7)			0.045 (1.3)	0.103	0.044
GLS return coeff.	-0.425 (-3.0)	0.376 (3.5)	0.006 (1.0)			0.056 (1.6)	0.254	0.058
GLS variance coeffi.	-7.537 (-4.4)	2.452 (2.0)	0.026 (0.4)			0.732 (1.6)		
OLS return coeff.	-0.339 (-2.4)	0.269 (2.6)			-0.011 (-0.4)		0.094	0.040
GLS return coeff.	-0.342 (-2.5)	0.246 (2.4)			0.031 (0.8)		0.186	0.049
GLS variance coeffi.	-5.508 (-3.0)	0.092 (0.1)			0.815 (2.0)			
OLS return coeff.	-0.301 (-2.3)	0.253 (2.9)		0.055 (1.1)			0.111	0.043
GLS return coeff.	-0.386 (-2.8)	0.317 (3.2)		0.075 (1.4)			0.222	0.054
GLS variance coeffi.	-6.590 (-3.8)	1.713 (1.5)		1.167 (1.8)				
OLS return coeff.	-0.380 (-2.8)	0.388 (3.4)		0.148 (2.1)	-0.079 (-1.8)		0.143	0.049
GLS return coeff.	-0.432 (-3.0)	0.394 (3.1)		0.128 (1.8)	-0.041 (-0.8)		0.249	0.057
GLS variance coeffi.	-5.899 (-3.2)	1.563 (0.4)		1.287 (0.3)	-.0578 (1.0)			

Panel B: Country-balanced international HML return (1983-1998)

Parameter estimate (t-statistic)	**Constant**	**Value spread**	**R^2**	**St. dev. $E_{t-1}(R_t)$**
OLS return coeff.	-0.117 (-0.5)	0.131 (0.7)	-0.030	0.013
GLS return coeff.	-0.151 (-0.8)	0.159 (1.0)	0.056	0.016
GLS variance coeffi.	-8.438 (-1.8)	2.309 (0.6)		

Table 6: Explaining the value spread

The table reports regressions explaining the spread in the book-to-market ratios of the HML portfolio's components. The regressions contain combinations of the following as explanatory variables: the lagged ROE of the HML portfolio, market BE/ME, and the default yield spread (Moody's BAA less AAA corporate-bond yield).

The HML value spread is defined as the difference between the log BE/ME of the H portfolio and the log BE/ME of the L portfolio. The HML ROE is defined as the difference between the log ROE of the H portfolio and the log ROE of the L portfolio. These portfolios are constructed following the Fama and French's (1993) methodology.

For each specification, we report the OLS estimates of linear-regression coefficients of the HML value spread on predictor variables. The OLS R^2 is adjusted for degrees of freedom. t-statistics are in parentheses.

Constant	Market BE/ME	Default yield spread	Lagged ROE	R^2
1.475 (14.6)	-0.017 (-0.1)			-0.016
1.333 (20.4)		0.153 (2.0)		0.239
1.084 (16.4)	-0.312 (-3.6)	0.256 (4.6)		0.421
1.043 (15.5)	-0.322 (-3.6)	-0.622 (-1.1)	0.244(3.9)	0.421

Figure 1: Decomposing the cross-sectional BE/ME variance (U.S. sample)

The figure shows the unconditional decomposition of the cross-sectional log book-to-market (BE/ME) variance estimated from the U.S. data sample (1937-1997, 192,661 firm-years). The x-axis shows the horizon N. The height of the top area shows the simple predictive regression coefficient of cross-sectionally demeaned, N-period discounted future stock return on cross-sectionally demeaned BE/ME. The height of the bottom area shows the negative of the simple predictive regression coefficient of cross-sectionally demeaned, N-period discounted future profitability (ROE) on cross-sectionally demeaned BE/ME. The height of the middle area shows the simple predictive regression coefficient of cross-sectionally demeaned, N-period-in-the-future discounted BE/ME on cross-sectionally demeaned BE/ME. All variables are log transformed before demeaning, as specified by the identity.

Figure 2: Time-series evolution of BE/MEs (U.S. sample)

The figure plots the time-series evolution (1937-1997) of the log book-to-market ratios of H, M, and L portfolios. The portfolios are constructed using Fama and French's (1993) methodology: H is a size-balanced portfolio of high-book-to-market stocks, M that of medium-book-to-market stocks, and L that of low-book-to-market stocks.

Figure 3: Conditional expected return and Sharpe ratio on HML (U.S. sample)

This figure shows a time series of the estimated conditional mean and Sharpe ratios on the HML portfolio. The estimates are produced from maximum-likelihood GLS regressions, shown in equation (19) of the text, that relate the expected return and log of the return variance using linear regressions to a constant and the HML value spread. The coefficient estimates are reported in the first row of Table 5 Panel A.

Figure 1: Decomposing the cross-sectional BE/ME variance (U.S. sample)

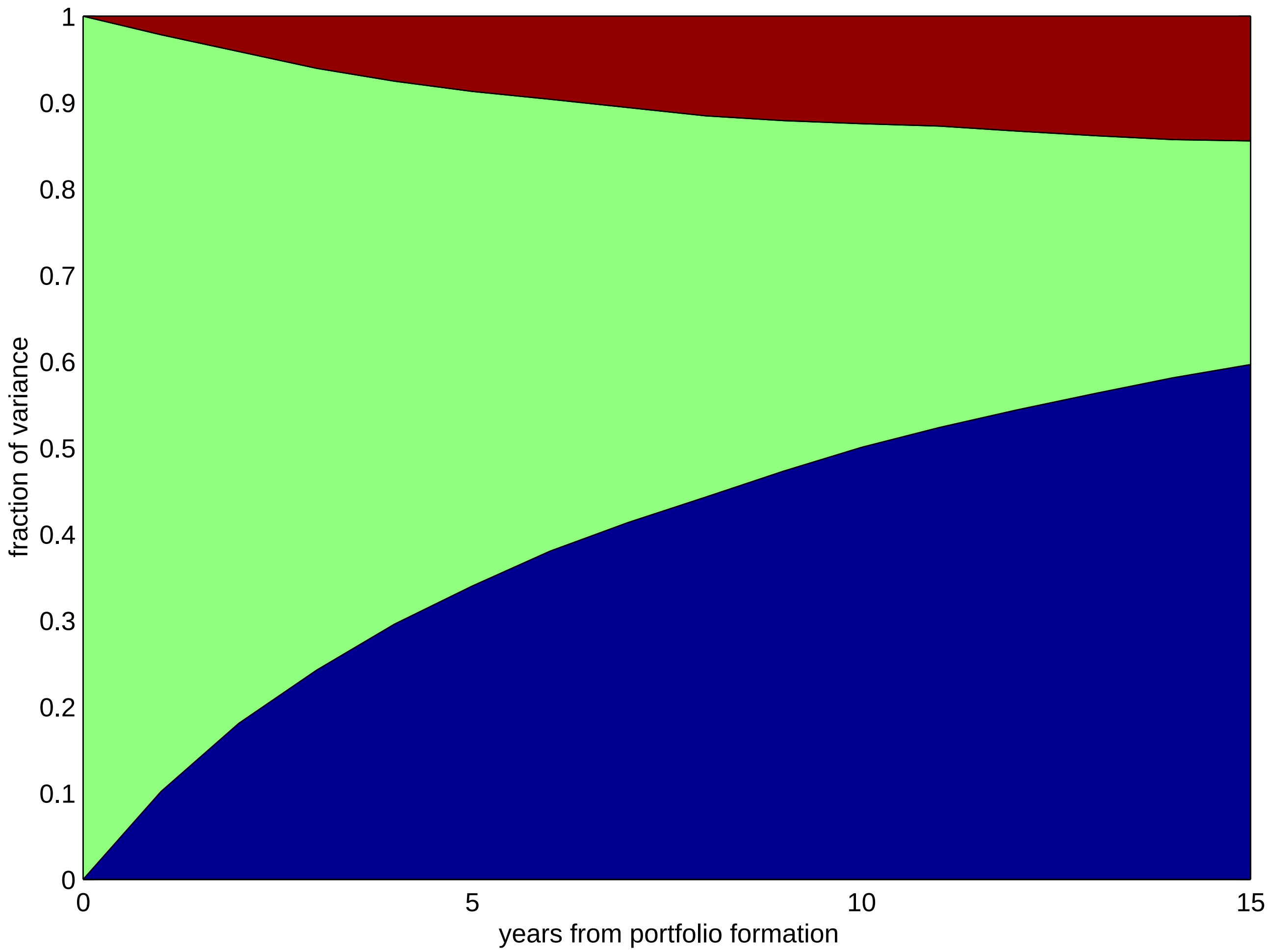

Figure 2: Time−series evolution of BE/MEs (U.S. sample)

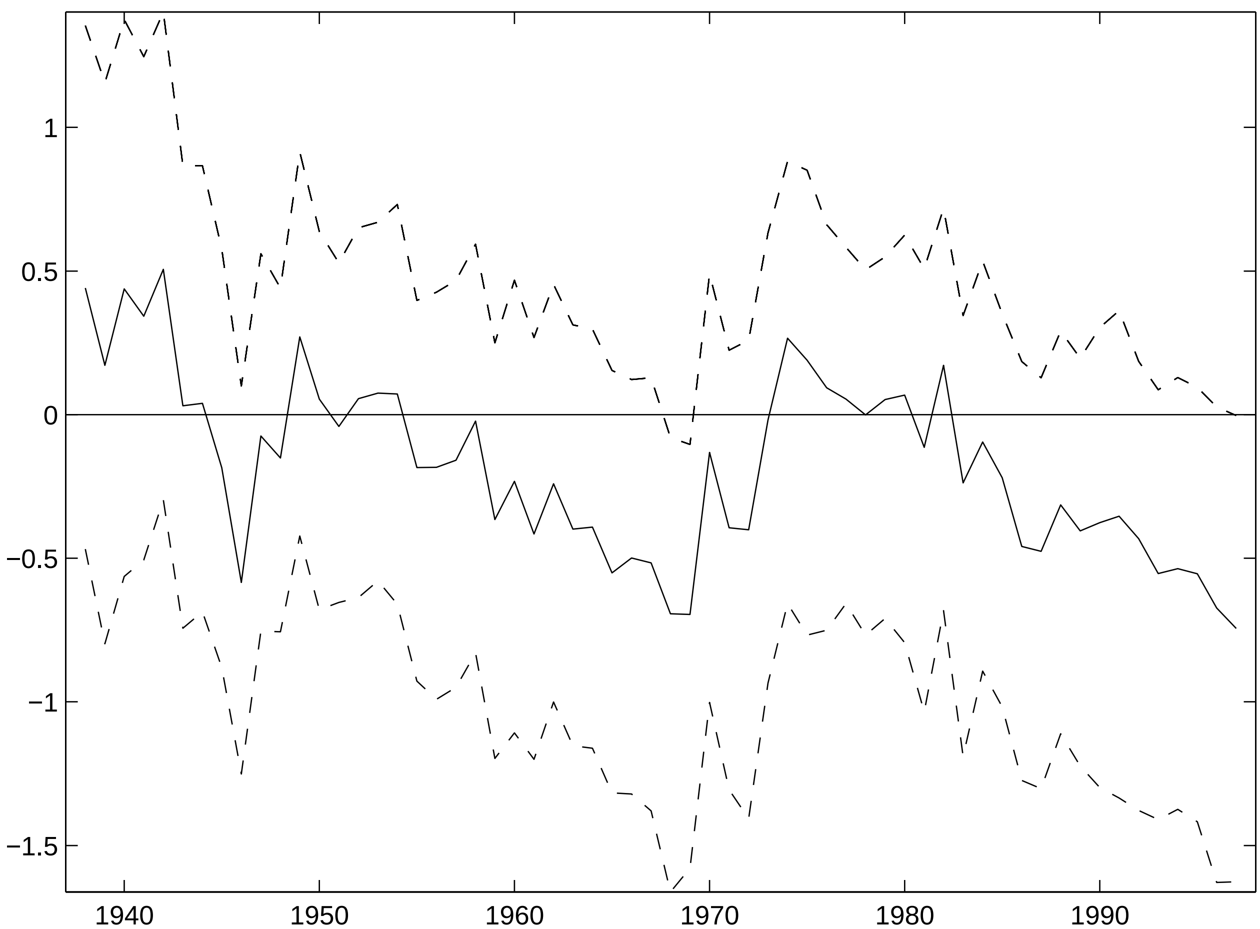

Figure 3: Conditional expected return and Sharpe ratio on HML (U.S. sample)