THE JOURNAL OF FINANCE • VOL. LXIV, NO. 6 • DECEMBER 2009

The Price Is (Almost) Right

RANDOLPH B. COHEN, CHRISTOPHER POLK, and TUOMO VUOLTEENAHO*

ABSTRACT

Most previous research tests market efficiency using average abnormal trading profits on dynamic trading strategies, and typically rejects the joint hypothesis of market efficiency and an asset pricing model. In contrast, we adopt the perspective of a buy-and-hold investor and examine stock price levels. For such an investor, the price level is more relevant than the short-horizon expected return, and betas of cash flow fundamentals are more important than high-frequency stock return betas. Our cross-sectional tests suggest that there exist specifications in which differences in relative price levels of individual stocks can be largely explained by their fundamental betas.

THE VAST MAJORITY of prior research uses average abnormal trading profits on dynamic trading strategies to test market efficiency and asset pricing models. The joint hypothesis of the capital asset pricing model (CAPM, Sharpe (1964), Lintner (1965)) and market efficiency is typically rejected by these tests. The economic significance of these rejections is usually evaluated on the basis of Sharpe ratios (average return over return standard deviation) of dynamic zero-investment strategies that do not expose the investor to systematic risks. The discovery of economically high Sharpe ratios has led many to reject the CAPM and efficient market hypothesis (EMH) as a good approximate description of the stock market.[1]

*Cohen is at Harvard Business School; Polk is at the London School of Economics; and Vuolteenaho is at Arrowstreet Capital, L.P. We would like to thank Ken French for providing us with some of the data used in this study. We are grateful to Gregor Andrade, John Campbell, John Cochrane, Josh Coval, Kent Daniel (discussant), Eugene Fama, Wayne Ferson (discussant), Kenneth French, John Heaton, Matti Keloharju, Owen Lamont, Rafael La Porta, Andre Perold, Antti Petäjistö, Vesa Puttonen, William Schwert, Jay Shanken, Andrei Shleifer, Jeremy Stein, and Sheridan Titman (discussant) for their comments and suggestions. We would also like to thank seminar participants at the American Finance Association 2003 meeting, Chicago Quantitative Alliance Spring 2002 meeting, European Finance Association 2002 and 2005 meetings, Harvard University Economics Department, Helsinki School of Economics and Business Administration, Kellogg School of Management (Northwestern), NBER Asset Pricing Program Meeting, Simon School (Rochester), Stanford Graduate School of Business, Texas Finance Festival, and Tuck School (Dartmouth). An earlier draft of this paper was circulated under the title "Does Risk or Mispricing Explain the Cross-section of Stock Prices?"

[1] Fama (1970, 1991) surveys the empirical literature on testing market efficiency. Daniel, Hirshleifer, and Subrahmanyam (1998) survey the recent evidence on trading strategies that would have produced abnormal profits and high Sharpe ratios. Hansen and Jagannathan (1991) show that in a frictionless rational expectations model, available Sharpe ratios are related to the variability of marginal utility. MacKinlay (1995) argues that the Sharpe ratios of some trading strategies, if taken at face value, are too large to be explained by a rational multifactor model. Shleifer (2000,

In contrast to that literature, we adopt the perspective of a buy-and-hold investor. This perspective leads us to deviate from the usual CAPM tests in two ways. First, we explain price levels instead of short-horizon expected returns. The price-level criterion is naturally motivated by the long-horizon buy-and-hold perspective. As holding periods increase, price levels become the dominant factor in determining holding-period expected returns. In the limit, the relevant measure of market efficiency becomes how well risks explain price levels.

We argue that our price-level criterion is superior to the Sharpe ratio criterion as a measure of the economic significance of market inefficiencies for many purposes. Although available Sharpe ratios are clearly the main object of interest to a professional money manager, price levels are more relevant to many other economic decision makers that effectively face long holding periods. For example, a corporate manager making a large long-term investment decision cannot engage in a dynamic trading strategy of investing or divesting a small fraction every month, depending on stock market conditions. Although short-run deviations from EMH may result in significant wealth transfers between investors who choose to trade frequently, they may not have any influence on decisions concerning real business investment. Thus, if the price is approximately "right," the impact of the stock market on managerial investment decisions is also likely to be consistent with market efficiency, and the high available Sharpe ratios only an interesting sideshow.

A second implication of our buy-and-hold perspective relates to the importance of measuring betas from firms' cash flow fundamentals. As the holding period increases, news about cash flows begins to dominate the second moments (covariances and variances) of returns. As a consequence, the risk in a company's cash flows is what really matters to an investor with a buy-and-hold perspective. Based on this insight, many of our price-level tests estimate CAPM betas using accounting data.

In addition to the buy-and-hold perspective, there is also another reason to prefer cash flow or long-horizon CAPM betas to those estimated from high-frequency stock returns. If markets are even slightly inefficient, mispricing may contaminate not only average returns but also measures of risk, as argued by Brainard, Shapiro, and Shoven (1991). For example, if end-of-month trading by mutual funds adds or subtracts a few percentage points to each month's measured stock return, prices may never deviate much from fundamental values but measured covariances may be substantially affected. In other words, the price level might be approximately "right," where the benchmark of "right" is a world with no mispricing, but tests that use high-frequency return betas might reject the joint hypothesis of the CAPM and market efficiency because the high-frequency betas are materially "wrong."

Building on these ideas, we test empirically the ability of the CAPM and EMH to explain the stock price levels of low price-to-book "value" stocks

p. 8) characterizes the impact of this evidence on the views of finance academicians: "We have learned a lot, and what we think now is quite a bit different from what we thought we knew in 1978. Among the many changes of views, the increased skepticism about market efficiency stands out."

and high price-to-book "growth" stocks. Our empirical tests concentrate on price-to-book-sorted portfolios for the following reasons. First, the average returns generated by value-minus-growth strategies (that buy value stocks and short growth stocks) cannot be explained by CAPM betas measured from high-frequency returns (Rosenberg, Reid, and Lanstein (1985), Fama and French (1992), and others). Furthermore, the pricing errors are highly economically significant when the Sharpe ratio criterion is used as the metric of economic significance (MacKinlay (1995)). Second, Fama and French (1995) and Cohen, Polk, and Vuolteenaho (2003) show that a firm's price-to-book ratio is a persistent variable that forecasts the returns on the firm's stock far in the future, and that the return predictability related to price-to-book ratios has a large price-level effect. Thus, price-to-book-sorted portfolios have the potential of being significantly mispriced by the price-level criterion as well.

Our empirical results suggest that mispricing relative to the CAPM is not the most important factor in determining the prices of value and growth stocks. In some of our model specifications, cash flow betas (measured by regressing a firm's profitability on the market's profitability) can explain much of the prices of and long-horizon returns on price-to-book-sorted portfolios, with premiums that are high but not implausible, ranging from 10.5% to 21.4% per annum. Furthermore, in general the premium on cash flow beta remains high when we include beta-sorted or size-sorted portfolios in the set of test assets, suggesting that the cash flow beta is not merely proxying for the price-to-book characteristic.

Previous results by Fama and French (1992, 1993, 1996), Lakonishok, Shleifer, and Vishny (1994), and others suggest that value stocks have lower, not higher, CAPM betas than growth stocks. We find the same for monthly return betas of annually rebalanced portfolios (as long as the pre-1941 Great Depression period is excluded) and thus expect the above seemingly contradictory results obtained with our cash flow beta regressions to be treated with healthy skepticism. To reconcile our results with those in the previous literature, we examine the long-run and short-run behavior of the average returns on stock return betas of price-to-book-sorted portfolios.

We form 10 portfolios by combining the same-rank value-weight deciles from N different sorts on $t-1$ to $t-N$ price-to-book ratios. Much as in event studies that use the calendar-time methodology, these portfolios approximate the N-year investor experience of investing in value and growth stocks in units that approximate price levels, and can be used as test assets in standard Black, Jensen, and Scholes (1972) or Gibbons, Ross, and Shanken (1989) time-series asset pricing tests. Consistent with the results of Fama and French (1992, 1993, 1996) and Lakonishok et al. (1994), we find that growth stocks have higher return betas than value stocks during the first year after portfolio formation in our sample that spans the 1941 to 2000 period. Because the betas of these portfolios are negatively related to their expected returns, the CAPM fails to explain the returns of value and growth stocks during the first year subsequent to portfolio formation.

Our novel finding is that value stocks' betas sharply increase and growth stocks' betas sharply decrease after portfolio formation. Within 5 years from portfolio formation, value stocks' (three lowest price-to-book deciles) betas have increased to approximately 1.11 and growth stocks' (three highest price-to-book deciles) betas have declined to approximately 0.95. Our tests detect continuation of this trend for 15 years after the sort. Thus, the lower long-run risk of growth stocks that we detect from cash flows can also be detected in long-horizon stock return betas.

Are these changes in betas sufficient to explain the substantial long-run return spread and the substantially different price levels of value and growth stocks? We argue that the answer from a return-based asset pricing test is yes, at least if we focus on the full 1941 to 2000 sample period. Consistent with our cash flow beta results, in our most successful specifications the CAPM (with betas measured from stock returns over a long horizon) explains between 56% and 85% of the variation in average returns when betas are measured over a 5- to 15-year horizon, with a risk premium estimate between 12% and 24%. Without the risk correction, the price levels of the three most-value deciles appear underpriced by 29% relative to those of the three most-growth deciles. After the risk correction, the three most-value deciles appear underpriced by only 13% relative to the three most-growth deciles. Thus, risks explain a significant part of the cross-sectional variation in the level of stock prices and the remaining mispricing is less significant than might be expected. For the modern, post-1963 sample period, the results are somewhat less impressive. While cash flow betas continue to explain the price levels of price-to-book-sorted deciles, our return-based asset pricing tests fail to pick up much of these long-horizon risks.

Our finding that the CAPM in conjunction with market efficiency may provide a good approximate description of the level of stock prices has important implications. For example, our results could justify corporations' current use of the CAPM in capital budgeting, documented by Graham and Harvey (2001), as most long-term investment decisions depend upon the level of net present value instead of near-term expected returns. Of course, this usage would only be truly justified if corporations use beta estimates that incorporate such long-term thinking, which may not often be the case. Similarly, the higher long-run risk of value stocks also explains why low-priced value stocks are not immediately acquired by healthier companies or bought out by a sophisticated buy-and-hold investor, such as Berkshire Hathaway or an LBO fund.

These findings also help rationalize an apparent contradiction in MBA curricula: Investment courses teach that beta is dead, and then corporate finance classes proceed to use the CAPM in firm or project valuation. Our price-level results could be interpreted as justifying this distinction—the CAPM fails to explain the one-period expected returns on some dynamic trading strategies but, we argue, gets stock prices and expected long-term returns approximately right. If our findings are correct, finance classes should teach CAPM implementations involving cash flow betas. With this modification, students would learn capital budgeting techniques that are broadly consistent not only with the empirical findings in capital markets research, but also with the estimates delivered by widely used multiples approaches. Researchers should likewise re-sentence beta from death row to probation in those analyses where firms' stock prices (rather than returns on dynamic trading strategies) are the objects of interest.

The remainder of the paper is organized as follows. Section I describes the data. Section II links cash flow betas to price-to-book ratios and then verifies these differences in fundamental risks using portfolio return evidence. Section III examines the robustness of our results. Section IV concludes.

I. Data

The basic U.S. data come from three databases. The first, 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 U.S. 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 cover the period 1928 to 2000. In the merged data set, the panel contains 208,804 firm-years. Table I Panel A shows descriptive statistics of the data.

Detailed data definitions are as follows. Book equity (BE) is defined as stockholders' equity, plus balance sheet deferred taxes (COMPUSTAT data item 74), investment tax credits (data item 208) (if available), and 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 item 130) (in that order) for the book value of preferred stock. In calculating stockholders' equity, 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 price-to-book 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 (ME_t). We require the firm to have a valid past price-to-book ratio. Moreover, in order to eliminate likely data errors, we discard those firms with price-to-book ratios less than 0.01 and greater than 100. When using COMPUSTAT as our source of accounting information, we require that the firm be on COMPUSTAT for 2 years. This requirement alleviates most of the potential survivor bias due to COMPUSTAT backfilling data. After imposing these data requirements, the cumulative number of firms sorted into portfolios

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

Table I

Descriptive Statistics

Panel A reports descriptive statistics of the raw data. ME is market value of equity, BE book value of equity, and D dividends. Data are annual, except monthly stock returns, and in nominal terms. The sample period is 1928 to 2000 (208,804 firm-years). Panel B reports descriptive statistics for price-to-book-sorted decile portfolios. The portfolios are formed by sorting stocks each year on ME_{t-1}/BE_{t-1} and then following each sort for 15 years. "Annual stock return" is the average 1-year net stock return immediately after the sort. "5-year stock return" is the average cumulative 5-year net stock return to buying the portfolios and holding them for 5 years after the sort. "15-year stock return" is the average cumulative net 15-year stock return to buying the portfolios and holding them for 15 years after the sort. $(BE_{t+n} - BE_{t-1})/BE_{t-1}$ is the average n-year growth in the buy-and-hold portfolios' book values of equity. Monthly return β is the estimated coefficient from a regression of monthly returns on the Fama-French market factor. All quantities are nominal.

Panel A: Descriptive Statistics of the Raw Data

Variable	Mean	Standard Deviation	5^{th} Percentile	25^{th} Percentile	Median	75^{th} Percentile	95^{th} Percentile
Monthly stock return	0.012	0.175	−0.211	−0.063	0.000	0.070	0.258
Annual stock return	0.155	0.709	−0.613	−0.198	0.063	0.360	1.147
ME_{t-1}/BE_{t-1}	2.884	5.917	0.393	0.836	1.417	2.664	9.147
D_{t-1}/ME_{t-1}	0.022	0.069	0.000	0.000	0.007	0.036	0.077
$(ME_t - ME_{t-1})/ME_{t-1}$	0.200	1.136	−0.606	−0.201	0.054	0.369	1.320
$(BE_t - BE_{t-1})/BE_{t-1}$	0.204	1.749	−0.441	0.000	0.081	0.185	0.853

Panel B: Selected Variable for Price-to-book-sorted Portfolios

Variable	High ME/BE	2	3	4	5	6	7	8	9	Low ME/BE
ME_{t-1}/BE_{t-1}	6.219	3.201	2.221	1.721	1.399	1.169	0.973	0.807	0.638	0.409
ME_t/BE_t	5.306	3.080	2.131	1.716	1.410	1.181	1.009	0.845	0.693	0.475
ME_{t+4}/BE_{t+4}	4.033	2.792	1.957	1.629	1.436	1.215	1.055	0.923	0.831	0.648
ME_{t+14}/BE_{t+14}	3.002	2.339	1.715	1.588	1.398	1.302	1.155	1.140	1.063	0.914
Annual stock return	0.125	0.148	0.125	0.135	0.143	0.146	0.178	0.175	0.215	0.217
5-year stock return	0.738	0.871	0.771	0.861	0.908	0.989	1.051	1.087	1.379	1.419
15-year stock return	4.397	5.154	4.563	5.228	5.553	5.92	6.148	6.563	7.004	6.700
$(BE_{t+1} - BE_{t-1})/BE_{t-1}$	0.244	0.127	0.116	0.088	0.078	0.067	0.053	0.045	0.026	−0.019
$(BE_{t+4} - BE_{t-1})/BE_{t-1}$	0.857	0.504	0.431	0.380	0.333	0.299	0.257	0.216	0.164	0.041
$(BE_{t+14} - BE_{t-1})/BE_{t-1}$	3.829	2.499	2.186	2.013	1.793	1.731	1.555	1.412	1.191	0.839
Monthly return β 1928–2000	0.990	1.051	0.997	1.068	1.031	1.114	1.114	1.223	1.321	1.415
Monthly return β 1941–2000	1.121	1.026	1.019	0.991	0.972	0.933	0.928	0.922	0.926	1.028

is 165,945. The annual panel spans the period 1928 to 1999; note that in our timing convention, the 1928 data are computed by using book values from the end of 1927 and returns through May 1929.

After portfolio formation, we follow the portfolios for 15 years while holding the portfolio definitions constant. Because we perform a new sort every year, our final annual data set is three dimensional: the number of portfolios formed in each sort times the number of years we follow the portfolios times the time dimension of our panel.

Missing data are treated as follows. If a stock was included in a portfolio but its book equity is temporarily unavailable at the end of some future year t, we assume that the firm's book-to-market ratio has not changed from $t-1$ and compute the book equity proxy from the last period's book-to-market and the time t market equity. We treat negative or zero book equity values as missing. We then use this book equity figure in computing clean surplus earnings. We follow standard practice and substitute zeros for CRSP missing returns as long as the firm is not delisted. For market equity, we use the latest available figure.

We deal with delisting firms as follows. First, we compute the stock return, profitability, and exit price-to-book ratio for the firm at the end of its delisting year. We use delisting data, when available on the CRSP tapes, in computing the stock returns and the exit market value. 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. If a firm is delisted but the delisting return is missing, we investigate the reason for disappearance. If the delisting is performance-related, we assume a −30% delisting return.[3] Otherwise, we assume a zero delisting return.

Second, we take the delisting market value of the firm and invest it in another firm that was originally sorted into the same portfolio as the disappearing firm. Among the firms in the same portfolio, we pick the one that has a current price-to-book ratio closest to the exit price-to-book ratio of the disappearing firm.

Table I Panel B shows selected variables for the price-to-book-sorted decile portfolios. Firms with low price-to-book ratios have on average higher subsequent stock returns than firms with high price-to-book ratios (Rosenberg et al. (1985), Fama and French (1992), and others). For a 5-year buy-and-hold strategy, the 10–1 difference in average cumulative return is approximately 70%. Simultaneously, differences in firms' price-to-book ratios are also related to differences in future average growth. High price-to-book firms grow faster and are persistently more profitable than low price-to-book firms. Value stocks have higher betas than growth stocks over the 1928 to 2000 period and slightly lower betas over the 1941 to 2000 period.

[3] The delisting return assumptions follow Shumway's (1997) results. Shumway tracks a sample of firms whose delisting returns are missing from CRSP and finds that performance-related delistings are associated with a significant negative return, on average approximately –30%. This assumption is unimportant to our final results, however.

Table I Panel B also presents interesting data about the evolution of firms' price-to-book ratios. There is considerable persistence in the ratio. The top price-to-book decile has a ratio over 6.0 (versus a median around 1.3). Five years later the same group of firms has a price-to-book ratio over 4.0, and even after 15 years the ratio surpasses 3.0. Similar persistence occurs for extreme value stocks, which start with price-to-book around 0.41, and whose ratio climbs only to 0.65 in 5 years and to 0.91 in 15 years.

II. Relating Long-Run Risks to Prices

Previous research finds that CAPM betas have essentially no explanatory power with respect to average returns generated by annually rebalanced value-minus-growth strategies, if betas are measured from high-frequency stock returns. In this section, we measure CAPM betas from proxies for firms' cash flows and find that these cash flow betas largely explain the prices of, and long-run average returns on, value and growth stocks.

A. Cross-sectional Tests with Cash Flow Betas

A.1. Cash Flow Betas

Testing EMH at the level of prices instead of returns requires comparing long-horizon average returns with long-horizon risks. One approach to measuring long-horizon risk is to calculate CAPM betas using long-horizon compound firm and market returns. However, this approach may be problematic because betas estimated from long-horizon compound returns are hard-wired to be higher for low-price and high-expected-return stocks. To see the mechanical link, suppose a firm pays a single terminal dividend at time 1 and that the covariance of this terminal dividend with the market's return is a known constant. Consider two time 0 hypothetical prices for the stock, \$10 and \$20. Holding the distribution of the time 1 terminal dividend constant, a stock purchased at \$10 will have a return covariance and return beta that is twice as high as those measures for the stock purchased at \$20. Obviously, the stock purchased at \$10 will also have a higher expected return than the stock purchased at \$20, and consequently the CAPM will perform very well when tested in such a world, especially if the risk premium parameter is not constrained by some prior beliefs. This effect could artificially increase the slope and R^2 in cross-sectional tests of the CAPM. Such a bias could render our failure to reject the CAPM in such tests meaningless; consequently, it might be inappropriate for us to rely on long-horizon return regressions to estimate betas. See the Appendix for a formal argument.

As an alternative to betas estimated from long-horizon simple returns, one can look directly at covariances of fundamentals using some measure of cash flow. Though all individual-firm cash flow measures contain error over short horizons, increasing the horizon and forming portfolios should eliminate much of the error. Furthermore, one could reasonably hope that whatever error there is in measured cash flow betas is not correlated with the mispricing-induced fluctuation of the stock price.

We choose return on equity (ROE) as the cash flow measure and define the cash flow beta as the regression coefficient of a firm's or a portfolio's discounted log ROE on the market portfolio's discounted log ROE:

$$\sum_{j=0}^{N-1} \rho^j \log(1 + ROE_{k,t+j,j+1}) = \beta_{k,0}^{CF} + \beta_{k,1}^{CF} \sum_{j=0}^{N-1} \rho^j \log(1 + ROE_{M,t+j}) + \varepsilon_{k,t+N-1}. \tag{1}$$

Above, ROE denotes the ratio of clean surplus earnings ($X_t = \mathrm{BE}_t - \mathrm{BE}_{t-1} + D_t^{\mathrm{gross}}$) to beginning-of-the-period book equity (BE_{t-1}), with subscript k corresponding to the firm or portfolio under scrutiny and subscript M to the market portfolio. The second subscript refers to the year of observation and the third to the number of years from the sort. The term D_t^{gross} is gross dividends computed from the difference between CRSP returns and returns excluding dividends. Finally, ρ is a constant equal to one minus the average dividend yield. We set ρ to 0.975 in our regressions.

This measure of cash flow risk can be motivated with the price-to-book decomposition used by Vuolteenaho (2001, 2002) and Cohen et al. (2003). This decomposition shows that, to a very close approximation,

$$\log\left(\frac{\mathrm{ME}_{t-1}}{\mathrm{BE}_{t-1}}\right) = \sum_{j=0}^{\infty} \rho^j \log(1 + ROE_{t+j}) - \sum_{j=0}^{\infty} \rho^j \log(1 + R_{t+j}). \tag{2}$$

Above, ME/BE denotes the price-to-book ratio and R the net return on a firm's stock.

Over an infinite horizon, the unexpected realizations of the first (ROE) term are equal to the unexpected realizations of the second (stock return) term for every sample path. Thus, measuring the risk from either infinite-horizon discounted log returns or profitabilities will necessarily yield the same result. However, if the sums in (2) are evaluated over a finite horizon, the covariances of the first and second term with a risk factor may be different. Furthermore, if the stock market is potentially inefficient, mispricing may contaminate not only the average returns but also short-horizon return covariances. (Alternatively, expected return variation due to omitted risk factors may have a large impact on high-frequency return covariances and de-link the cash flow and stock return covariances.) Thus, measuring CAPM risks from the cash flow term of (2) instead of the return term may result in a cleaner risk measure. At a minimum, it will provide an interesting alternative perspective to that obtained from stock return betas alone.

Table II Panel A measures the cash flow betas for 10 price-to-book-sorted portfolios over different horizons. Columns (2) to (11) correspond to price-to-book-sorted portfolios and rows to selected horizons N. The regressions are estimated from overlapping observations using OLS. We use Newey and West (1987) standard error formulas, which correct for the cross-sectional and time dependence of the residuals, with N leads and lags.

Table II

Cash Flow Betas

The table reports the estimated cash flow betas for value and growth stocks. The sample period is 1928 to 1999. Panel A column (1) shows the horizon N. Panel A columns (2) to (11) report the estimated cash flow betas of value-weight price-to-book-sorted decile portfolios. The cash flow betas are the slopes of the regressions

$$\sum_{j=0}^{N-1} \rho^j \log(1 + ROE_{k,t+j,j+1}) = \beta_{k,0} + \beta_{k,1} \sum_{j=0}^{N-1} \rho^j \log(1 + ROE_{M,t+j}) + \varepsilon_{k,t+N-1},$$

where k denotes the decile portfolio, M the market portfolio, and ROE a portfolio's aggregate clean surplus earnings divided by the beginning-of-year aggregate book equity. ρ is a constant equal to 0.975. Panel A column (12) reports the cash flow beta of decile 1 minus that of decile 10. Panel A column (13) reports the cash flow beta of the average of deciles 1, 2, and 3 minus that of the average of deciles 8, 9, and 10. Panel B column (1) shows the alternative cash flow definitions used in computing cash flow betas at the 5-year horizon. X is earnings, ME market value of equity, and Δd log dividend growth rate. Panel B columns (2) to (11) correspond to price-to-book-sorted portfolios. Panel B column (12) reports the cash flow beta of decile 1 minus that of decile 10. Panel B column (13) reports the cash flow beta of the average of deciles 1, 2, and 3 minus that of the average of deciles 8, 9, and 10. All regressions are estimated with OLS. Hansen's (1982) GMM standard errors are computed using the Newey–West formula with N leads and lags (which account for both the estimation uncertainty of the cash flow betas and for the cross-sectional and time-series correlation of the error terms) are reported in parentheses.

Panel A: Cash Flow Betas at Different Horizons												
N	High ME/BE	2	3	4	5	6	7	8	9	Low ME/BE	1–10	(1,2,3)–(8,9,10)
1	1.00	0.85	0.72	1.13	1.03	1.07	1.08	1.02	1.28	1.35	−0.35	−0.36
	(0.54)	(0.37)	(0.25)	(0.75)	(0.34)	(0.29)	(0.41)	(0.40)	(0.49)	(0.39)	(0.33)	(0.12)
2	0.79	0.93	0.80	1.05	1.00	1.08	1.14	1.21	1.29	1.42	−0.63	−0.46
	(0.59)	(0.35)	(0.13)	(0.49)	(0.16)	(0.12)	(0.31)	(0.33)	(0.39)	(0.41)	(0.33)	(0.12)
3	0.73	0.90	0.91	0.88	1.11	1.05	1.03	1.28	1.42	1.50	−0.76	−0.55
	(0.53)	(0.31)	(0.10)	(0.18)	(0.25)	(0.10)	(0.22)	(0.36)	(0.38)	(0.45)	(0.31)	(0.10)
5	0.67	0.86	0.96	1.04	0.99	0.99	1.03	1.20	1.38	1.68	−1.01	−0.59
	(0.40)	(0.28)	(0.11)	(0.19)	(0.13)	(0.12)	(0.15)	(0.26)	(0.35)	(0.35)	(0.18)	(0.08)
10	0.90	0.90	0.99	1.05	1.05	1.09	1.03	1.17	1.22	1.47	−0.57	−0.36
	(0.26)	(0.17)	(0.10)	(0.10)	(0.17)	(0.09)	(0.12)	(0.17)	(0.20)	(0.35)	(0.20)	(0.12)
15	0.95	0.97	1.02	1.06	1.11	1.14	1.07	1.08	1.15	1.17	−0.22	−0.15
	(0.16)	(0.18)	(0.15)	(0.09)	(0.12)	(0.07)	(0.18)	(0.18)	(0.09)	(0.17)	(0.13)	(0.10)

(*continued*)

Table II—*Continued*

Panel B: Alternative Cash Flow Definitions												
Alternative Cash Flow Definition ($N = 5$)	High ME/BE	2	3	4	5	6	7	8	9	Low ME/BE	1–10	(1,2,3)–(8,9,10)
$\sum_{j=0}^{N-1} \rho^j ROE_{k,t+j,j+1}$	0.72	0.91	0.94	0.96	0.95	0.96	0.97	1.11	1.28	1.51	−0.79	−0.44
	(0.50)	(0.31)	(0.12)	(0.25)	(0.14)	(0.12)	(0.14)	(0.24)	(0.32)	(0.30)	(0.21)	(0.10)
$\sum_{j=0}^{N-1} \rho^j \frac{X_{k,t+j,j+1}}{\mathrm{ME}_{k,t+j-1,j}}$	0.35	0.66	0.93	1.18	1.25	1.61	1.91	2.92	4.09	11.05	−10.70	−5.38
	(0.32)	(0.31)	(0.17)	(0.17)	(0.28)	(0.68)	(1.00)	(2.19)	(3.23)	(10.58)	(4.17)	(2.12)
$\frac{\sum_{j=0}^{N-1} \rho^j X_{k,t+j,j+1}}{\mathrm{ME}_{k,t-1,0}}$	0.48	0.72	0.96	1.13	1.22	1.40	1.50	2.00	3.13	7.63	−7.14	−3.53
	(0.18)	(0.18)	(0.17)	(0.15)	(0.19)	(0.35)	(0.41)	(1.18)	(2.21)	(8.85)	(3.45)	(1.59)
$\frac{X_{k,t+N-1,j+N} - X_{k,t-1,0}}{\mathrm{ME}_{k,t-1,0}}$	0.21	0.66	1.46	1.61	0.24	1.83	2.74	5.50	2.38	2.64	−2.43	−2.73
	(0.19)	(0.08)	(0.52)	(0.28)	(0.61)	(0.60)	(1.24)	(2.69)	(0.60)	(1.65)	(0.57)	(0.22)
$\sum_{j=0}^{N-1} \rho^j \Delta d_{k,t+j,j+1}$	0.79	0.90	0.96	1.03	1.32	1.42	1.12	1.44	1.37	1.20	−0.41	−0.45
	(0.19)	(0.14)	(0.10)	(0.13)	(0.27)	(0.45)	(0.30)	(0.91)	(0.74)	(0.92)	(0.41)	(0.33)

The first row of Table II Panel A shows the 1-year cash flow betas of value and growth stocks immediately after the sort. Apart from the highest price-to-book decile, the cash flow betas of the stocks in our sample line up roughly with their price-to-book ratios: The second-highest price-to-book decile has a cash flow beta of 0.85 and the lowest price-to-book decile a cash-flow beta of 1.35. The highest price-to-book decile has a cash flow beta of 1.00, which is slightly higher than expected.

Moving down the rows of Table II Panel A and increasing the horizon to 5 years further strengthens the results. The highest price-to-book portfolio now has the lowest cash flow beta and the lowest price-to-book portfolio the highest cash flow beta for all horizons from 2 to 15 years. The differences are economically significant: The 5-year cash flow beta of the extreme decile of growth stocks is 0.67 and that of the extreme decile of value stocks is 1.68. The difference in betas at the 10- and 15-year horizons is slightly lower, but the spread remains economically significant (0.90 vs. 1.47 and 0.95 vs. 1.17, respectively).

Columns (12) and (13) of Table II Panel A show the cash flow betas of "high-minus-low" portfolios. Column (12) shows the difference in cash flow betas between the highest and lowest price-to-book deciles, and column (13) between the top three and the bottom three. The difference in cash flow betas is statistically significant for both differences at all horizons, except for the 1–10 difference at the 1-year horizon. Thus, there is statistical evidence of value stocks' cash flow betas being higher than those of growth stocks. This finding alone should be interesting to buy-and-hold investors that tilt their portfolios to value or growth stocks.

We should point out that though we report results out to 15 years, the reader should be careful in putting too much weight on the longest-horizon results. This is because of the well-known statistical inference problems that occur in long-horizon regression, and it is likely that the statistical uncertainty about the point estimates as indicated by the standard errors is understated. While we do need a horizon that is long enough so that any errors in the process that generates accounting data can sufficiently wash out (so that ROE and similar cash flow measures can closely approximate true cash flow news), we hope that by the 5-year horizon this has happened.[4] In Section II.B we employ an alternative calendar-time approach that uses returns instead of cash flows. This approach allows us to have reliable inference at horizons as long as 15 years.

Note that when measuring the cash flow betas of price-to-book-sorted portfolios with a finite number of periods in formula (1), our definition of cash flow beta is likely to result in an upward bias for growth and a downward bias for

[4] Of course, the ROE realizations may also be persistent. However, Table II on page 241 of Vuolteenaho (2002) estimates a (partial) autocorrelation coefficient of about 0.5 for ROE in annual firm-level data, which suggests (but does not guarantee) a fast decay. For some other measures of cash flow fundamentals, such as dividend growth used in our Table II Panel B, shocks are even more transitory. This problem is even less important for our various independent variables, as the market's dividend growth and other cash flow measures are essentially uncorrelated over time.

value stocks. This is because the book equity data are contaminated with measurement error that affects the ROE levels, and the sort disproportionately selects negative-measurement-error firms to the high price-to-book portfolio and positive-measurement-error firms to the low price-to-book portfolio. In the ROE formula, value stocks' earnings are divided by an artificially high number and growth stocks' by an artificially low number, scaling the covariances against our finding reported in Table II Panel A.

To show that the cash flows of value stocks are unarguably riskier than those of growth stocks, Table II Panel B shows cash flow betas measured using cash flow definitions proposed in previous research. (We only show the results for the 5-year horizon, at which our preferred definition using ROE is most successful, to save space.) Our general conclusion from the tests using alternative definitions of cash flow beta is that our results are robust to variations in the way this variable is defined.

Row (1) of Table II Panel B shows cash flow betas measured as in formula (1), except using ROE (in levels) in place of $\log(1 + ROE)$. Not surprisingly, the spread in cash flow betas remains strong and statistically significant.

Rows (2) to (4) use cash flow measures similar to those suggested by Ball and Brown (1969) and Beaver, Kettler, and Scholes (1970). These measures normalize earnings by lagged market value instead of book value:

$$\begin{aligned}
&\text{(a)} \quad \sum_{j=0}^{N-1} \rho^j \frac{X_{k,t+j,j+1}}{\mathrm{ME}_{k,t+j-1,j}} = \beta_{k,0}^{CF} + \beta_{k,1}^{CF} \sum_{j=0}^{N-1} \rho^j \frac{X_{M,t+j}}{\mathrm{ME}_{M,t+j-1}} + \varepsilon_{k,t+N-1} \\
&\text{(b)} \quad \frac{\sum_{j=0}^{N-1} \rho^j X_{k,t+j,j+1}}{\mathrm{ME}_{k,t-1,0}} = \beta_{k,0}^{CF} + \beta_{k,1}^{CF} \frac{\sum_{j=0}^{N-1} \rho^j X_{M,t+j}}{\mathrm{ME}_{M,t-1}} + \varepsilon_{k,t+N-1} \\
&\text{(c)} \quad \frac{X_{k,t+N-1,j+N} - X_{k,t-1,0}}{\mathrm{ME}_{k,t-1,0}} = \beta_{k,0}^{CF} + \beta_{k,1}^{CF} \frac{X_{M,t+N-1} - X_{M,t-1}}{\mathrm{ME}_{M,t-1}} + \varepsilon_{k,t+N-1}.
\end{aligned} \tag{3}$$

Definition (a) in equation (3) is similar to our discounted ROE formula, except that earnings are normalized by market value instead of book value. Definition (b) normalizes the discounted N-year sum of earnings with the market value at the time of portfolio formation. Definition (c) proxies for cash flows with the N-year change in annual earnings and normalizes with the market value at the time of portfolio formation. If the market is efficient, these measures in equation (3) have the advantage of normalizing with a measurement error-free value metric, market capitalization, thereby avoiding the bias resulting from the use of error-ridden book values. However, using market values in the definition of cash flow can also be a disadvantage as the resulting measure may be influenced by mispricing. Empirically, rows (2) to (4) show that these measures induce a large spread in value and growth stocks betas, and this spread is consistent with value stocks' cash flows being riskier than those of growth stocks.

Our final cash flow measure, similar to one used by Bansal, Dittmar, and Lundblad (2005), is motivated by Campbell and Shiller's (1988) dividend growth model. This beta measure is generated by regressing the portfolio's discounted N-year sum of log dividend growth rates (Δd) on the market's:

$$\sum_{j=0}^{N-1} \rho^j \Delta d_{k,t+j,j+1} = \beta_{k,0}^{\mathrm{CF}} + \beta_{k,1}^{\mathrm{CF}} \sum_{j=0}^{N-1} \rho^j \Delta d_{M,t+j} + \varepsilon_{k,t+N-1}. \tag{4}$$

To mitigate potential outlier problems (some portfolios occasionally pay zero or near-zero dividends), we censor the log dividend growth rates to the interval [log(1/5), log(5)]. The beta measure in equation (4) has the advantage of being directly related to the cash flows to investors, but the disadvantages of being dependent on largely arbitrary dividend policies of firms. Furthermore, since gross dividends are never negative, for low values of N this risk measure is likely to be a poor one for both extreme growth stocks (high growth companies that currently need external financing) and extreme value stocks (distress companies that currently cannot afford to pay dividends). Empirically, row (5) of Table II Panel B shows that this risk measure induces a slightly smaller but still economically significant spread in cash flow betas.

A.2. Price-Level Alphas

Although it is interesting to see that value stocks have riskier cash flows than growth stocks, one would like to ultimately measure the importance of these cash flow risks to price levels and examine the magnitude of price-level pricing errors. To do so, we need to construct a stationary price-level dependent variable to regress on cash flow betas.

Reorganizing (2) and taking conditional expectation yields

$$\log \mathrm{ME}_{t-1} - \left[\log \mathrm{BE}_{t-1} + \sum_{j=0}^{\infty} \rho^j E_{t-1} \log(1 + ROE_{t+j})\right] = -\sum_{j=0}^{\infty} \rho^j E_{t-1} \log(1 + R_{t+j}). \tag{5}$$

In words, the difference between the market price and the cash flow fundamentals equals the negative of the discounted long-horizon sum of expected future returns. The expected discounted long-horizon return equals the negative of log price (the first term) plus log book value adjusted for the expected cash flow growth (second term). We call the right-hand side of equation (5) simply the price level.

Suppose we can decompose expected returns into a constant zero-beta rate, a constant risk premium due to known beta, and a pricing error, $E_{t-1} r_{t+j} = \lambda_0 + \lambda_1 \beta_{t+j} - E_{t-1} \alpha_{t+j}$. The price level can then be decomposed into a component explained by risk and a pricing-error term that we call price-level alpha:

$$-\sum_{j=0}^{\infty}\rho^{j}E_{t-1}r_{t+j} = -\sum_{j=0}^{\infty}\rho^{j}(\lambda_0+\lambda_1\beta_{t+j}) - \sum_{j=0}^{\infty}\rho^{j}E_{t-1}\alpha_{t+j}. \tag{6}$$

We use equations (5) and (6) to motivate the dependent variable in our cross-sectional regressions. The dependent variable in the pricing regressions is the cumulative N-period discounted stock return (sample price level) and the independent variable is the estimated cash flow beta,

$$-\hat{E}\left[\sum_{j=0}^{N-1}\rho^{j}R_{k,t+j,j+1}\right] = \lambda_0' + \lambda_1'\hat{\beta}_{1,k}^{\text{CF}} + u_k, \tag{7}$$

where $\hat{E}$ denotes the sample mean and $\hat{\beta}_{1,k}^{CF}$ the estimated cash flow beta. The dependent variable of regression (7) differs from the price-level metric in equation (4) due to the finite horizon and choice between log and simple returns. Primes on premia indicate price-level units. u is our empirical price-level mispricing measure, which we name (sample) price-level alpha.

Columns (14)–(16) of Table III measure how well the cash flow betas defined in equation (1) explain the sample price levels of value and growth stocks. The cross-sectional regression R^2s of average discounted long-horizon returns on cash flow betas is over 60% for all horizons including 1 year. At the 5-year horizon, which roughly corresponds to the frequency of the business cycle, the regression R^2 is over 87%.

Are these impressive R^2s obtained with implausible premia? In Table III, the estimated annualized intercepts of the regression range from −7.6% to 5.4% and annualized slopes range from 10.5% to 21.4%, which are high but not obviously implausible in our opinion. (These premia are annualized by dividing the regression coefficients by $-\sum_{j=0}^{N-1}\rho^{j}$.) One way to judge whether the premium on cash flow beta is reasonable is to recognize that λ_0 should equal the (nominal) risk-free rate and λ_1 the average discounted net return on the market portfolio less the risk-free rate. These predicted λ_0 and λ_1 are thus approximately 4% and 10%, which are close to the low end of the unrestricted estimates of the risk premium and to the high end of the unrestricted estimates of the zero-beta premium.

If we restrict the premia to those in-sample values as predicted by the Sharpe–Lintner CAPM, the R^2s of the cross-sectional regressions we obtain are, of course, lower than the unrestricted R^2s. The restricted R^2s (reported in Table III) are 31%, 54%, 65%, 68%, 68%, and 36% at the 1-, 2-, 3-, 5-, 10-, and 15-year horizons. Overall, we consider these R^2s to be quite close to the unrestricted R^2s for most horizons and somewhat lower for the 1- and 15-year horizons.

It should be noted that these restricted R^2s are sensitive to the assumed values for λ_0 and λ_1, especially at the 15-year horizon. This sensitivity arises from the restriction being placed on both the intercept and the slope. Instead, if one restricts only the risk premium but allows the intercept to be freely

Table III
Price-Level Alphas

The table reports the estimated price-level alphas for value and growth stocks. We also report the regression coefficients and the R^2 of the regressions. The cash flow betas are from Table II Panel A. The first column of the table reports the horizon N. Columns (14) to (16) show the intercept, slope, and R^2 of a cross-sectional regression of the sample price level on estimated cash flow betas:

$$-\hat{E}\sum_{j=0}^{N-1}\rho^j R_{k,t+j,j+1} = \lambda_0' + \lambda_1'\hat{\beta}_{1,k} + u_k,$$

where $R_{k,t,j}$ is the year t simple (net) return on decile portfolio k during the jth year from the sort and $\hat{B}_{1,k}$ the estimated cash flow beta. $\hat{E}$ denotes the sample mean. The premia estimates are annualized. Columns 2–11 show the dependent variable, sample pricing-level alpha (u), price-level alpha standard error (in parentheses), and restricted pricing-level alpha for each decile portfolio. The restricted pricing-level alpha is the resulting alpha when we restrict the premia to the values predicted by the Sharpe-Lintner CAPM. The in-sample means of the risk-free rate, $\lambda_0 = 0.04$, and the N-horizon annualized market premium used in the restriction, as well as the resulting R^2 from the restricted pricing equation are reported in the corresponding row in columns (14), (15), and (16), respectively. All regressions are estimated with OLS. Hansen's (1982) GMM standard errors computed using the Newey–West formula with N leads and lags (which account for both the estimation uncertainty of the cash flow betas and for the cross-sectional and time-series correlation of the error terms) are reported in parentheses. The sample period is 1928 to 1999.

	N	High ME/BE	2	3	4	5	6	7	8	9	Low ME/BE	1–10	(1,2,3)–(8,9,10)	λ_0	λ_1	R^2 %
Dependent variable	1	0.036	0.013	0.036	0.025	0.017	0.014	−0.017	−0.014	−0.055	−0.057	0.093	0.070	0.008	0.145	60.47
Price-level alpha		0.029	−0.017	−0.012	0.036	0.014	0.017	−0.013	−0.019	−0.022	−0.013	0.042	0.018	(0.227)	(0.255)	
Alpha standard error		(0.084)	(0.049)	(0.064)	(0.121)	(0.046)	(0.044)	(0.048)	(0.050)	(0.062)	(0.047)	(0.118)	(0.029)			
Restricted alpha		0.015	−0.023	−0.013	0.017	−0.001	0.000	−0.030	−0.033	−0.048	−0.043	0.058	0.034	0.040	0.099	30.86
Dependent variable	2	0.082	0.034	0.066	0.058	0.023	0.010	−0.028	−0.037	−0.098	−0.110	0.192	0.142	−0.009	0.158	88.94
Price-level alpha		−0.005	−0.009	−0.019	0.053	0.000	0.014	−0.007	0.005	−0.030	−0.002	−0.003	−0.002	(0.200)	(0.192)	
Alpha standard error		(0.110)	(0.070)	(0.104)	(0.161)	(0.046)	(0.055)	(0.063)	(0.092)	(0.130)	(0.089)	(0.163)	(0.029)			
Restricted alpha		−0.003	−0.023	−0.017	0.025	−0.021	−0.017	−0.045	−0.041	−0.085	−0.073	0.070	0.052	0.040	0.099	54.01
Dependent variable	3	0.118	0.058	0.092	0.076	0.040	0.004	−0.032	−0.049	−0.141	−0.166	0.285	0.208	0.024	0.128	91.68
Price-level alpha		−0.012	−0.009	0.027	0.002	0.052	−0.009	−0.049	0.024	−0.015	−0.010	−0.002	0.003	(0.137)	(0.130)	
Alpha standard error		(0.125)	(0.078)	(0.069)	(0.056)	(0.106)	(0.069)	(0.082)	(0.119)	(0.140)	(0.144)	(0.206)	(0.044)			
Restricted alpha		−0.026	−0.037	−0.002	−0.025	0.006	−0.050	−0.088	−0.035	−0.086	−0.088	0.062	0.048	0.040	0.099	65.16

(*continued*)

Table III—*Continued*

	N	High ME/BE	2	3	4	5	6	7	8	9	Low ME/BE	1–10	(1,2,3)–(8,9,10)	λ_0	λ_1	R^2 %
Dependent variable	5	0.172	0.094	0.139	0.106	0.067	0.016	−0.027	−0.076	−0.222	−0.270	0.442	0.324	0.054	0.105	87.62
Price-level alpha		−0.032	−0.015	0.077	0.088	0.024	−0.030	−0.052	−0.017	−0.070	0.028	−0.060	0.030	(0.087)	(0.082)	
Alpha standard error		(0.145)	(0.068)	(0.079)	(0.059)	(0.058)	(0.074)	(0.127)	(0.094)	(0.151)	(0.082)	(0.126)	(0.093)			
Restricted alpha		−0.096	−0.078	0.014	0.025	−0.038	−0.093	−0.115	−0.080	−0.132	−0.033	−0.062	0.028	0.040	0.105	68.21
Dependent variable	10	0.243	0.162	0.210	0.141	0.103	0.001	−0.061	−0.145	−0.288	−0.366	0.609	0.471	0.018	0.127	82.78
Price-level alpha		0.034	−0.055	0.103	0.097	0.061	0.004	−0.130	−0.050	−0.131	0.068	−0.034	0.065	(0.098)	(0.098)	
Alpha standard error		(0.156)	(0.102)	(0.105)	(0.127)	(0.171)	(0.063)	(0.167)	(0.148)	(0.078)	(0.067)	(0.133)	(0.082)			
Restricted alpha		0.011	−0.076	0.058	0.039	0.002	−0.064	−0.183	−0.137	−0.232	−0.092	0.102	0.151	0.040	0.100	67.75
Dependent variable	15	0.319	0.197	0.250	0.150	0.091	−0.018	−0.091	−0.195	−0.313	−0.390	0.708	0.555	−0.076	0.214	68.00
Price-level alpha		−0.005	−0.080	0.112	0.125	0.192	0.172	−0.112	−0.169	−0.108	−0.126	0.121	0.143	(0.181)	(0.169)	
Alpha standard error		(0.212)	(0.218)	(0.197)	(0.191)	(0.374)	(0.135)	(0.293)	(0.311)	(0.178)	(0.233)	(0.381)	(0.140)			
Restricted alpha		0.085	−0.015	0.103	0.056	0.056	−0.012	−0.183	−0.265	−0.300	−0.349	0.434	0.362	0.040	0.100	35.88

estimated, one finds that, first, the resulting intercept estimate is plausible and, second, the resulting restricted R^2s are not only high but also no longer sensitive to the value of the risk premium restriction. For example, at the 15-year horizon the unrestricted intercept is 5.17%, the resulting restricted R^2 is 49%, and this restricted R^2 remains above 30% for risk premia restrictions as low as 5.5%.

The cash flow beta premium is statistically insignificant in regressions that use decile portfolios. Finer sorts into 20 or 30 portfolios increase the statistical precision and lower the premium standard errors that account for the estimation uncertainty due to the first-stage regressions. Of course, some slight decline in the cross-sectional R^2s is to be expected because the test assets are slightly less diversified. We find that the premia and R^2 point estimates obtained from 20 or 30 portfolios are lower but not very different from those we report in Table III, at least at the 5- and 10-year horizon, but have much smaller standard errors and cash flow beta premia that are consistently statistically significantly different from zero. Specifically, at the 5- and 10-year horizons the R^2s drop by less than 12% on average. At the other horizons, the drop in R^2 averages a larger 33.37%. Nevertheless, for all horizons greater than 1 year, the intercepts and slopes estimated from 30 portfolios are reasonably close to those predicted by the Sharpe-Lintner CAPM. Specifically, the zero-beta rate ranges from 3.7% to 6.9% while the risk premium ranges from 8.5% to 11.2%. Thus, the difference in terms of intercept and slope estimates when moving from the decile tests to those involving 30 portfolios represents an improvement. Despite the lower statistical power, we use 10 price-to-book-sorted portfolios as test assets in this section of the paper to keep the presentation of our results consistent. We discuss results (found in Table V below) from cross-sectional regressions using alternative test asset sets, including 30 price-to-book-sorted portfolios in Section III.A.

Table III also reports the sample price level, price-level alpha, price-level alpha standard error, and restricted price-level alpha for the price-to-book deciles on each of the three rows per horizon. The price-level alphas u are simply the residuals of equation (7). At the 15-year horizon, the difference in sample price levels between the top three value deciles and the top three growth deciles is 55.5%. However, the difference in price-level alphas is only 14.3% with an associated standard error of 14.0%. Even more impressive, while the difference between the sample price levels of the highest and lowest price-to-book decile is a gargantuan 70.8%, the difference in price-level alphas is a reasonably small 12.1%. A statistical test of the null hypothesis that the difference in price-level alphas is zero produces a t-statistic of 0.32.

The restricted price-level alphas are reasonably close to the unrestricted estimates for many horizons. For example, at the 5-year horizon, the difference in unrestricted price-level alphas between the highest and the lowest price-to-book deciles is -6.0% while the restricted estimated is -6.2%. In fact, at this horizon the difference between the restricted price-level alphas of the top three growth deciles and the top three value deciles (2.8%) is actually lower than its unrestricted counterpart (3.0%).

However, a fly remains in the ointment. If one would like to make the case against cash flow betas explaining stock price levels, one could focus on the price-level alphas of a 15-year regression with the slope and intercept constrained to the in-sample market premium and T-bill rate. Although most of the decile portfolios have small price-level alphas in that regression, the three extreme value portfolios have price-level alphas over 25%. For our cash flow betas to explain away these alphas at the 15-year horizons, we would need a cash flow beta premium that is approximately twice the in-sample average market premium. As for the aforementioned tests pricing 30 portfolios for which the unrestricted premia estimates are close to the Sharpe–Linter CAPM's predictions, the 5-year and 10-year horizon alphas are very close to zero, but the 15-year alphas are still about half the expected return spread.

B. Calendar-Time Tests with Total Betas

We also present more traditional evidence from portfolio returns and confirm our results using simple portfolio trading rules, monthly returns, and bootstrapped confidence levels. The portfolio return evidence complements the above cash flow–based results for the following reasons. First, the cash flows are measured annually, while our portfolio return tests use monthly stock returns. Second, statistical inference in the previous tests relies on asymptotic Newey and West (1987) standard errors, while our return tests use more reliable bootstrap methods. Third, the portfolio return tests allow us to establish a direct link to the previous literature on the performance of value-minus-growth strategies.

We first sort stocks into price-to-book deciles. Every year, we run 15 different sorts: deciles sorted on year $t-1$ price-to-book ratios, deciles sorted on year $t-2$ price-to-book ratios, . . . , and deciles sorted on year $t-15$ price-to-book ratios. As a result, we have 715 months of returns on 150 portfolios for the period June 1941 to December 2000 (the maximum period for which our data make it possible to compute returns for the portfolios formed by sorting on the year $t-15$ price-to-book ratios).

We compute our measure of risk by regressing the monthly returns on the resulting 150 portfolios (15 different horizons by 10 price-to-book categories) on the contemporaneous and lagged market returns. Note that for each regression we then sum up the regression coefficients on the market return into what we call "total beta," in contrast to "contemporaneous beta," that is, beta estimated without the lagged market returns in the regression. The logic behind our use of total beta returns is the following. We argue that the betas measured on the basis of only contemporaneous monthly returns may be misleading for a number of reasons. If some price-to-book deciles systematically contain illiquid securities, the measured monthly returns may be asynchronous, and some portfolios' returns disproportionately so. In addition, relatively short-horizon effects such as tax-loss harvesting by individual investors, window dressing by institutional investors, and/or delayed reaction to information for stocks that are not extensively covered by analysts may garble the relevant long-run relations in contemporaneous monthly returns. The impact of asynchronous price reaction on beta estimates has been studied by Scholes and Williams (1977) and Dimson (1979), who propose simple techniques to measure market betas by utilizing summed betas from regressions of returns on both contemporaneous and lagged market returns. We follow the spirit of their suggestion when measuring betas, and include up to five lags in our regressions.[5]

B.1. Post-sort Evolution of Beta

Figure 1 shows the evolution of the CAPM beta of value and growth portfolios as a function of years from the sort. The dependent variables in the regressions are an equal-weight portfolio of the three value-weight lowest price-to-book deciles (marked with a solid line and triangles) and an equal-weight portfolio of the three value-weight highest price-to-book deciles (marked with just a solid line). The upper-left plot is produced with no lagged market returns in the regressions, the upper-right with one lag, the lower-left with two lags, and the lower-right with five lags.

Figure 1 clearly illustrates how the long-run risks of value and growth stocks are very different from the risks in the short run. Focusing on the contemporaneous betas in the upper-left plot, growth stocks have much higher contemporaneous betas than value stocks immediately after the sort. However, as time passes from the sort, the risk of value stocks increases while the risk of growth stocks decreases. Between years 5 and 10, contemporaneous betas cross, with value stocks reaching their permanently high and growth stocks their permanently low contemporaneous betas. The time pattern in total betas is very similar, but the total betas of growth stocks are much lower than their contemporaneous betas at all horizons, and the crossing takes place much earlier. Across specifications, value stocks have statistically significantly higher betas than growth stocks 15 years after the sort: t-statistics of the difference in total betas are 4.9, 5.0, 5.0, and 4.6 for regressions with zero, one, two, and five lags, respectively. Thus, we conclude that the long-run permanent level of CAPM beta is significantly higher for value stocks than for growth stocks, a difference as large as 0.2 for these portfolios (and larger for extreme deciles 1 and 10). As seen in the figures the basic effect that drives these results exists when using only one or two lags to measure "total beta." However, in the pricing tests below we compute total beta using five lags to ensure we have fully captured the non-contemporaneous dynamics discussed above.

B.2. Calendar Time Price-Level Tests

We examine N-year holding-period strategies based on return series computed from the 150 portfolios used in the beta tests. The returns are measured

[5] Kothari, Shanken, and Sloan (1995), as well as Handa, Kothari, and Wasley (1993), show that the CAPM performs better when betas are measured using annual instead of monthly returns. Their focus is in explaining short-horizon expected returns, differentiating our tests from theirs.

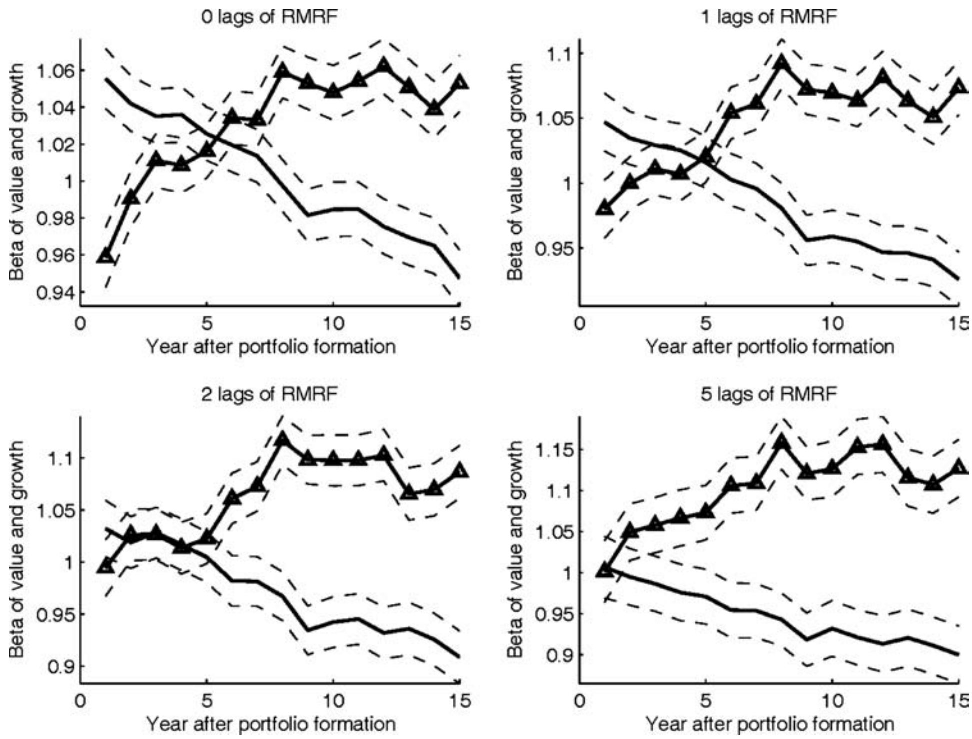

Figure 1. Evolution of CAPM beta after portfolio formation. This figure shows the evolution of total CAPM beta for value and growth stocks after portfolio formation. We first sort stocks into price-to-book deciles. Every year, we run 15 different sorts: deciles sorted on year $t-1$ price-to-book ratios, deciles sorted on year $t-2$ price-to-book ratios, . . . , and deciles sorted on year $t-15$ price-to-book ratios. As a result, we have 715 months of returns on 150 portfolios for the period June 1941 to December 2000 (the maximum period for which our data make it possible to compute the 15-years-from-the-sort portfolio). We compute our measure of risk by regressing the monthly returns on the portfolios on the contemporaneous and lagged market returns. We then sum the regression coefficients for each dependent variable to obtain what we call "total beta." The upper-left plot is produced with no lagged market returns in the regressions, the upper-right with one lag, the lower-left with two lags, and the lower-right with five lags. The dependent variables in the regressions are an equal-weight portfolio of the three value-weight lowest-price-to-book deciles and an equal-weight portfolio of the three value-weight highest-price-to-book deciles. The total beta of value stocks is plotted with a solid line and triangles and the total beta of growth stocks with just a solid line. The dashed lines show one-standard-error bounds.

in excess of the Treasury bill return. We define the N-year decile M as a portfolio strategy that invests in N portfolios: decile M sorted on year $t-1$ price-to-book ratios, decile M sorted on year $t-2$ price-to-book ratios, . . . , and decile M sorted on year $t-N$ price-to-book ratios. Furthermore, the weight on each of these different portfolios is negative and declines exponentially, the weight being ρ to the power of years from the sort minus one. For example, a 2-year holding-period strategy for the highest price-to-book portfolio (2-year decile 10) shorts \$1 of stocks that are the highest price-to-book stocks in the beginning of the return period and shorts ρ times \$1 of stocks that were the highest price-to-book stocks a year before that. We extend these "holding periods" out to 15 years. After multiplying these monthly returns by 12, we have series with means that approximate the right-hand side of equation (4), that is, the price level. Consequently, the 15-year decile portfolios approximate a buy-and-hold investor's experience in price-level units and allow us to examine long-horizon effects at a higher frequency and with more reliable statistical tools than in the cross-sectional tests.

Recall that our analysis of Section II.A may be somewhat unreliable at long horizons due to well-known statistical problems. That problem does not apply to the return-based analysis of this section; in fact, we actually require a very long horizon in these return-based tests as we require the discount-rate news of returns to be dominated by the cash flow news component to such an extent that returns and cash flow news are approximately equal. Though we weight more heavily the 15-year horizon in our return-based tests and the 5-year horizon in the cash flow–based tests, we report results out to 15 years for both methodologies, ultimately letting the reader decide.[6]

For all of the statistics we report in Table IV, we also report asymptotic standard errors (reported inside parentheses) as well as bootstrapped p-values (reported inside braces). The bootstrap procedure proceeds as follows. First, we repeat the regression of the 150 portfolios on the market return and five lags setting the coefficient on the constant to zero. We preserve the 6×1 beta vector and the 715×150 error matrix. We demean the error matrix using the time-series mean of each column of errors, since under the null the mean error from the regression is zero. We then begin 30,000 bootstrap iterations. At each iteration we produce a random design matrix by sampling 715 rows from the original 715×6 design matrix of market returns. We separately randomly sample 715 rows from the demeaned error matrix. All sampling is done with replacement. We produce a new dependent variable matrix using the newly selected design and error matrices in conjunction with the beta estimate ($Y = X \times \text{beta} + \text{errors}$). Finally, we regress the new dependent variable matrix on the new design matrix to get a draw of the intercept vector and corresponding GRS statistic (Gibbons et al. (1989)), as well as other statistics under the null. Then, we compute the percentiles of our point estimates in our sample of 30,000 bootstrap iterations.

[6] The use of a longer preferred time horizon for our return-based tests in comparison to those based on cash flows is consistent with the empirical estimates of Vuolteenaho (2002). As mentioned above, in order for our long-horizon return-based tests to deliver a reasonable approximation of a true cash flow beta, it is sufficient that returns approximately equal cash flow news. This condition is guaranteed to be approximately the case if the time horizon is sufficiently long, since the variance of discount-rate news grows more slowly than the total amount of the news. Figure 4 on page 258 of Vuolteenaho (2002) shows the coefficient of returns on cash flow news (of individual firms) at different horizons. One way to interpret this figure is that it takes approximately 8 years for returns to closely approximate cash flow news. Of course, we also need market returns to be close to market cash flow news; this is likely to take even longer as discount-rate news is a greater fraction of returns for the market than for firms, as shown by the empirical results of Campbell (1991) and others.

Table IV

Price-Level Tests with Calendar-Time Portfolio Returns

This table reports results for price-level tests that use calendar-time portfolio returns. We first sort stocks into price-to-book deciles and then calculate the value-weight monthly returns on each decile over the next 15 years (without re-sorting the stocks). We define the N-year decile M as a portfolio strategy that invests in N portfolios with weights $-12\rho^j$: decile M sorted on year $t-1$ price-to-book ratios, decile M sorted on year $t-2$ price-to-book ratios, . . . , decile M sorted on year $t-j$ price-to-book ratios, . . . , and decile M sorted on year $t-N$ price-to-book ratios. We extend the "holding periods" (i.e., N) out to 15 years. The final sample has 715 months of returns on 150 portfolios for the period June 1941 to December 2000. We call these returns price-level realizations. The first column reports the horizon N. Column (2) reports the GRS statistic testing the intercepts in regressions of the N-year price-level realizations on the excess market stock return and five lags of the excess market stock return. Column (3) reports the sample price-level difference of a strategy that goes long the top three decile portfolios (low price-to-book) and shorts the bottom three decile portfolios (high price-to-book). Column (4) reports the price-level alpha in regressions on the excess market return and five lags. Columns (5) and (6) report the intercept and coefficient of a cross-sectional regression of the average returns on the 10 N-year decile portfolios on the total betas of those portfolios. We construct total betas by summing the individual partial betas on the excess market return and five lags of the excess market return. Column (7) reports the (unadjusted) R^2 from that cross-sectional regression. Standard errors are in brackets except in column (2) where we report the probability value associated with the GRS statistic. We provide bootstrapped probability values in braces under the null hypothesis that the Sharpe–Lintner CAPM is true, except in column (3) where the null hypothesis is that the sample price-level difference of the value-minus-growth portfolio is zero.

N	GRS [asympt. p-val.] {bootstrap p-val.}	μ (asympt. std. err.) {bootstrap p-val.}	α (asympt. std. err.) {bootstrap p-val.}	λ_0 (asympt. std. err.) {bootstrap p-val.}	λ_1 (asympt. std. err.) {bootstrap p-val.}	R^2 % (asympt. std. err.) {bootstrap p-val.}
1	1.9441	−0.0442	−0.0446	−0.0011	0.1004	9.21
	[0.0368]	[0.0135]	[0.0144]	[0.1136]	[0.1114]	[24.96]
	{0.0358}	{0.0011}	{0.0022}	{0.7297}	{0.5497}	{0.1725}
2	2.7026	−0.0946	−0.0902	−0.0307	0.1309	14.88
	[0.0029]	[0.0244]	[0.0262]	[0.1132]	[0.1107]	[28.20]
	{0.0029}	{0.0005}	{0.0006}	{0.4030}	{0.2710}	{0.1698}
3	2.6134	−0.1309	−0.1206	−0.0859	0.1856	31.00
	[0.0040]	[0.0346]	[0.0373]	[0.1004]	[0.0979]	[32.80]
	{0.0044}	{0.0009}	{0.0014}	{0.0760}	{0.0462}	{0.2557}
5	2.8122	−0.1965	−0.1705	−0.1385	0.2362	56.45
	[0.0020]	[0.0543]	[0.0586]	[0.0754]	[0.0733]	[28.06]
	{0.0021}	{0.0026}	{0.0041}	{0.0107}	{0.0063}	{0.4206}
10	1.4202	−0.2766	−0.1832	−0.0791	0.1743	81.57
	[0.1667]	[0.0954]	[0.1028]	[0.0304]	[0.0293]	[09.62]
	{0.1710}	{0.0211}	{0.0783}	{0.0876}	{0.0593}	{0.6613}
15	1.2287	−0.2904	−0.1260	−0.0250	0.1204	84.98
	[0.2687]	[0.1301]	[0.1400]	[0.0185]	[0.0179]	[06.84]
	{0.2684}	{0.0889}	{0.3722}	{0.5272}	{0.4156}	{0.6848}

The second column of Table IV reports the GRS statistic of CAPM tests of the 10 portfolios at different horizons, along with the asymptotic and bootstrapped probability values. For the sake of brevity, we only report results for 1-, 2-, 3-, 5-, 10-, and 15-year deciles. The first row reports the well-known result that the CAPM cannot price returns over the next year on portfolios formed by sorting on the most recent price-to-book ratio. The GRS statistic is 1.94, which rejects the null hypothesis that the 1-year deciles' intercepts are jointly zero at the 5% level of significance. This pattern holds true and strengthens over holding periods up to 5 years. However, for 10-year and 15-year holding period returns (10-year and 15-year deciles), we are unable to reject the hypothesis that the CAPM can price the returns on the price-to-book deciles.

The significance of the horizon for price-level alphas is further illustrated in Figure 2. The top panel of Figure 2 shows the evolution of sample price levels as a function of the horizon. The price-to-book pattern in sample price levels is strong even at the 15-year holding period. In the price-level alphas displayed in the bottom panel, however, the pattern has disappeared almost completely at the 15-year horizon. A simple calculation demonstrates the economic importance of CAPM risk adjustment. Concentrating on deciles 10 and 1 at the 15-year horizon (not reported in tables), the difference in price levels returns is approximately 40%. However, adjusting price levels by the portfolios' total CAPM betas leads to a very different conclusion: The difference in price-level alphas is a statistically insignificant 13%. The economic significance of the difference between 13% and 40% mispricing is large.

The next two columns of Table IV analyze similar value-minus-growth long-short portfolios in more detail. We report the sample price levels and price-level alphas of a strategy that goes long the top three value-weight portfolios (low price-to-book) and shorts the bottom three value-weight portfolios (high price-to-book) with equal weights. Thus, at the 1-year horizon, the strategy is quite similar to Fama and French's (1993) HML, except that there is no size stratification. As Fama and French show, in the year following portfolio formation, all of the average return can be attributed to mispricing vis-à-vis the CAPM. This fact is true even for the strategy that buys value and sells growth and holds the positions for 3 years. For the 3-year holding portfolio, the sample price level and price-level alpha are −13.1% and −12.1%, respectively. In a statistical test not reported in the table, we cannot reject the null that the ratio of price-level alpha to price level is equal to one at the 5% level of significance.

However, as the horizon grows beyond 3 years, the CAPM explains more and more of the price-level differential. At the 10-year horizon, the long-short portfolio generates a price-level difference of 27.7%. Approximately one-third of this is justified by the CAPM, as the price-level alpha is only −18.3%. For the 15-year holding period strategy, the price-level alpha has dropped to −12.6%, though the difference in price levels has continued to grow some to −29.0%. In a statistical test not reported, we are unable to reject the hypothesis that the ratio of price-level alpha to price level is zero at the 5% level of significance. This result confirms the findings of the previous section.

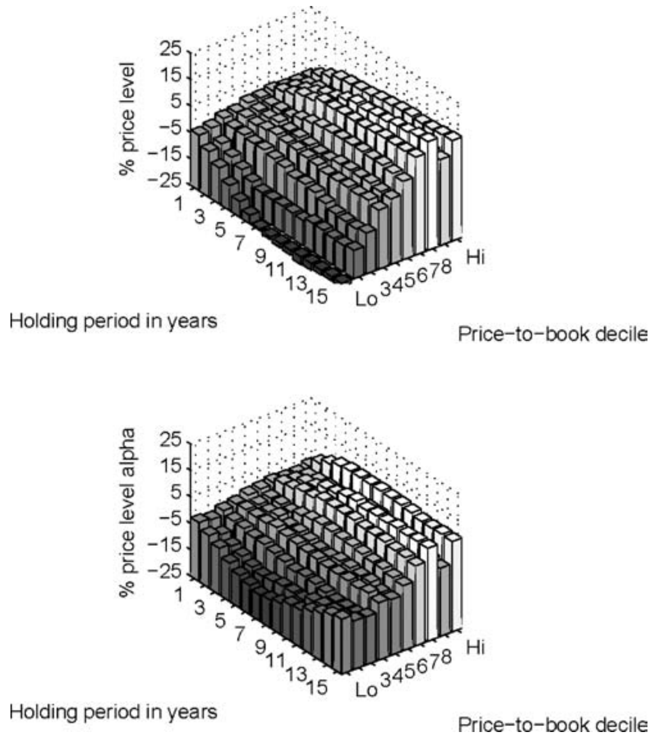

Figure 2. Price levels and price level alphas. This figure shows sample price levels (top graph) and price level alphas (bottom graph) for book-to-price–sorted portfolios. The sample price levels and price level alphas are cross-sectionally demeaned within each horizon N for the purpose of presentation. The sample period (June 1941 to December 2000) and estimation methods are the same as in Table IV.

The remaining columns in Table IV report results from a cross-sectional regression of the sample price levels of the 10 portfolios on the total betas of these portfolios. Column (5) reports the annualized intercept (λ_0) from this regression; column (6) reports the annualized coefficient on total beta (λ_1), and column (7) gives the (unadjusted) R^2. As in Fama and MacBeth (1973), under the null that the CAPM is true, the intercept from a regression of mean excess returns on betas is an estimate of the excess return on the riskless (zero-beta) portfolio. The annualized regression slope is an estimate of the market premium (premium for an additional unit of beta).

For intermediate holding periods (3 to 10 years) the annualized estimated λ_1 is far higher than the historical market premium, often over 20% per annum. The hypothesis that the estimate equals the market premium is strongly rejected for horizons from 3 to 5 years (p-value in column (6)). This is because the value portfolios substantially outperform the growth portfolios, but there is only a small difference in the portfolio betas, so a large beta premium is necessary to explain differences in average returns. The 15-year horizon portfolios, on the other hand, imply a market premium estimate of 12.0% per year, quite similar to the historical market premium, because the spread in betas is large. We are unable to reject the null that the price-level alphas are zero and the hypothesis that the beta premium is equal to the historical average excess return on the market at the 15-year horizon.

Column (7) of Table IV shows the R^2 from the regression of means on betas. For short holding periods, betas explain virtually none of the difference in mean excess returns. For the longest-horizon portfolio, however, the R^2 is 85.0%; we manifestly fail to reject the null that the cross-sectional R^2 is equal to 100%, with a bootstrapped p-value of 0.68.

III. Additional Robustness Checks

A. Alternative Test Assets

We also sort firms into portfolios on firm size and stock return beta. The firm size sort is analogous to the market-to-book sort, except the sort variable is the market value of equity. When we sort on the estimated stock return beta, we first construct the sort variable by running firm-by-firm OLS regressions of firms' monthly stock return on the CRSP value-weight index return. We use up to 5 years of data and require at least 36 valid monthly observations for each firm.

The logic behind including beta-sorted and size-sorted portfolios as test assets is the following. The evidence presented in the main body of the paper shows that there is a monotonically decreasing relationship between price-to-book ratios and both cash flow betas and long-run stock return betas. Previous research shows that the relationship between price-to-book ratios and average returns is also monotonically decreasing. Thus, given this evidence, it is not surprising that the cash flow betas explain average returns well.

To subject the model to a tougher test, we adapt the idea of Daniel and Titman (1997) and include beta-sorted and size-sorted portfolios in the test asset sets. Portfolios sorted on stock return beta and firm size show variation in cash flow betas that is independent from their price-to-book ratios. If the risk loading (instead of the book-to-market characteristic) determines the average return, the inclusion of these risk-sorted portfolios should not significantly decrease the premium on cash flow beta.

While there exists an extensive literature on estimating and forecasting firms' stock return betas, the prediction of cash flow betas is mostly an uncharted territory. Sorts on firms' or industries' past 5-year cash flow betas do not induce any pattern in post-formation cash flow betas. When we sort stocks on size, the difference between the top three and bottom three deciles' cash flow betas is statistically significant at the 5% level for horizons from 2 to 15 years. When we sort stocks on estimated stock return betas, the difference between the top three and bottom three deciles' cash flow betas is marginally statistically significant for the 1-year horizon (t-statistic 1.85) but insignificant for horizons from 2 to 15 years. In other words, characteristics such as the price-to-book ratio and firm size forecast long-horizon cash flow betas, whereas past stock return betas do not.

Of course, because the second-stage regression uses estimated betas, it is subject to the errors-in-variables bias. The magnitude of this bias depends on both the variance of the beta estimation error and the cross-sectional variance of true betas across portfolios. The lower the estimation error variance and the higher the cross-sectional variance of true betas (i.e., the higher the signal-to-noise ratio), the less significant the downward bias in the slope coefficient and R^2 of the second-stage regression. Because the price-to-book-sorted portfolios exhibit more spread in estimated cash flow betas than the risk-sorted portfolios, it is reasonable to conjecture that including the risk-sorted portfolios as test assets will lower the cross-sectional variance of the true betas and thus lower the signal-to-noise ratio. Therefore, even if the pricing model has a true R^2 of 100% when explaining population means, we would expect the estimated second-stage slope and R^2 to decline slightly as we add the portfolios sorted on stock return betas to the set of test assets.

Table V measures whether the cash flow betas can simultaneously explain the price levels of value and growth stocks and portfolios sorted on risk proxies. The dependent variable in the pricing regressions is the N-period sample price level and the independent variable the estimated cash flow beta, as in Table III. We use three sets of test assets. First, we examine 30 price-to-book-sorted portfolios. We then turn to 30 price-to-book-sorted portfolios and 30 portfolios sorted on past OLS stock return betas. Finally, we consider 30 price-to-book-sorted and 30 size-sorted portfolios. We sort stocks into 30 portfolios to improve the statistical power of our tests.

Columns (2) to (10) of Table V show premia and R^2 estimated from these alternative asset sets. Adding the stock return beta-sorted portfolios to the test assets lowers the annualized beta premium estimate, but only slightly. For example, at the 5-year horizon, price-to-book-sorted portfolios indicate a beta premium of 8.5% and adding beta-sorted portfolios lowers the estimate to 6.9%.[7] Replacing the beta-sorted portfolios with size-sorted portfolios yields a closer beta premium estimate of 7.4%. The high R^2s are also robust to the addition of risk-sorted portfolios: R^2s of the cross-sectional regressions remain what we consider high (from 28% to 53% for horizons from 2 to 10 years). Taking into account the increased attenuation bias due to the lower signal-to-noise ratio, we thus conclude that our finding that cash flow betas explain the sample price levels well is robust to including risk-sorted portfolios as test assets.

We also repeat the calendar-time tests with monthly stock returns on these alternative test asset sets and report the results in Table VI. As evident from the table, these tests essentially break the stock return–based model. Adding beta-sorted portfolios has a particularly devastating effect on the beta premium and

[7] When estimating the cash flow betas of beta-sorted and ME/BE-sorted portfolios, we use the maximum number of data points available for each portfolio return series (1933 to 1999 for beta-sorted and 1928 to 1999 for price-to-book-sorted portfolios). When computing the moment error covariance matrix used in the GMM standard error formulas, we only use the period for which the return data are available for all portfolios.

Table V

Price-Level Alphas, Alternative Test Assets

The table reports the regression coefficients and the R^2 of the regression of the sample price levels on cash flow betas for different sets of portfolios. Columns (2) to (4) use 30 price-to-book-sorted portfolios. Columns (5) to (7) use 30 price-to-book-sorted portfolios and 30 portfolios sorted on 5-year OLS stock return betas. Columns (8) to (10) use 30 price-to-book-sorted portfolios and 30 size-sorted portfolios. Betas are estimated from the full 1928 to 1999 sample, except for the beta-sorted portfolios, for which the cash flow beta estimation period is 1933 to 1999. Footnotes in Table II apply.

	30 ME/BE-Sorted Portfolios			30 ME/BE-Sorted Portfolios and 30 Beta-Sorted Portfolios			30 ME/BE-Sorted Portfolios and 30 Size-Sorted Portfolios		
N	λ_0	λ_1	R^2 %	λ_0	λ_1	R^2 %	λ_0	λ_1	R^2 %
1	0.109	0.048	18.78	0.130	0.024	12.10	0.139	0.029	5.15
	(0.059)	(0.036)		(0.028)	(0.013)		(0.037)	(0.015)	
2	0.069	0.088	51.43	0.113	0.043	27.78	0.086	0.079	39.19
	(0.085)	(0.072)		(0.023)	(0.017)		(0.040)	(0.034)	
3	0.057	0.102	64.58	0.101	0.057	36.36	0.078	0.087	51.38
	(0.052)	(0.049)		(0.019)	(0.019)		(0.028)	(0.032)	
5	0.078	0.085	75.26	0.091	0.069	53.48	0.096	0.074	61.81
	(0.046)	(0.043)		(0.022)	(0.022)		(0.026)	(0.028)	
10	0.037	0.112	71.91	0.079	0.072	51.28	0.083	0.071	57.97
	(0.054)	(0.054)		(0.018)	(0.019)		(0.029)	(0.031)	
15	0.042	0.107	40.84	0.111	0.039	17.66	0.081	0.072	44.52
	(0.039)	(0.035)		(0.019)	(0.020)		(0.027)	(0.032)	

cross-sectional R^2 in the first four columns of Table VI: The 15-year-horizon beta premium (12.0% per year) obtained in Table IV drops to one-sixth its previous value in column (4) of Table VI (2.0% per year). To summarize our results, by including risk-sorted portfolios in the analysis we are unable to break pricing models that link cash flow betas to price levels but are "successful" in breaking pricing models that use stock return betas.

B. Beta Drift

To verify that the surprising crossing pattern in Figure 1 is not an artifact of a time trend in value and growth stocks' betas, in Table VII we estimate a parametric specification for the betas:

$$R_{i,t} - R_{rf,t} = \alpha_i + \sum_{l=0}^{L} \beta_{0,l} \times RMRF_{t-l} + \sum_{l=0}^{L} \beta_{1,l} \times TREND_t \times RMRF_{t-l} + \sum_{l=0}^{L} \beta_{2,l} \times YEARS_i \times RMRF_{t-l} + \sum_{l=0}^{L} \beta_{3,l} \times YEARS_i \times TREND_t \times RMRF_{t-l} + \varepsilon_{i,t}. \quad (8)$$

Table VI

Price-Level Tests with Calendar-Time Portfolio Returns, Alternative Test Assets

This table reports results from calendar-time tests produced with different test asset sets. We first sort stocks into deciles (based on ME/BE, size, or estimated stock return beta) and then calculate the value–weight monthly returns on each decile over the next 15 years (without re-sorting the stocks). We define the N-year decile M as a portfolio strategy that invests in N portfolios with weights -12ρ : decile M sorted on year $t-1$ price-to-book ratios, decile M sorted on year $t-2$ price-to-book ratios, . . . , decile M sorted on year $t-j$ price-to-book ratios, . . . , and decile M sorted on year $t-N$ price-to-book ratios. We extend the "holding periods" (i.e., N) out to 15 years. The final sample has 655 months of returns on 300 portfolios in each panel (450 in total) for the period June 1946 to December 2000. We call these returns price-level realizations. The first column of the table reports the horizon N. Column (1) of each panel reports the GRS statistic testing the intercepts in regressions of the N-year price-level realizations on the excess market stock return and five lags of the excess market stock return. Columns (2) and (3) of each panel report the intercept and coefficient of a cross-sectional regression of the average returns on the 10 N-year decile portfolios on the total betas of those portfolios. We construct total betas by summing the individual partial betas on the excess market return and five lags of the excess market return. Column (4) of each panel reports the (unadjusted) R^2 from that cross-sectional regression. Asymptotic standard errors are in brackets except in column (2), where we report the asymptotic probability value associated with the GRS statistic. We provide bootstrapped probability values in braces under the null hypothesis that the Sharpe–Lintner CAPM is true.

	Panel A: Ten ME/BE-Sorted Portfolios and 10 Beta-Sorted Portfolios				Panel B: Ten ME/BE-Sorted Portfolios and 10 Size-Sorted Portfolios			
N	GRS [asympt. p-val.] {bootstrap p-val.}	λ_0 (asympt. std. err.) {bootstrap p-val.}	λ_1 (asympt. std. err.) {bootstrap p-val.}	R^2 % (asympt. std. err.) {bootstrap p-val.}	GRS [asympt. p-val.] {bootstrap p-val.}	λ_0 (asympt. std. err.) {bootstrap p-val.}	λ_1 (asympt. std. err.) {bootstrap p-val.}	R^2 % (asympt. std. err.) {bootstrap pval.}
1	1.953	0.0906	−0.0041	0.38	2.3363	0.0504	0.0465	26.52
	[0.0078]	[0.0157]	[0.0155]	[1.95]	[0.0009]	[0.0213]	[0.0183]	[20.39]
	{0.0085}	{0.0008}	{0.0142}	{0.0035}	{0.0013}	{0.2213}	{0.2678}	{0.0223}
2	2.3527	0.0867	0.0010	0.02	2.7288	0.0553	0.0439	25.34
	[0.0010]	[0.0169]	[0.0166]	[0.46]	[0.0001]	[0.0207]	[0.0178]	[16.72]
	{0.0013}	{0.0016}	{0.0268}	{0.0006}	{0.0001}	{0.1844}	{0.2576}	{0.0227}
3	2.3221	0.0790	0.0098	1.90	2.4030	0.0625	0.0378	21.76
	[0.0010]	[0.0170]	[0.0167]	[4.54]	[0.0006]	[0.0196]	[0.0169]	[12.86]
	{0.0011}	{0.0038}	{0.0528}	{0.0079}	{0.0008}	{0.1376}	{0.2087}	{0.0229}
5	2.5440	0.0671	0.0222	8.62	2.7252	0.0693	0.0310	15.71
	[0.0003]	[0.0172]	[0.0170]	[9.44]	[0.0001]	[0.0195]	[0.0169]	[8.71]
	{0.0004}	{0.0123}	{0.1067}	{0.0146}	{0.0002}	{0.1014}	{0.1673}	{0.0213}
10	2.2668	0.0614	0.0270	21.87	1.7142	0.0724	0.0260	16.64
	[0.0013]	[0.0122]	[0.0120]	[15.17]	[0.0269]	[0.0157]	[0.0137]	[12.09]
	{0.0017}	{0.0245}	{0.1364}	{0.0232}	{0.0296}	{0.0906}	{0.1413}	{0.0282}
15	1.8472	0.0681	0.0195	21.39	1.3456	0.0743	0.0230	21.89
	[0.0138]	[0.0089]	[0.0088]	[17.34]	[0.1427]	[0.0116]	[0.0102]	[12.88]
	{0.0155}	{0.0135}	{0.0809}	{0.0207}	{0.1468}	{0.2339}	{0.2629}	{0.1165}

Table VII

Parametric Model of Beta Evolution

This table shows an estimated parametric specification for betas:

$$R_{i,t} - R_{rf,t} = \alpha_i + \sum_{l=0}^{L} \beta_{0,l} \times RMRF_{t-l} + \sum_{l=0}^{L} \beta_{1,l} \times TREND_t \times RMRF_{t-l} + \sum_{l=0}^{L} \beta_{2,l} \times YEARS_i \times RMRF_{t-l} + \sum_{l=0}^{L} \beta_{3,l} \times YEARS_i \times TREND_t \times RMRF_{t-l} + \varepsilon_{i,t}.$$

TREND is a linear time trend in centuries (month index divided by 1,200), normalized to zero in the middle of the sample. *YEARS* is the number of years from the sort divided by 100, or more accurately the number of lags we used in firms' price-to-book ratios when sorting the portfolios into deciles divided by 100. *RMRF* is the excess return on the market portfolio. *L* is the number of monthly *RMRF* lags included in the regressions. The table reports the sums of coefficients for value, growth, and value-minus-growth portfolios:

$$b_{(\text{intercept})} = \sum_{l=0}^{L} \beta_{0,l}, \; b_{(\text{trend})} = \sum_{l=0}^{L} \beta_{1,l}, \; b_{(\text{years from sort})} = \sum_{l=0}^{L} \beta_{2,l}, \; b_{(\text{years from sort} \times \text{trend})} = \sum_{l=0}^{L} \beta_{3,l}.$$

The dependent variables are constructed as follows. We first sort stocks into price-to-book deciles. Every year, we run 15 different sorts: deciles sorted on year $t-1$ price-to-book ratios, deciles sorted on year $t-2$ price-to-book ratios, …, and deciles sorted on year $t-15$ price-to-book ratios. As a result, we have 715 months of returns on 150 portfolios for the period June 1941 to December 2000 (the maximum period for which our data made it possible to compute the 15-years-from-the-sort portfolio). The dependent variables in the regressions are an equal-weight portfolio of the three value-weight lowest price-to-book deciles (Panel A), an equal-weight portfolio of the three value-weight highest price-to-book deciles (Panel B), and the difference of the two (Panel C).

Lags of RMRF (L)	0	1	2	5
		Panel A: Value		
b(intercept)	**1.03**	**1.03**	**1.04**	**1.04**
Standard error	0.02	0.02	0.03	0.04
t-statistic	62.79	46.28	38.65	28.11
b(trend)	**−1.01**	**−1.08**	**−1.19**	**−0.95**
Standard error	0.09	0.13	0.15	0.20
t-statistic	−10.76	−8.62	−8.00	−4.77
b(time from sort)	**0.50**	**0.55**	**0.56**	**0.79**
Standard error	0.11	0.14	0.17	0.24
t-statistic	4.68	3.80	3.24	3.28
b(time from sort × trend)	**1.51**	**2.60**	**3.01**	**3.03**
Standard error	0.61	0.81	0.96	1.29
t-statistic	2.49	3.21	3.15	2.35
		Panel B: Growth		
b(intercept)	**1.05**	**1.05**	**1.04**	**1.01**
Standard error	0.01	0.01	0.01	0.02
t-statistic	115.82	85.30	69.91	49.43
b(trend)	**0.28**	**0.38**	**0.48**	**0.55**
Standard error	0.05	0.07	0.08	0.11
t-statistic	5.38	5.47	5.92	4.97
b(time from sort)	**−0.62**	**−0.79**	**−0.80**	**−0.69**
Standard error	0.07	0.09	0.11	0.15
t-statistic	−9.22	−8.66	−7.23	−4.52

(*continued*)

Table VII—*Continued*

Lags of RMRF (L)	0	1	2	5
b(time from sort × trend)	**−1.63**	**−2.01**	**−2.28**	**−2.14**
Standard error	0.39	0.52	0.61	0.82
t-statistic	−4.21	−3.89	−3.75	−2.60
Panel C: Difference (value minus growth)				
b(intercept)	**−0.02**	**−0.02**	**0.01**	**0.03**
Standard error	0.02	0.03	0.04	0.05
t-statistic	−0.93	−0.57	0.18	0.63
b(trend)	**−1.29**	**−1.46**	**−1.67**	**−1.50**
Standard error	0.13	0.17	0.20	0.27
t-statistic	−10.22	−8.67	−8.40	−5.58
b(time from sort)	**1.12**	**1.34**	**1.36**	**1.48**
Standard error	0.14	0.18	0.22	0.31
t-statistic	8.27	7.30	6.15	4.83
b(time from sort × trend)	**3.13**	**4.61**	**5.30**	**5.17**
Standard error	0.77	1.03	1.22	1.65
t-statistic	4.05	4.46	4.34	3.14

Above, *TREND* is a linear time trend in centuries (month index divided by 1,200), normalized to zero in the middle of the sample, and *YEARS* is the number of years from the sort divided by 100; or more informatively, the number of lags we used in firms' price-to-book ratios when sorting the portfolios into deciles, divided by 100. Table VII reports the sums of coefficients (i.e., total betas) for the value, growth, and difference portfolios as a function of L (the number of monthly lags). The results suggest that even after controlling for the time trend, growth stocks' betas decline and value stocks' betas increase after the sort. Based on the coefficient of the interaction term, these patterns appear to be especially strong in the later years of the sample. The above results show that value stocks do have higher long-run betas than growth stocks.

C. Modern Subperiod

Most of the evidence documenting the CAPM's failure to explain the average (one-period) returns on price-to-book-sorted portfolios comes from the so-called COMPUSTAT subperiod starting in 1963. Davis et al. (2000) argue that the value premium in U.S. stock returns is not sample-specific, as that premium is as strong for the pre-COMPUSTAT subperiod (1929 to 1962) as it is for the modern subperiod. However, Campbell and Vuolteenaho (2004) and others show that the usual implementation of the CAPM does a reasonable job of explaining that premium in the early sample. This section investigates whether the early subperiod drives our results.

Table VIII reports estimates of cash flow betas in the modern subperiod. As in the full period, all measures of cash flow betas are higher for value stocks than for growth stocks. In the first row of Table VIII, we report cash flow betas

Table VIII

Price-Level Alphas and Cash Flow Betas, Modern Subperiod

The table reports the price-level alphas and cash flow betas for value and growth stocks in the 1963 to 1999 period. The alternative cash flow definitions are defined in Table II. Columns (3) to (14) report price-level alphas and cash flow betas for price-to-book-sorted portfolios. Per each cash flow measure, the first and second rows report the price-level alpha and its standard error (in parentheses), defined in Table III as the cross-sectional regression residual of the sample price level on the estimated cash flow beta. The third and fourth rows reports the cash flow beta and its standard error. The annualized premia and the cross-sectional R^2 are reported in columns (15)–(17). All regressions are estimated with OLS. Hansen's (1982) GMM standard errors computed using the Newey–West formula with N leads and lags (which account for both the estimation uncertainty of the cash flow betas and for the cross-sectional and time-series correlation of the error terms) are reported in parentheses.

Alternative Cash Flow Definition ($N = 5$)		High ME/BE	2	3	4	5	6	7	8	9	Low ME/BE	1–10	(1,2,3)–(8,9,10)	λ_0	λ_1	R^2 %
$\sum_{j=0}^{N-1} \rho^j roe_{k,t+j,j+1}$	Price-level α	−0.030	−0.008	0.101	0.092	0.078	0.027	0.033	−0.071	−0.124	−0.097	0.067	0.118			33.18
	(α se)	(0.038)	(0.061)	(0.050)	(0.051)	(0.052)	(0.041)	(0.030)	(0.071)	(0.055)	(0.065)	(0.042)	(0.073)	0.1393	0.0149	
	Cash flow β	−1.43	−0.28	0.37	0.55	0.65	0.90	0.76	0.33	0.46	1.57	−3.00	−1.23	(0.0374)	(0.0187)	
	(β se)	(0.93)	(0.70)	(0.37)	(0.40)	(0.41)	(0.41)	(0.34)	(0.15)	(0.25)	(0.87)	(0.84)	(0.42)			
$\sum_{j=0}^{N-1} \rho^j ROE_{k,t+j,j+1}$	Price-level α	−0.027	0.000	0.105	0.095	0.078	0.025	0.033	−0.067	−0.122	−0.119	0.091	0.129			34.64
	(α se)	(0.024)	(0.067)	(0.049)	(0.048)	(0.050)	(0.036)	(0.027)	(0.067)	(0.053)	(0.077)	(0.060)	(0.081)	0.1596	0.0221	
	Cash flow β	−1.73	−0.33	0.37	0.55	0.62	0.88	0.75	0.32	0.43	1.35	−3.08	−1.26	(0.0381)	(0.0202)	
	(β se)	(1.11)	(0.74)	(0.38)	(0.41)	(0.40)	(0.40)	(0.34)	(0.16)	(0.25)	(0.77)	(0.87)	(0.45)			
$\sum_{j=0}^{N-1} \rho^j \frac{X_{k,t+j,j+1}}{ME_{k,t+j-1,j}}$	Price-level α	0.012	0.005	0.087	0.095	0.088	0.034	0.039	−0.073	−0.126	−0.152	0.164	0.148			23.46
	(α se)	(0.060)	(0.048)	(0.038)	(0.046)	(0.059)	(0.044)	(0.052)	(0.084)	(0.078)	(0.169)	(0.186)	(0.116)	0.1083	0.0517	
	Cash flow β	0.50	0.80	1.02	1.23	1.34	1.45	1.37	1.09	1.15	1.35	−0.85	−0.42	(0.0677)	(0.0532)	
	(β se)	(0.12)	(0.18)	(0.23)	(0.22)	(0.18)	(0.16)	(0.10)	(0.09)	(0.24)	(1.09)	(0.64)	(0.24)			
$\frac{\sum_{j=0}^{N-1} \rho^j X_{k,t+j,j+1}}{ME_{k,t-1,0}}$	Price-level α	0.020	−0.004	0.089	0.090	0.081	0.026	0.047	−0.060	−0.109	−0.180	0.200	0.151			21.56
	(α se)	(0.065)	(0.051)	(0.039)	(0.041)	(0.053)	(0.036)	(0.052)	(0.063)	(0.054)	(0.168)	(0.211)	(0.115)	0.1155	0.0445	
	Cash flow β	0.45	0.76	1.04	1.22	1.34	1.46	1.51	1.21	1.33	1.16	−0.72	−0.49	(0.0560)	(0.0445)	
	(β se)	(0.10)	(0.17)	(0.24)	(0.29)	(0.28)	(0.32)	(0.10)	(0.12)	(0.26)	(0.99)	(0.59)	(0.21)			
$\frac{X_{k,t+N-1,j+N} - X_{k,t-1,0}}{ME_{k,t-1,0}}$	Price-level α	0.008	−0.004	0.064	0.078	0.068	0.026	0.036	0.021	−0.158	−0.139	0.147	0.115			27.38
	(α se)	(0.135)	(0.083)	(0.039)	(0.051)	(0.048)	(0.036)	(0.065)	(0.060)	(0.138)	(0.343)	(0.447)	(0.191)	0.1376	0.0271	
	Cash flow β	0.01	0.56	0.63	1.04	1.17	1.49	1.42	2.10	0.73	1.57	−1.56	−1.07	(0.0709)	(0.0377)	
	(β se)	(0.22)	(0.36)	(0.36)	(0.54)	(0.38)	(0.25)	(0.72)	(1.30)	(1.20)	(3.24)	(1.85)	(0.64)			
$\sum_{j=0}^{N-1} \rho^j \Delta d_{k,t+j,j+1}$	Price-level α	−0.010	−0.027	0.082	0.093	0.104	0.004	−0.035	−0.088	−0.077	−0.048	0.038	0.086			55.08
	(α se)	(0.128)	(0.052)	(0.033)	(0.048)	(0.060)	(0.055)	(0.088)	(0.089)	(0.056)	(0.042)	(0.115)	(0.080)	0.1225	0.0464	
	Cash flow β	0.15	0.46	0.81	1.04	1.28	1.05	0.64	0.80	1.34	1.95	−1.80	−0.89	(0.0657)	(0.0581)	
	(β se)	(0.56)	(0.33)	(0.28)	(0.14)	(0.35)	(0.32)	(0.21)	(0.14)	(0.27)	(0.97)	(0.79)	(0.35)			

using the same variable, 5-year sums of discounted log ROE, as in Table II Panel A. The spread in cash flow beta across the extreme ME/BE deciles is now −3.00, reported in column (13), about three times that estimated from the full subperiod. This large spread is statistically significant as well, with a t-statistic of 3.57. A statistically and economically significant gap also exists between broader definitions of growth and value. And, again, this gap is bigger than that estimated in the full period.

As in the full period, these conclusions are not sensitive to our proxy for firm cash flow. For the five alternative definitions we consider, value deciles consistently have higher cash flow betas than growth stocks. All of the estimates of the spread in cash flow beta between the top three and bottom three market-to-book deciles are statistically significant.

Table VIII also reports the sample price-level alpha and price-level alpha standard error for the price-to-book deciles for each of the cash flow measures at the 5-year horizon. At this horizon, the difference in sample price levels between the top three value deciles and the top three growth deciles is 20.6% (not reported). Given the reported spread in cash flow betas, it is not surprising that the price-level alphas for this difference portfolio are smaller for all six different measures of cash flow beta, ranging from 15.1% to 8.6%. Moreover, none of the six different cash flow beta measures have sample price-level alphas for this difference portfolio that are significant at the 10% level. Finally, while the difference in price levels of the highest and lowest price-to-book decile is a large 28.0% (not reported), for our preferred measure, the difference in price-level alphas is only 6.7%, over 75% smaller.

Consistent with the estimate of the interaction coefficient of Table VII, Figure 3 indicates that even in the modern subperiod, long-run risks of value and growth stocks remain very different from these risks in the short run. A careful look indicates that the major difference between the full period and the modern subperiod is that now growth stocks start out with a much higher contemporaneous stock return beta relative to value stocks as of the time of classification. The same is true for various specifications of total stock return beta. Nevertheless, as time passes from the sort, the risk of value stocks increases while the risk of growth stocks decreases. Due to the larger initial gap, contemporaneous as well as total betas cross much later after the initial classification. Still, value stocks have statistically significantly higher betas than growth stocks 15 years after the sort across all specifications of beta. Thus, we conclude that our novel finding of the dramatic post-sort evolution of stock return betas of growth and value stocks is present in the modern subperiod. Moreover, the size of the long-run permanent difference in CAPM beta found in the modern subperiod remains similar in magnitude.

Table IX reports the pricing results for our calendar-time tests when restricted to the modern sample. As before, the CAPM cannot explain sample price levels for horizons up to 5 years. Similarly, in the long-horizon tests (where the test assets are 10-year and 15-year deciles), we are also unable to reject the hypothesis that the CAPM explains the sample price levels of price-to-book deciles.

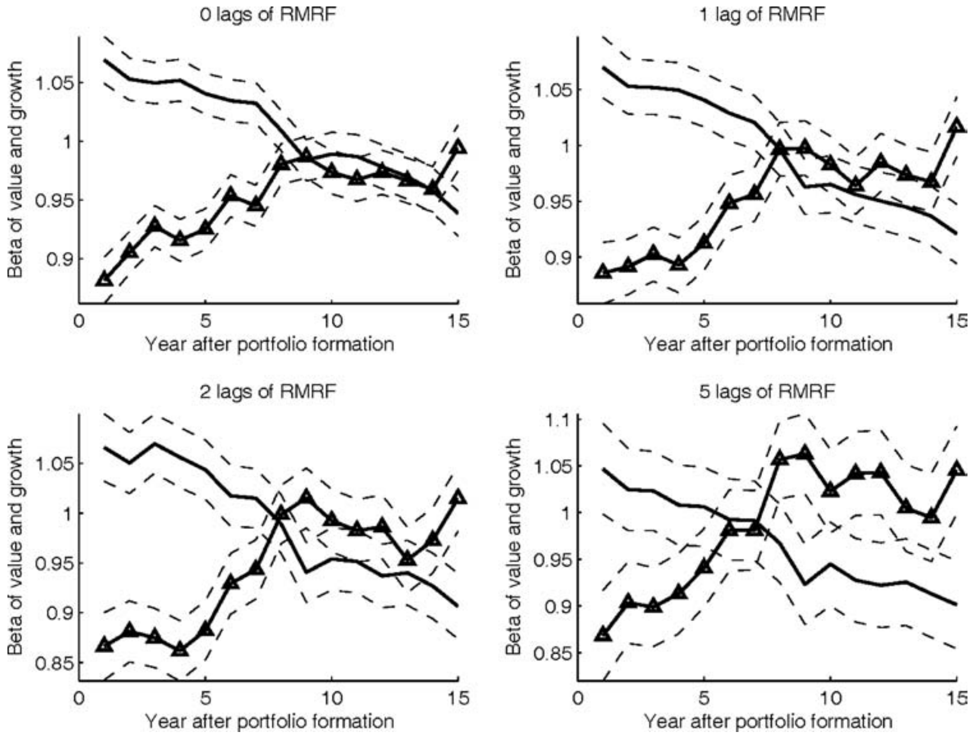

Figure 3. Evolution of CAPM beta after portfolio formation, modern subperiod. This figure shows the evolution of total CAPM beta for value and growth stocks after portfolio formation. We first sort stocks into price-to-book deciles. Every year, we run 15 different sorts: Deciles sorted on year $t-1$ price-to-book ratios, deciles sorted on year $t-2$ price-to-book ratios, . . . , and deciles sorted on year $t-15$ price-to-book ratios. As a result, we have 451 months of returns on 150 portfolios for the period June 1963 to December 2000. We compute our measure of risk by regressing the monthly returns on the portfolios on the contemporaneous and lagged market returns. We then sum the regression coefficients for each dependent variable to obtain what we call "total beta." The upper-left plot is produced with no lagged market returns in the regressions, the upper-right with one lag, the lower-left with two lags, and the lower-right with five lags. The dependent variables in the regressions are an equal-weight portfolio of the three value-weight lowest price-to-book deciles and an equal-weight portfolio of the three value-weight highest price-to-book deciles. The total beta of value stocks is plotted with a solid line and triangles and the total beta of growth stocks with just a solid line. The dashed lines show one-standard-error bounds.

In contrast to the full period results, however, the stock return CAPM does not explain much of the price-level differential at any of the horizons we study. At the 15-year horizon, the long-short portfolio generates a price-level difference of 21.8%, with an accompanying price-level alpha of 20.9%. The fact that sample price levels cannot be explained by stock return betas can also be seen in Figure 4. There is some consolation in that for both estimates, we fail to reject the null that each estimate is equal to zero at bootstrapped p-values greater than 20%.

Table IX

Price-Level Tests with Calendar-Time Portfolio Returns, Modern Subperiod

This table reports results for price-level tests that use calendar-time portfolio returns. We first sort stocks into price-to-book deciles and then calculate the value-weight monthly returns on each decile over the next 15 years (without re-sorting the stocks). We define the N-year decile M as a portfolio strategy that invests in N portfolios with weights $-12\rho^j$: decile M sorted on year $t-1$ price-to-book ratios, decile M sorted on year $t-2$ price-to-book ratios, . . . , decile M sorted on year $t-j$ price-to-book ratios, . . . , and decile M sorted on year $t-N$ price-to-book ratios. We extend the "holding periods" (i.e., N) out to 15 years. The final sample has 451 months of returns on 150 portfolios for the period June 1963 to December 2000. We call these returns price-level realizations. The first column reports the horizon N. Column (2) reports the GRS statistic testing the intercepts in regressions of the N-year price-level realizations on the excess market stock return and five lags of the excess market stock return. Column (3) reports the sample price-level difference of a strategy that goes long the top three decile portfolios (low price-to-book) and shorts the bottom three decile portfolios (high price-to-book). Column (4) reports the price-level alpha in regressions on the excess market return and five lags. Columns (5) and (6) report the intercept and coefficient of a cross-sectional regression of the average returns on the 10 N-year decile portfolios on the total betas of those portfolios. We construct total betas by summing the individual partial betas on the excess market return and five lags of the excess market return. Column (7) reports the (unadjusted) R^2 from that cross-sectional regression. Standard errors are in brackets except in column (2), where we report the probability value associated with the GRS statistic. We provide bootstrapped probability values in braces under the null hypothesis that the Sharpe-Lintner CAPM is true, except in column (3), where the null hypothesis is that the sample price-level difference of the value-minus-growth portfolio is zero.

N	GRS [asympt. p-val.] {bootstrap p-val.}	μ (asympt. std. err.) {bootstrap p-val.}	α (asympt. std. err.) {bootstrap p-val.}	λ_0 (asympt. std. err.) {bootstrap p-val.}	λ_1 (asympt. std. err.) {bootstrap p-val.}	R^2 % (asympt. std. err.) {bootstrap p-val.}
1	1.8379	−0.0413	−0.0521	0.1363	−0.0674	12.43
	[0.0522]	[0.0177]	[0.0180]	[0.0610]	[0.0633]	[19.74]
	{0.0559}	{0.0198}	{0.0044}	{0.0276}	{0.0400}	{0.3110}
2	2.2118	−0.0846	−0.1024	0.1661	−0.0953	21.86
	[0.0163]	[0.0317]	[0.0322]	[0.0615]	[0.0637]	[24.88]
	{0.0192}	{0.0160}	{0.0024}	{0.0120}	{0.0193}	{0.4326}
3	2.2892	−0.1138	−0.1385	0.1694	−0.0968	20.04
	[0.0127]	[0.0449]	[0.0455]	[0.0662]	[0.0684]	[25.66]
	{0.0146}	{0.0291}	{0.0037}	{0.0143}	{0.0240}	{0.4228}

5	2.4422	−0.1677	−0.2005	0.1447	−0.0707	8.32
	[0.0077]	[0.0705]	[0.0715]	[0.0804]	[0.0830]	[15.79]
	{0.0082}	{0.0467}	{0.0054}	{0.0551}	{0.0843}	{0.2658}
10	1.8766	−0.2253	−0.2421	0.0539	0.0206	0.79
	[0.0465]	[0.1235]	[0.1271]	[0.0802]	[0.0817]	[0.0732]
	{0.0468}	{0.1551}	{0.0572}	{0.5317}	{0.6840}	{0.0926}
15	1.1814	−0.2183	−0.2093	0.0098	0.0639	12.39
	[0.3012]	[0.1673]	[0.1733]	[0.0590]	[0.0601]	[23.87]
	{0.3054}	{0.3230}	{0.2328}	{0.9127}	{0.7519}	{0.3709}

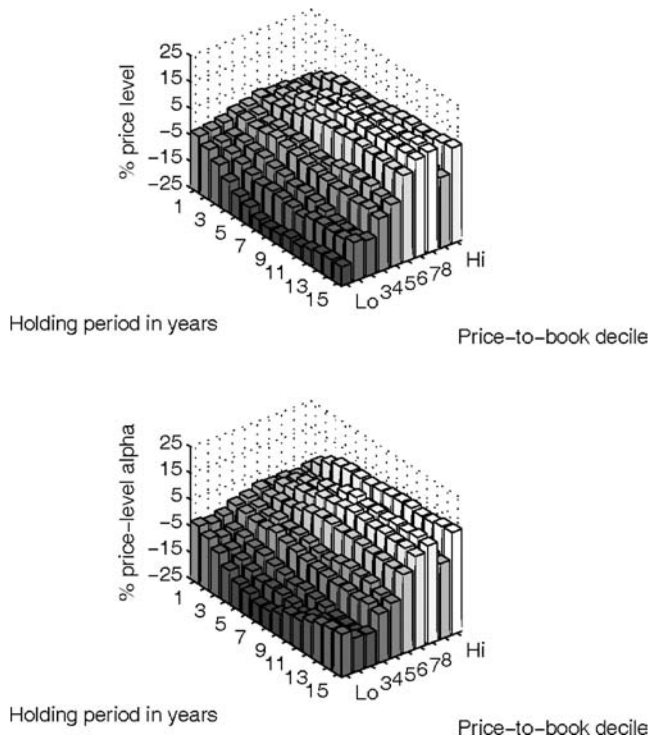

Figure 4. Price levels and price-level alphas, modern subperiod. This figure shows sample price levels (top graph) and price-level alphas (bottom graph) for book-to-price sorted portfolios. The sample price levels and price-level alphas are cross-sectionally demeaned within each horizon N for the purpose of presentation. The sample period (June 1963 to December 2000) and estimation methods are the same as in Table IX.

IV. Conclusions

The goal of this paper is to evaluate the relative importance of risk and mispricing to the cross-sectional variation in firms' stock prices. Our approach differs from the previous cross-sectional research in two important ways.

First, unlike most previous cross-sectional studies, we follow Summers (1986) and concentrate on stock price levels instead of trading profits. We argue that focusing on price levels has important advantages. A common definition of market efficiency states that stock prices reflect information to the point that the marginal benefits of acquiring information and trading on it do not exceed the marginal costs (Jensen (1978)). One problem in testing market efficiency is that what constitutes a reasonable level of information and transaction costs is ambiguous. The interpretation of before-cost trading profits on high-turnover investment strategies can crucially depend on the assumed level of costs. On the contrary, the price-level criterion we advocate is largely immune to this concern. Evaluating market efficiency at the price level is analogous to evaluating trading profits on a simple strategy of buying or short-selling a stock once and holding the position forever. Thus, the price-level criterion is clearly less sensitive to assumptions about reasonable trading and information costs.

Similarly, the price-level criterion is interesting to an investor who, for some reason, is constrained to a long holding period. For example, the level of price is the appropriate measure for a host of economically important decisions including firms' real investment decisions as well as merger and acquisition activity—endeavors essentially requiring buy-and-hold behavior.

Second, following Brainard et al. (1991) we measure risk by covariances of cash flow fundamentals instead of covariances of stock returns. If the objective is to test the joint hypothesis of market efficiency and an asset pricing model being literally true, a valid test of this joint hypothesis examines the relation between first and second moments of high-frequency stock returns. However, if the objective is to measure how well the joint hypothesis predicts stock prices in a possibly inefficient market, tests relying solely on the properties of stock returns are handicapped by the following disadvantage. Market inefficiencies can affect not only average returns but also return covariances, and this problem is likely to be more severe the higher the frequency of the returns. The price-level tests we advocate connect stock prices to covariances or betas of cash flows. Regressing prices on cash flow betas is in our opinion a cleaner way to measure a model's explanatory power than regressing average returns on return betas, because the cash flow betas are less affected by mispricing.

We test empirically the ability of the CAPM to explain value and growth stocks' price levels. Our empirical results suggest that mispricing relative to the CAPM is not necessarily an important factor in determining the price levels of value and growth stocks. Cash flow betas (measured by regressing firms' log ROEs on the market's log ROE) essentially explain the prices of and long-horizon returns on price-to-book-sorted portfolios, with a premium consistent with the theory.

We confirm and extend these findings with tests on stock returns. When we sort stocks on price-to-book ratios, immediately after the sort the low price-to-book portfolios have lower CAPM betas than the high price-to-book portfolios. However, this lower risk of value stocks is entirely temporary: As time since the sort increases, the beta of the value-stock portfolio increases while the beta of the growth-stock portfolio decreases. Within 10 to 15 years, the betas of these portfolios have reached their long-run permanent levels, and the long-run CAPM betas of value stocks are much higher than those of growth stocks. If an investor has a 15-year buy-and-hold investment horizon, value and growth portfolios' average returns line up closely with their CAPM betas.

Of course, our results do not change the fact that the CAPM cannot explain the abnormal performance of an annually rebalanced value-minus-growth strategy. That strategy will have a high return and low stock return beta, at least before accounting for transaction costs, irrespective of what happens to those stocks after they are sold or bought back on the short side. However, the long-run betas are crucial when diagnosing the economic significance of the value-minus-growth anomaly. We argue that, for many purposes, the joint hypothesis of the

CAPM and market efficiency approximates the pricing of value and growth stocks well at the price level.

Our results may validate what beforehand might have been seen as a common but inappropriate use of CAPM-based hurdle rates by firms, given the empirical evidence on the CAPM's inability to explain one-period expected returns. For example, Graham and Harvey (2001, p. 232) state: "It is very interesting that CFOs pay very little attention to risk factors based on momentum and book-to-market value." Our empirical results, like the theoretical results by Stein (1996), support the use of the CAPM in capital budgeting, as long as the betas are measured from cash flows or long-term stock returns. Unlike Stein, however, our results also suggest that once a project is undertaken, the stock market values it approximately "right," that is, consistently with the model's present value calculation.

Shleifer and Vishny (2001) model merger and acquisition decisions and suggest that these transactions are motivated by acquirers (targets) being overpriced (underpriced). Their model makes the implicit assumption that deviations from fundamental values are economically significant. Our findings suggest that high book-to-market "fallen angels" within industries are not necessarily obvious takeover targets based on their valuations alone, because the average takeover premium and other transaction costs are an order of magnitude higher than the mispricing we detect (Bradley (1980)). At minimum, our results suggest that empirical tests of this valuation motive should carefully estimate the risk-adjusted price-level impact of any return predictability assumed to be due to market inefficiencies.

Our evidence is also directly relevant to the interpretation of Baker and Wurgler's (2002) empirical evidence on equity issues. Based on their finding that the historical sequence of past book-to-market ratios forecasts the capital structure far into the future, Baker and Wurgler argue that a firm's long-run capital structure is determined by the sequence of opportunistic equity issuance and share repurchase decisions. Our finding that firms' book-to-market ratios are associated with only modest levels of relative mispricing suggests that the benefits from this timing activity are small. If the benefits are small, the costs of deviating from the "optimal" capital structure must also be small, and the optimal capital structure must be well approximated by the Modigliani and Miller (1958) irrelevancy principle.

Appendix: How Mispricing Can Inflate Cross-sectional Beta Premium and R^2 Estimates

In this appendix, we argue that betas calculated with long-horizon returns can be hard-wired to make the CAPM look good in cross-sectional regressions. We show that under reasonable conditions, an arbitrary type of mispricing will increase the cross-sectional beta premium estimated from the data with a cross-sectional regression. Consequently, even if the CAPM is not the true model of market equilibrium (e.g., the true premium in an efficient market for beta risk would be zero), if the market is informationally inefficient we can expect to find a positive premium for beta risk and obtain artificially high R^2s in cross-sectional tests of the CAPM. We also argue that the effect is stronger at longer time horizons.

Consider an informationally efficient market. For each stock indexed by i,

$$\begin{aligned} k_i &\equiv \text{gross required return} \\ R_i &\equiv \text{gross realized return} \\ \beta_i &\equiv \text{beta (observed or estimated without error).} \end{aligned} \tag{A1}$$

Returns are expressed in gross units, that is, one plus net returns. For simplicity, assume that the cross-sectional mean of β_i is one.

We are interested in the cross-sectional premium for beta risk, λ_1, in the regression

$$E(R_i) = k_i = \lambda_0 + \lambda_1\beta_i. \tag{A2}$$

In an efficient market, a cross-sectional regression (without an error term) recovers this beta premium. Note that λ_0 is in gross return units and therefore normally greater than one but certainly larger than zero.

Let us now introduce mispricing into the market. Each stock is mispriced such that mispricing is resolved by the factor f_i, which is also assumed to have a mean of one. The expected (by an outside observer, not necessarily by any market participant) and realized returns on each stock are now given by

$$\begin{aligned} k_i' &\equiv f_i k_i \\ R_i' &\equiv f_i R_i, \end{aligned} \tag{A3}$$

where we denote variables observed in the world with mispricing with a prime. For simplicity, assume that f_i and β_i are independent and have nonzero variances and that the mispricing resolution does not correlate with market weights such that it would affect market returns. Therefore, $R_M' = R_M$.

In the world with mispricing, each firm's beta will be changed by its degree of mispricing:

$$\beta_i' = \frac{\text{cov}(R_i', R_M)}{\text{var}(R_M)} = \frac{\text{cov}(f_i R_i, R_M)}{\text{var}(R_M)} = f_i\frac{\text{cov}(R_i, R_M)}{\text{var}(R_M)} = f_i\beta_i. \tag{A4}$$

In the mispriced world we have an observed beta premium, λ_1':

$$k_i' = f_i k_i = \lambda_0' + \lambda_1'(f_i\beta_i) + \varepsilon_i', \tag{A5}$$

where λ_1' is chosen by a least-squares regression. We wish to show that $\lambda_1' > \lambda_1$.

Substituting $k_i = \lambda_0 + \lambda_1\beta_i$ in equation (A5) gives

$$f_i\lambda_0 + f_i\lambda_1\beta_i = \lambda_0' + \lambda_1'(f_i\beta_i) + \varepsilon_i'. \tag{A6}$$

Since we use a cross-sectional least squares regression to choose λ_1', we can split the above equation and λ_1' into two separate regressions. The first term of

λ_1' is the regression coefficient of $f_i\lambda_0$ on $f_i\beta_i$. The second term of λ_1' is a trivial regression of $f_i\lambda_1\beta_i$ on $f_i\beta_i$, which simply recovers the coefficient λ_1:

$$\lambda_1' = \lambda_0 \frac{\text{cov}(f, f\beta)}{\text{var}(f\beta)} + \lambda_1. \tag{A7}$$

Note that we drop i subscripts to underscore that the "cov" and "var" estimates are cross-sectional ones. At this point, the assumption that f and β are independent is useful, because it allows us to unambiguously sign the effect:

$$\begin{aligned}\frac{\text{cov}(f, f\beta)}{\text{var}(f\beta)} &= E(\beta)\frac{\text{var}(f)}{\text{var}(f\beta)} \\ &= E(\beta)\frac{\text{var}(f)}{E^2(\beta)\text{var}(f) + E^2(f)\text{var}(\beta) + \text{var}(f)\text{var}(\beta)} \\ &= \frac{\text{var}(f)}{\text{var}(f) + \text{var}(\beta) + \text{var}(f)\text{var}(\beta)} \\ &= \frac{1}{1 + \text{var}(\beta) + \dfrac{\text{var}(\beta)}{\text{var}(f)}},\end{aligned} \tag{A8}$$

since f and β have mean equal to one. Therefore,

$$\lambda_1' = \lambda_0 \frac{1}{1 + \text{var}(\beta) + \dfrac{\text{var}(\beta)}{\text{var}(f)}} + \lambda_1 > \lambda_1. \tag{A9}$$

The R^2 for the cross-sectional regression equation (A5) is $\text{var}^2(f_i)/[\text{var}(f_i\beta_i)\text{var}(f_i\lambda_0 + f_i\lambda_1\beta_i)]$.

Moreover, it is reasonable to assume that underlying β does not change with time horizon. In contrast, the variance of the mispricing resolution factor f likely increases with time horizon (more mispricing will be resolved in a year than, say, in a day) because the multi-period mispricing resolution factor is simply the product of one-period mispricing resolution factors: $R_{i,t}'R_{i,t+1}' \equiv f_{i,t}f_{i,t+1}R_{i,t}R_{i,t+1}$. Therefore, we conjecture that the longer the beta-estimation estimation horizon, the stronger the effect in the cross-sectional R^2.

Calibration of equation (A9) indicates that the effect is economically significant. Consider a world where the zero-beta rate is 2% per annum. A reasonable amount of cross-sectional variation in β might be 0.2, such that under a normal distribution 95% of firms have βs between 0.60 and 1.40. Let us further assume that the mispricing resolution factor has the following standard deviation: 0.050, 0.072, 0.105, and 0.126 for 1-year, 2-year, 5-year, and 10-year horizons. The relative magnitudes of these variances are proportional to the variance of the expected return component of Cohen et al.'s (2003) Table I at these horizons. These assumptions result in λ_1's of 5.99%, 11.79%, 23.63%, and 35.34% respectively, when λ_1, the true cross-sectional premium for β, is zero. More importantly, the cross-sectional R^2s grow with the horizon to be

5.64%, 10.47%, 17.56%, and 18.96% at the 1-year, 2-year, 5-year, and 10-year horizons.

REFERENCES

Baker, Malcolm, and Jeff Wurgler, 2002, Market timing and capital structure, *Journal of Finance* 57, 1–32.

Ball, Ray, and Philip Brown, 1969, Portfolio theory and accounting, *Journal of Accounting Research* 7, 300–323.

Bansal, Ravi, Robert F. Dittmar, and Christian T. Lundblad, 2005, Consumption, dividends, and the cross-section of equity returns, *Journal of Finance* 60, 1639–1672.

Beaver, William, Paul Kettler, and Myron Scholes, 1970, The association between market determined and accounting determined risk measures, *Accounting Review* 45, 654–682.

Black, Fisher, Michael C. Jensen, and Myron Scholes, 1972, The capital asset pricing model: Some empirical tests, in Michael Jensen, ed. *Studies in the Theory of Capital Markets* (Praeger, New York).

Bradley, Michael, 1980, Interfirm tender offers and the market for corporate control, *Journal of Business* 53, 345–376.

Brainard, William C., Matthew D. Shapiro, and John B. Shoven, 1991, Fundamental value and market value, in William C. Brainard, William D. Nordhaus, and Harold W. Watts, eds. *Money, Macroeconomics, and Economic Policy: Essays in Honor of James Tobin* (MIT Press, Cambridge, MA).

Campbell, John Y., 1991, A variance decomposition for stock returns, *Economic Journal* 101, 157–179.

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

Campbell, John Y., and Tuomo Vuolteenaho, 2004, Bad beta, good beta, *American Economic Review* 94, 1249–1275.

Cohen, Randolph B., Christopher Polk, and Tuomo Vuolteenaho, 2003, The value spread, *Journal of Finance* 58, 609–641.

Daniel, Kent, David Hirshleifer, and Avanidhar Subrahmanyam, 1998, Investor psychology and securities market under- and overreactions, *Journal of Finance* 53, 1839–1885.

Daniel, Kent, and Sheridan Titman, 1997, Evidence on the characteristics of cross-sectional variation in stock returns, *Journal of Finance* 52, 1–33.

Davis, James L., Eugene F. Fama, and Kenneth R. French, 2000, Characteristics, covariances, and average returns: 1929 to 1997, *Journal of Finance* 55, 389–406.

Dimson, Elroy, 1979, Risk measurement when shares are subject to infrequent trading, *Journal of Financial Economics* 7, 197–226.

Fama, Eugene F., 1970, Efficient capital markets, *Journal of Finance* 25, 383–417.

Fama, Eugene F., 1991, Efficient capital markets: II, *Journal of Finance* 46, 1575–1617.

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

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

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

Fama, Eugene F., and Kenneth R. French, 1996, Multifactor explanations of asset pricing anomalies, *Journal of Finance* 51, 55–84.

Fama, Eugene F., and James MacBeth, 1973, Risk, return, and equilibrium: Empirical tests, *Journal of Political Economy* 81, 607–636.

Gibbons, Michael R., Stephen A. Ross, and Jay Shanken, 1989, A test of the efficiency of a given portfolio, *Econometrica* 57, 1121–1152.

Graham, John R., and Campbell R. Harvey, 2001, The theory and practice of corporate finance: Evidence from the field, *Journal of Financial Economics* 60, 187–243.

Handa, Puneet, S. P. Kothari, and Charles Wasley, 1993, Sensitivity of multivariate tests of the capital asset pricing model to the return measurement interval, *Journal of Finance* 48, 1543–1551.

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

Hansen, Lars P., and Ravi Jagannathan, 1991, Implications of security market data for models of dynamic economies, *Journal of Political Economy* 99, 225–262.

Jensen, Michael C., 1978, Some anomalous evidence regarding market efficiency, *Journal of Financial Economics* 6, 95–101.

Kothari, S. P., Jay Shanken, and Richard G. Sloan, 1995, Another look at the cross-section of expected stock returns, *Journal of Finance* 50, 185–224.

Lakonishok, J., A. Shleifer, and R. W. Vishny, 1994, Contrarian investment, extrapolation, and risk, *Journal of Finance* 49, 1541–1578.

Lintner, John, 1965, The valuation of risk assets and the selection of risky investments in stock portfolios and capital budgets, *Review of Economics and Statistics* 47, 13–37.

MacKinlay, A. Craig, 1995, Multifactor models do not explain deviations from the Capital Asset Pricing Models, *Journal of Financial Economics* 38, 3–28.

Modigliani, Franco, and Merton H. Miller, 1958, The cost of capital, corporation finance, and the theory of investment, *American Economic Review* 48, 655–669.

Newey, Whitney K., and Kenneth D. West, 1987, A simple positive semi-definite heteroskedasticity and autocorrelation consistent covariance matrix, *Econometrica* 55, 703–708.

Rosenberg, Barr, Kenneth Reid, and Ronald Lanstein, 1985, Persuasive evidence of market inefficiency, *Journal of Portfolio Management* 11, 9–17.

Scholes, Myron, and Joseph Williams, 1977, Estimating betas from nonsynchronous data, *Journal of Financial Economics* 5, 309–327.

Sharpe, William F., 1964, Capital asset prices: A theory of market equilibrium under conditions of risk, *Journal of Finance* 19, 425–442.

Shleifer, Andrei, 2000, *Inefficient Markets: An Introduction to Behavioral Finance* (Oxford University Press).

Shleifer, Andrei, and Robert W. Vishny, 2001, Stock market driven acquisitions, Working paper 8439, NBER.

Shumway, Tyler, 1997, The delisting bias in CRSP data, *Journal of Finance* 52, 327–340.

Stein, Jeremy C., 1996, Rational capital budgeting in an irrational world, *Journal of Business* 69, 429–455.

Summers, Lawrence H., 1986, Does the stock market rationally reflect fundamental values? *Journal of Finance* 44, 1115–1153.

Vuolteenaho, Tuomo, 2001, Understanding the aggregate book-to-market ratio and its implications to current equity-premium expectations, Working paper, Harvard University Department of Economics.

Vuolteenaho, Tuomo, 2002, What drives firm-level returns? *Journal of Finance* 57, 233–264.