PART III

13

CHAPTER THIRTEEN

Empirical Evidence on Security Returns

IN THIS CHAPTER, we turn to the vast literature testing models of risk and return. The very existence of such a vast literature suggests a serious problem is involved—testing these models is not trivial. Indeed, an important part of the work here is to understand the challenges in doing so.

All models of capital asset pricing have two parts. First, they derive the optimal portfolio of an individual investor, conditional on a utility function (describing how an investor trades off risk against expected return) and an input list that includes estimates of portfolio expected returns and risk. Second, they derive predictions about expected returns on capital assets in equilibrium, when investors complete the trades necessary to arrive at their personal optimal portfolios.

Obviously, the flow of new information alone will change input lists and thus desired portfolios. Here is where the efficient market hypothesis (EMH) kicks in. If asset prices reflect all available information, then *changes* of asset prices resulting from new information will have zero means, that is, prices will follow random walks.[1] The response to new information will introduce noise around the predictions of the model, but by itself this should not cause any difficulty that cannot be overcome with appropriate statistical methods and lots of data. But when the EMH is off, even temporarily, by economically significant margins, changes in prices and expected returns will not change randomly and model predictions can be affected. This is why a test of an asset pricing model is of necessity a joint test of the EMH.

The single-factor CAPM has one key implication that can be expressed in either of two ways: The market portfolio is mean-variance efficient, and (equivalently) the risk premium (expected excess return) on each individual asset is proportional to its beta, $E(R_i) = \beta_i E(R_M)$. The first statement is, in practice, untestable because we do not observe the market portfolio. However, if a broad index is sufficiently well diversified, even if not mean-variance efficient, it may nevertheless support the mean-beta relationship (the SML) using the arguments of the APT.

Testing the ex-ante mean-variance efficiency of a particular market index can never

[1] Actually, prices will show an upward drift since expected rates of return are positive. But over short time horizons, this drift is trivial compared to volatility. For example, at a daily horizon, the expected rate of return is around 5 basis points (corresponding to an annual return of 12%). The daily standard deviation of stock prices is an order of magnitude higher, typically exceeding 2% for individual stocks.

(concluded)

be a conclusive test of the CAPM. In any sample, there always is an ex-post efficient portfolio that will never be identical to the index. How do we measure "distance from efficiency," and what would constitute a rejection of the model? Given these difficulties, the mean-beta equation has been the test arena of most research. However, most of these tests are better interpreted as tests of the APT (rather than the CAPM) since we know from the outset that the index may not be mean-variance efficient but may nevertheless be well-diversified.

We begin with tests of the single-factor security market line, the theater where the basic methodologies have been developed, and then proceed to multifactor models with emphasis on the empirically motivated Fama-French three-factor model. We show how this research may be interpreted as tests of Merton's multifactor ICAPM. We end this part of the chapter with a section that brings liquidity into the empirical framework. We devote a section to the theoretically appealing consumption CAPM in order to present the equity premium puzzle, and end with an assessment of where research into asset pricing is headed.

13.1 The Index Model and the Single-Factor APT

The Expected Return–Beta Relationship

Recall that if the expected return–beta relationship holds with respect to an observable ex ante efficient index, *M,* the expected rate of return on any security *i* is

$$E(r_i) = r_f + \beta_i[E(r_M) - r_f] \tag{13.1}$$

where β_i is defined as $\text{Cov}(r_i, r_M)/\sigma_M^2$.

This is the most commonly tested implication of the CAPM. Early simple tests followed three basic steps: establishing sample data, estimating the SCL (security characteristic line), and estimating the SML (security market line).

Setting Up the Sample Data Determine a sample period of, for example, 60 monthly holding periods (5 years). For each of the 60 holding periods, collect the rates of return on 100 stocks, a market portfolio proxy (e.g., the S&P 500), and 1-month (risk-free) T-bills. Your data thus consist of

r_{it} = 6,000 returns on the 100 stocks over the 60-month sample period; $i = 1, \ldots, 100$, and $t = 1, \ldots, 60$.

r_{Mt} = 60 observations of the returns on the S&P 500 index over the sample period (one each month).

r_{ft} = 60 observations of the risk-free rate (one each month).

This constitutes a table of $102 \times 60 = 6{,}120$ rates of return.

Estimating the SCL View Equation 13.1 as a security characteristic line (SCL), as in Chapter 8. For each stock, *i,* you estimate the beta coefficient as the slope of a **first-pass regression** equation. (The terminology *first-pass* regression is due to the fact that the estimated coefficients will be used as input into a **second-pass regression.**)

$$r_{it} - r_{ft} = a_i + b_i(r_{Mt} - r_{ft}) + e_{it}$$

You will use the following statistics in later analysis:

$\overline{r_i - r_f}$ = Sample averages (over the 60 observations) of the excess return on each of the 100 stocks.

b_i = Sample estimates of the beta coefficients of each of the 100 stocks.

$\overline{r_M - r_f}$ = Sample average of the excess return of the market index.

$\sigma^2(e_i)$ = Estimates of the variance of the residuals for each of the 100 stocks.

The sample average excess returns on each stock and the market portfolio are taken as estimates of expected excess returns, and the values of b_i are estimates of the true beta coefficients for the 100 stocks during the sample period. $\sigma^2(e_i)$ estimates the nonsystematic risk of each of the 100 stocks. It is understood that all these statistics include estimation errors.

CONCEPT CHECK 13.1

a. How many regression estimates of the SCL do we have from the sample?

b. How many observations are there in each of the regressions?

c. According to the CAPM, what should be the intercept in each of these regressions?

Estimating the SML Now view Equation 13.1 as a security market line (SML) with 100 observations for the stocks in your sample. You can estimate γ_0 and γ_1 in the following second-pass regression equation with the estimates b_i from the first pass as the independent variable:

$$\overline{r_i - r_f} = \gamma_0 + \gamma_1 b_i \qquad i = 1, \ldots, 100 \tag{13.2}$$

Compare Equations 13.1 and 13.2; you should conclude that if the CAPM is valid, then γ_0 and γ_1 should satisfy

$$\gamma_0 = 0 \text{ and } \gamma_1 = \overline{r_M - r_f}$$

In fact, however, you can go a step further and argue that the key property of the expected return–beta relationship described by the SML is that the expected excess return on securities is determined *only* by the systematic risk (as measured by beta) and should be independent of the nonsystematic risk, as measured by the variance of the residuals, $\sigma^2(e_i)$, which also were estimated from the first-pass regression. These estimates can be added as a variable in Equation 13.2 of an expanded SML that now looks like this:

$$\overline{r_i - r_f} = \gamma_0 + \gamma_1 b_i + \gamma_2 \sigma^2(e_i) \tag{13.3}$$

This *second-pass* regression equation is estimated with the hypotheses

$$\gamma_0 = 0; \;\; \gamma_1 = \overline{r_M - r_f}; \;\; \gamma_2 = 0$$

The hypothesis that $\gamma_2 = 0$ is consistent with the notion that nonsystematic risk should not be "priced," that is, that there is no risk premium earned for bearing nonsystematic risk. More generally, according to the CAPM, the risk premium depends only on beta. Therefore, *any* additional right-hand-side variable in Equation 13.3 beyond beta should have a coefficient that is insignificantly different from zero in the second-pass regression.

Tests of the CAPM

Early tests of the CAPM performed by John Lintner,[2] and later replicated by Merton Miller and Myron Scholes,[3] used annual data on 631 NYSE stocks for 10 years, 1954 to 1963, and produced the following estimates (with returns expressed as decimals rather than percentages):

Coefficient:	$\gamma_0 = .127$	$\gamma_1 = .042$	$\gamma_2 = .310$
Standard error:	.006	.006	.026
Sample average:		$\overline{r_M - r_f} = .165$	

These results are inconsistent with the CAPM. First, the estimated SML is "too flat"; that is, the γ_1 coefficient is too small. The slope should equal $\overline{r_M - r_f} = .165$ (16.5% per year), but it is estimated at only .042. The difference, .122, is about 20 times the standard error of the estimate, .006, which means that the measured slope of the SML is less than it should be by a statistically significant margin. At the same time, the intercept of the estimated SML, γ_0, which is hypothesized to be zero, in fact equals .127, which is more than 20 times its standard error of .006.

CONCEPT CHECK 13.2

a. What is the implication of the empirical SML being "too flat"?
b. Do high- or low-beta stocks tend to outperform the predictions of the CAPM?
c. What is the implication of the estimate of γ_2?

The two-stage procedure employed by these researchers (i.e., first estimate security betas using a time-series regression and then use those betas to test the SML relationship between risk and average return) seems straightforward, and the rejection of the CAPM using this approach is disappointing. However, it turns out that there are several difficulties with this approach. First and foremost, stock returns are extremely volatile, which lessens the precision of any tests of average return. For example, the average standard deviation of annual returns of the stocks in the S&P 500 is about 40%; the average standard deviation of annual returns of the stocks included in these tests is probably even higher.

In addition, there are fundamental concerns about the validity of the tests. First, the market index used in the tests is surely not the "market portfolio" of the CAPM. Second, in light of asset volatility, the security betas from the first-stage regressions are necessarily estimated with substantial sampling error and therefore cannot readily be used as inputs to the second-stage regression. Finally, investors cannot borrow at the risk-free rate, as assumed by the simple version of the CAPM. Let us investigate the implications of these problems in turn.

The Market Index

In what has come to be known as *Roll's critique,* Richard Roll[4] pointed out that:

1. There is a single testable hypothesis associated with the CAPM: The market portfolio is mean-variance efficient.
2. All the other implications of the model, the best-known being the linear relation between expected return and beta, follow from the market portfolio's efficiency

[2]John Lintner, "Security Prices, Risk and Maximal Gains from Diversification," *Journal of Finance* 20 (December 1965).

[3]Merton H. Miller and Myron Scholes, "Rate of Return in Relation to Risk: A Reexamination of Some Recent Findings," in *Studies in the Theory of Capital Markets,* ed. Michael C. Jensen (New York: Praeger, 1972).

[4]Richard Roll, "A Critique of the Asset Pricing Theory's Tests: Part I: On Past and Potential Testability of the Theory," *Journal of Financial Economics* 4 (1977).

and therefore are not independently testable. There is an "if and only if" relation between the expected return–beta relationship and the efficiency of the market portfolio.

3. In any sample of observations of individual returns there will be an infinite number of ex post (i.e., after the fact) mean-variance efficient portfolios using the sample-period returns and covariances (as opposed to the ex ante *expected* returns and covariances). Sample betas of individual assets estimated against each such ex-post efficient portfolio will be exactly linearly related to the sample average returns of these assets. In other words, if betas are calculated against such portfolios, they will satisfy the SML relation exactly whether or not the true market portfolio is mean-variance efficient in an ex ante sense.
4. The CAPM is not testable unless we know the exact composition of the true market portfolio and use it in the tests. This implies that the theory is not testable unless *all* individual assets are included in the sample.
5. Using a proxy such as the S&P 500 for the market portfolio is subject to two difficulties. First, the proxy itself might be mean-variance efficient even when the true market portfolio is not. Conversely, the proxy may turn out to be inefficient, but obviously this alone implies nothing about the true market portfolio's efficiency. Furthermore, most reasonable market proxies will be very highly correlated with each other and with the true market portfolio whether or not they are mean-variance efficient. Such a high degree of correlation will make it seem that the exact composition of the market portfolio is unimportant, whereas the use of different proxies can lead to quite different conclusions. This problem is referred to as **benchmark error,** because it refers to the use of an incorrect benchmark (market proxy) portfolio in the tests of the theory.

Roll and Ross[5] and Kandel and Stambaugh[6] expanded Roll's critique. Essentially, they argued that tests that reject a positive relationship between average return and beta point to inefficiency of the market proxy used in those tests, rather than refuting the theoretical expected return–beta relationship. They demonstrate that even if the CAPM is true, highly diversified portfolios, such as the value- or equally weighted portfolios of all stocks in the sample, may fail to produce a significant average return–beta relationship.

Kandel and Stambaugh considered the properties of the usual two-pass test of the CAPM in an environment in which borrowing is restricted but the zero-beta version of the CAPM holds. In this case, you will recall that the expected return–beta relationship describes the expected returns on a stock, a portfolio E on the efficient frontier, and that portfolio's zero-beta companion, Z (see Equation 9.12):

$$E(r_i) - E(r_Z) = \beta_i[E(r_E) - E(r_Z)] \tag{13.4}$$

where β_i denotes the beta of security i on efficient portfolio E.

We cannot construct or observe the efficient portfolio E (because we do not know expected returns and covariances of all assets), and so we cannot estimate Equation 13.4 directly. Kandel and Stambaugh asked what would happen if we followed the common procedure of using a market proxy portfolio M in place of E, and used as well the more

[5]Richard Roll and Stephen A. Ross, "On the Cross-Sectional Relation between Expected Return and Betas," *Journal of Finance* 50 (1995), pp. 185–224.

[6]Schmuel Kandel and Robert F. Stambaugh, "Portfolio Inefficiency and the Cross-Section of Expected Returns," *Journal of Finance* 50 (1995), pp. 185–224; "A Mean-Variance Framework for Tests of Asset Pricing Models," *Review of Financial Studies* 2 (1989), pp. 125–56; "On Correlations and Inferences about Mean-Variance Efficiency," *Journal of Financial Economics* 18 (1987), pp. 61–90.

efficient generalized least squares regression procedure in estimating the second-pass regression for the zero-beta version of the CAPM, that is,

$$r_i - r_Z = \gamma_0 + \gamma_1 \times (\text{Estimated } \beta_i)$$

They showed that the estimated values of γ_0 and γ_1 will be biased by a term proportional to the relative efficiency of the market proxy. If the market index used in the regression is fully efficient, the test will be well specified. But the second-pass regression will provide a poor test of the CAPM if the proxy for the market portfolio is not efficient. Thus, we still cannot test the model in a meaningful way without a reasonably efficient market proxy. Unfortunately, it is impossible to determine how efficient our market index is, so we cannot tell how good our tests are.

Given the impossibility of testing the CAPM directly, we can retreat to testing the APT, which produces the same mean-beta equation (the security market line).[7] This model depends only on the index portfolio being well diversified. Choosing a broad market index allows us to test the SML as applied to the chosen index.

Measurement Error in Beta

It is well known in statistics that if the right-hand-side variable of a regression equation is measured with error (in our case, beta is measured with error and is the right-hand-side variable in the second-pass regression), then the slope coefficient of the regression equation will be biased downward and the intercept biased upward. This is consistent with the findings cited above; γ_0 was higher than predicted by the CAPM and γ_1 was lower than predicted.

Indeed, a well-controlled simulation test by Miller and Scholes[8] confirms these arguments. In this test a random-number generator simulated rates of return with covariances similar to observed ones. The average returns were made to agree exactly with the CAPM. Miller and Scholes then used these randomly generated rates of return in the tests we have described as if they were observed from a sample of stock returns. The results of this "simulated" test were virtually identical to those reached using real data, despite the fact that the simulated returns were *constructed* to obey the SML, that is, the true γ coefficients were $\gamma_0 = 0$, $\gamma_1 = \overline{r_M - r_f}$, and $\gamma_2 = 0$.[9]

This postmortem of the early test gets us back to square one. We can explain away the disappointing test results, but we have no positive results to support the CAPM-APT implications.

The next wave of tests was designed to overcome the measurement error problem that led to biased estimates of the SML. The innovation in these tests, pioneered by Black, Jensen, and Scholes,[10] was to use portfolios rather than individual securities. Combining securities into portfolios diversifies away most of the firm-specific part of returns, thereby

[7]Although the APT strictly applies only to well-diversified portfolios, the discussion in Chapter 9 shows that optimization in a single-index market as prescribed by Treynor and Black will generate strong pressure on single securities to satisfy the mean-beta equation as well.

[8]Miller and Scholes, "Rate of Return in Relation to Risk."

[9]In statistical tests, there are two possible errors: Type I and Type II. A Type I error means that you reject a null hypothesis (for example, a hypothesis that beta does not affect expected returns) when it is actually true. This is sometimes called a *false positive,* in which you incorrectly decide that a relationship exists when it actually does not. The probability of this error is called the *significance* level of the test statistic. Thresholds for rejection of the null hypothesis are usually chosen to limit the probability of Type I error to below 5%. Type II error is a false negative, in which a relationship actually does exist, but you fail to detect it. The *power* of a test equals (1 − probability of Type II). Miller and Scholes's experiment showed that early tests of the CAPM had low power.

[10]Fischer Black, Michael C. Jensen, and Myron Scholes, "The Capital Asset Pricing Model: Some Empirical Tests," in *Studies in the Theory of Capital Markets,* ed. Michael C. Jensen (New York: Praeger, 1972).

enhancing the precision of the estimates of beta and the expected rate of return of the portfolio of securities. This mitigates the statistical problems that arise from measurement error in the beta estimates.

Testing the model with diversified portfolios rather than individual securities completes our retreat to the APT. Additionally, combining stocks into portfolios reduces the number of observations left for the second-pass regression. Suppose we group the 100 stocks into five portfolios of 20 stocks each. If the residuals of the 20 stocks in each portfolio are practically uncorrelated, the variance of the portfolio residual will be about one-twentieth the residual variance of the average stock. Thus the portfolio beta in the first-pass regression will be estimated with far better accuracy. However, with portfolios of 20 stocks each, we are left with only five observations for the second-pass regression.

To get the best of this trade-off, we need to construct portfolios with the largest possible dispersion of beta coefficients. Other things equal, a regression yields more accurate estimates the more widely spaced the observations of the independent variables. We therefore will attempt to maximize the range of the independent variable of the second-pass regression, the portfolio betas. Rather than allocate 20 stocks to each portfolio randomly, we first rank stocks by betas. Portfolio 1 is formed from the 20 highest-beta stocks and portfolio 5 the 20 lowest-beta stocks. A set of portfolios with small nonsystematic components, e_P, and widely spaced betas will yield reasonably powerful tests of the SML.

Fama and MacBeth (FM)[11] used this methodology to verify that the observed relationship between average excess returns and beta is indeed linear and that nonsystematic risk does not explain average excess returns. Using 20 portfolios constructed according to the Black, Jensen, and Scholes methodology, FM expanded the estimation of the SML equation to include the square of the beta coefficient (to test for linearity of the relationship between returns and betas) and the estimated standard deviation of the residual (to test for the explanatory power of nonsystematic risk). For a sequence of many subperiods, they estimated for each subperiod the equation

$$r_i = \gamma_0 + \gamma_1\beta_i + \gamma_2\beta_i^2 + \gamma_3\sigma(e_i) \tag{13.5}$$

The term γ_2 measures potential nonlinearity of return, and γ_3 measures the explanatory power of nonsystematic risk, $\sigma(e_i)$. According to the CAPM, both γ_2 and γ_3 should have coefficients of zero in the second-pass regression.

FM estimated Equation 13.5 for every month of the period January 1935 through June 1968. The results are summarized in Table 13.1, which shows average coefficients and *t*-statistics for the overall period as well as for three subperiods. FM observed that the coefficients on residual standard deviation (nonsystematic risk), denoted by γ_3, fluctuated greatly from month to month, and its *t*-statistics were insignificant despite large average values. Thus, the overall test results were reasonably favorable to the security market line of the CAPM (or perhaps more accurately of the APT that FM actually tested). But time has not been favorable to the CAPM since.

Recent replications of the FM test show that results deteriorate in later periods (since 1968). Worse, even for the FM period, 1935–1968, when the equally weighted

CONCEPT CHECK 13.3

a. According to the CAPM and the data in Table 13.1, what are the predicted values of γ_0, γ_1, γ_2, and γ_3 in the Fama-MacBeth regressions for the period 1946–1955?

b. What would you conclude if you performed the Fama and MacBeth tests and found that the coefficients on β^2 and $\sigma(e)$ were positive?

[11] Eugene Fama and James MacBeth, "Risk, Return, and Equilibrium: Empirical Tests," *Journal of Political Economy* 81 (March 1973).

Table 13.1

Summary of Fama and MacBeth (1973) study (all rates in basis points per month)

Period	1935/6–1968	1935–1945	1946–1955	1956/6–1968
Av. r_f	13	2	9	26
Av. $\gamma_0 - r_f$	8	10	8	5
Av. $t(\gamma_0 - r_f)$	0.20	0.11	0.20	0.10
Av. $r_M - r_f$	130	195	103	95
Av. γ_1	114	118	209	34
Av. $t(\gamma_1)$	1.85	0.94	2.39	0.34
Av. γ_2	−26	−9	−76	0
Av. $t(\gamma_2)$	−0.86	−0.14	−2.16	0
Av. γ_3	516	817	−378	960
Av. $t(\gamma_3)$	1.11	0.94	−0.67	1.11
Av. R-SQR	0.31	0.31	0.32	0.29

NYSE-stock portfolio they used as the market index is replaced with the more appropriate value-weighted index, results turn against the model. In particular, the slope of the SML clearly is too flat.

13.2 Tests of the Multifactor CAPM and APT

Three types of factors are likely candidates to augment the market risk factor in a multifactor SML: (1) Factors that hedge consumption against uncertainty in prices of important consumption categories (e.g., housing or energy) or general inflation; (2) factors that hedge future investment opportunities (e.g., interest rates or the market risk premium); and (3) factors that hedge assets missing from the market index (e.g., labor income or private business).

As we learned from Merton's ICAPM (Chapter 9), these extra-market sources of risk will command a risk premium if there is significant demand to hedge them. We begin with the third source because there is little doubt that nontraded assets in the personal portfolios of investors affect demand for traded risky assets. Hence, a factor representing these assets, that is, one correlated with their returns, should affect risk premiums.

Labor Income

The major factors in the omitted asset category are labor income and private business. Taking on labor income first, Mayers[12] viewed each individual as being endowed with labor income but able to trade only securities and an index portfolio. His model creates a wedge between betas measured against the traded, index portfolio and betas measured against the true market portfolio, which includes aggregate labor income. The result of his model is an SML that is flatter than the simple CAPM's. Most of this income is positively correlated with the market index, and it has substantial value compared to the market value of the securities in the market index. Its absence from the index pushes the slope

[12] David Mayers, "Nonmarketable Assets and Capital Market Equilibrium under Uncertainty," in *Studies in the Theory of Capital Markets,* ed. Michael C. Jensen (New York: Praeger, 1972), pp. 223–48.

of the observed SML (return vs. beta measured against the index) below the return of the index portfolio.[13]

If the value of labor income is not perfectly correlated with the market-index portfolio, then the possibility of negative returns to labor will represent a source of risk not fully captured by the index. But suppose investors can trade a portfolio that is correlated with the return on aggregate human capital. Then their hedging demands against the risk to the value of their human capital might meaningfully influence security prices and risk premia. If so, human capital risk (or some empirical proxy for it) can serve as an additional factor in a multifactor SML. Stocks with a positive beta on the value of labor exaggerate exposure to this risk factor; therefore, they will command lower prices, or equivalently, provide a larger-than-CAPM risk premium. Thus, by adding this factor, the SML becomes multidimensional.

Jagannathan and Wang[14] used the rate of change in aggregate labor income as a proxy for changes in the value of human capital. In addition to the standard security betas estimated using the value-weighted stock market index, which we denote β^{vw}, they also estimated the betas of assets with respect to labor income growth, which we denote β^{labor}. Finally, they considered the possibility that business cycles affect asset betas, an issue that has been examined in a number of other studies.[15] These may be viewed as *conditional* betas, as their values are conditional on the state of the economy. Jagannathan and Wang used the spread between the yields on low- and high-grade corporate bonds as a proxy for the state of the business cycle and estimate asset betas relative to this business cycle variable; we denote this beta as β^{prem}. With the estimates of these three betas for several stock portfolios, Jagannathan and Wang estimated a second-pass regression which includes firm size (market value of equity, denoted ME):

$$E(R_i) = c_0 + c_{size}\log(\text{ME}) + c_{vw}\beta^{vw} + c_{prem}\beta^{prem} + c_{labor}\beta^{labor} \tag{13.6}$$

Jagannathan and Wang test their model with 100 portfolios that are designed to spread securities on the basis of size and beta. Stocks are sorted into 10 size portfolios, and the stocks within each size decile are further sorted by beta into 10 subportfolios, resulting in 100 portfolios in total. Table 13.2 shows a subset of the various versions of the second-pass estimates. The first two rows in the table show the coefficients and *t*-statistics of a test of the CAPM along the lines of the Fama and MacBeth tests introduced in the previous section. The result is a sound rejection of the model, as the coefficient on beta is negative, albeit not significant.

The next two rows show that the model is not helped by the addition of the size factor. The dramatic increase in *R*-square (from 1.35% to 57%) shows that size explains variations in average returns quite well while beta does not. Substituting the default premium and labor income for size (panel B) results in a similar increase in explanatory power (*R*-square of 55%), but the CAPM expected return–beta relationship is not redeemed. The default premium is significant, while labor income is borderline significant. When we add size as

[13]Asset betas on the index portfolio are likely positively correlated with their betas on the omitted asset (for example, aggregate labor income). Therefore, the coefficient on asset beta in the SML regression (of returns on index beta) will be downward biased, resulting in a slope smaller than average R_M. In Equation 9.13 the observed beta of most assets will be larger than the true beta whenever $\beta_{iM} > \beta_{iH}\dfrac{\sigma_H^2}{\sigma_M^2}$.

[14]Ravi Jagannathan and Zhenyu Wang, "The Conditional CAPM and the Cross-Section of Expected Returns," *Journal of Finance* 51 (March 1996), pp. 3–54.

[15]For example, Campbell Harvey, "Time-Varying Conditional Covariances in Tests of Asset Pricing Models," *Journal of Financial Economics* 24 (October 1989), pp. 289–317; Wayne Ferson and Campbell Harvey, "The Variation of Economic Risk Premiums," *Journal of Political Economy* 99 (April 1991), pp. 385–415; and Wayne Ferson and Robert Korajczyk, "Do Arbitrage Pricing Models Explain the Predictability of Stock Returns?" *Journal of Business* 68 (July 1995), pp. 309–49.

Coefficient	c_0	c_{vw}	c_{prem}	c_{labor}	c_{size}	R^2
A. The Static CAPM without Human Capital						
Estimate	1.24	−0.10				1.35
t-value	5.16	−0.28				
Estimate	2.08	−0.32			−0.11	57.56
t-value	5.77	−0.94			−2.30	
B. The Conditional CAPM with Human Capital						
Estimate	1.24	−0.40	0.34	0.22		55.21
t-value	4.10	−0.88	1.73	2.31		
Estimate	1.70	−0.40	0.20	0.10	−0.07	64.73
t-value	4.14	−1.06	2.72	2.09	−1.30	

Table 13.2

Evaluation of various CAPM specifications

This table gives the estimates for the cross-sectional regression model

$$E(R_{it}) = c_0 + c_{size}\log(ME_i) + c_{vw}\beta_i^{vw} + c_{prem}\beta_i^{prem} + c_{labor}\beta_i^{labor}$$

with either a subset or all of the variables. Here, R_{it} is the return on portfolio i ($i = 1, 2, \ldots, 100$) in month t (July 1963–December 1990), R_t^{vw} is the return on the value-weighted index of stocks, R_{t-1}^{prem} is the yield spread between low- and high-grade corporate bonds, and R_t^{labor} is the growth rate in per capita labor income. The β_i^{vw} is the slope coefficient in the OLS regression of R_{it} on a constant and R_t^{vw}. The other betas are estimated in a similar way. The portfolio size, log(ME_i), is calculated as the equally weighted average of the logarithm of the market value (in millions of dollars) of the stocks in portfolio *i*. The regression models are estimated by using the Fama-MacBeth procedure. The "corrected *t*-values" take sampling errors in the estimated betas into account. All R^2s are reported as percentages.

well, in the last two rows, we find it is no longer significant and only marginally increases explanatory power.

Despite the clear rejection of the CAPM, we do learn two important facts from Table 13.2. First, conventional first-pass estimates of security betas are greatly deficient. They clearly do not fully capture the cyclicality of stock returns and thus do not accurately measure the systematic risk of stocks. This actually can be interpreted as good news for the CAPM in that it may be possible to replace the simple beta with better estimates of systematic risk and transfer the explanatory power of instrumental variables such as size and the default premium to the index rate of return. Second, and more relevant to the work of Jagannathan and Wang, is the conclusion that human capital will be important in any version of the CAPM that better explains the systematic risk of securities.

Private (Nontraded) Business

Whereas Jagannathan and Wang focus on labor income, Heaton and Lucas[16] estimate the importance of proprietary business. We expect that private-business owners will reduce demand for traded securities that are positively correlated with their specific entrepreneurial income. If this effect is sufficiently important, aggregate demand for traded securities will be determined in part by the covariance with aggregate noncorporate business income. The risk premium on securities with high covariance with noncorporate business income should be commensurately higher.

[16]John Heaton and Debora Lucas, "Portfolio Choice and Asset Prices: The Importance of Entrepreneurial Risk," *Journal of Finance* 55, no. 3 (June 2000), pp. 1163–98.

Consistent with theory, Heaton and Lucas find that households with higher investments in private business do in fact reduce the fraction of total wealth invested in equity. Table 13.3 presents excerpts from their regression analysis, in which allocation of the overall portfolio to stocks is the dependent variable. The share of private business in total wealth (labeled "relative business") receives negative and statistically significant coefficients in these regressions. Notice also the negative and significant coefficient on risk attitude based on a self-reported degree of risk aversion.

Finally, Heaton and Lucas extend Jagannathan and Wang's equation to include the rate of change in proprietary-business wealth. They find that this variable also is significant and improves the explanatory power of the regression. Here, too, the market rate of return does not help explain the rate of return on individual securities and, hence, this implication of the CAPM still must be rejected.

Early Versions of the Multifactor CAPM and APT

The multifactor CAPM and APT are elegant theories of how exposure to systematic risk factors should influence expected returns, but they provide little guidance concerning which factors (sources of risk) ought to result in risk premiums. A test of this hypothesis would require three stages:

Table 13.3

Determinants of stockholdings

	Share of Stock in Assets		
	Stock Relative to Liquid Assets	**Stock Relative to Financial Assets**	**Stock Relative to Total Assets**
Intercept	0.71	0.53	0.24
	(14.8)	(21.28)	(10.54)
Total income $\times 10^{-10}$	−1.80	−.416	−1.72
	(−0.435)	(−0.19)	(−0.85)
Net worth $\times 10^{-10}$	2.75	5.04	7.37
	(0.895)	(3.156)	(5.02)
Relative business	−0.14	−0.50	−0.32
	(−4.34)	(−29.31)	(−20.62)
Age of respondent	-7.94×10^{-4}	-6.99×10^{-5}	2.44×10^{-3}
	(−1.26)	(−0.21)	(−4.23)
Risk attitude	−0.05	−0.02	−0.02
	(−4.74)	(−3.82)	(−4.23)
Relative mortgage	0.05	0.43	0.30
	(1.31)	(20.90)	(16.19)
Relative pension	0.07	−0.41	−0.31
	(1.10)	(−11.67)	(−9.60)
Relative real estate	−0.04	−0.44	−0.31
	(−1.41)	(−27.00)	(−20.37)
Adjusted *R*-square	0.03	0.48	0.40

Note: *t*-statistics in parentheses.
Source: John Heaton and Debora Lucas, "Portfolio Choice and Asset Prices: The Importance of Entrepreneurial Risk," *Journal of Finance* 55, no. 3 (June 2000), pp. 1163–98. Reprinted by permission of the publisher, Blackwell Publishing, Inc.

1. Specification of risk factors.
2. Identification of portfolios that hedge these fundamental risk factors.
3. Test of the explanatory power and risk premiums of the hedge portfolios.

A Macro Factor Model

Chen, Roll, and Ross[17] identify several possible variables that might proxy for systematic factors:

IP = Growth rate in industrial production.
EI = Changes in expected inflation measured by changes in short-term (T-bill) interest rates.
UI = Unexpected inflation defined as the difference between actual and expected inflation.
CG = Unexpected changes in risk premiums measured by the difference between the returns on corporate Baa-rated bonds and long-term government bonds.
GB = Unexpected changes in the term premium measured by the difference between the returns on long- and short-term government bonds.

With the identification of these potential economic factors, Chen, Roll, and Ross skipped the procedure of identifying factor portfolios (the portfolios that have the highest correlation with the factors). Instead, by using the factors themselves, they implicitly assumed that factor portfolios exist that can proxy for the factors. They use these factors in a test similar to that of Fama and MacBeth.

A critical part of the methodology is the grouping of stocks into portfolios. Recall that in the single-factor tests, portfolios were constructed to span a wide range of betas to enhance the power of the test. In a multifactor framework the efficient criterion for grouping is less obvious. Chen, Roll, and Ross chose to group the sample stocks into 20 portfolios by size (market value of outstanding equity), a variable that is known to be associated with average stock returns.

They first used 5 years of monthly data to estimate the factor betas of the 20 portfolios in 20 first-pass regressions.

$$r = a + \beta_M r_M + \beta_{\mathrm{IP}}\mathrm{IP} + \beta_{\mathrm{EI}}\mathrm{EI} + \beta_{\mathrm{UI}}\mathrm{UI} + \beta_{\mathrm{CG}}\mathrm{CG} + \beta_{\mathrm{GB}}\mathrm{GB} + e \tag{13.7a}$$

where M stands for the stock market index. Chen, Roll, and Ross used as the market index both the value-weighted NYSE index (VWNY) and the equally weighted NYSE index (EWNY).

Using the 20 sets of first-pass estimates of factor betas as the independent variables, they now estimated the second-pass regression (with 20 observations):

$$r = \gamma_0 + \gamma_M\beta_M + \gamma_{\mathrm{IP}}\beta_{\mathrm{IP}} + \gamma_{\mathrm{EI}}\beta_{\mathrm{EI}} + \gamma_{\mathrm{UI}}\beta_{\mathrm{UI}} + \gamma_{\mathrm{CG}}\beta_{\mathrm{CG}} + \gamma_{\mathrm{GB}}\beta_{\mathrm{GB}} + e \tag{13.7b}$$

where the gammas become estimates of the risk premiums on the factors.

Chen, Roll, and Ross ran this second-pass regression for every month of their sample period, reestimating the first-pass factor betas once every 12 months. The estimated risk premiums (the values for the parameters, γ) were averaged over all the second-pass regressions.

Note in Table 13.4 that the two market indexes EWNY and VWNY are not statistically significant (their t-statistics of 1.218 and $-.633$ are less than 2). Note also that the VWNY

[17] Nai-Fu Chen, Richard Roll, and Stephen Ross, "Economic Forces and the Stock Market," *Journal of Business* 59 (1986).

Table 13.4

Economic variables and pricing (percent per month × 10), multivariate approach

A	EWNY	IP	EI	UI	CG	GB	Constant
	5.021	14.009	−0.128	−0.848	0.130	−5.017	6.409
	(1.218)	(3.774)	(−1.666)	(−2.541)	(2.855)	(−1.576)	(1.848)
B	**VWNY**	**IP**	**EI**	**UI**	**CG**	**GB**	**Constant**
	−2.403	11.756	−0.123	−0.795	8.274	−5.905	10.713
	(−0.633)	(3.054)	(−1.600)	(−2.376)	(2.972)	(−1.879)	(2.755)

VWNY = Return on the value-weighted NYSE index; EWNY = Return on the equally weighted NYSE index; IP = Monthly growth rate in industrial production; EI = Change in expected inflation; UI = Unanticipated inflation; CG = Unanticipated change in the risk premium (Baa and under return − Long-term government bond return); GB = Unanticipated change in the term structure (long-term government bond return − Treasury-bill rate); Note that *t*-statistics are in parentheses.

Source: Modified from Nai-Fu Chen, Richard Roll, and Stephen Ross, "Economic Forces and the Stock Market," *Journal of Business* 59 (1986). Reprinted by permission of the publisher, The University of Chicago Press.

factor has the "wrong" sign in that it seems to imply a negative market-risk premium. Industrial production (IP), the risk premium on corporate bonds (CG), and unanticipated inflation (UI) are the factors that appear to have significant explanatory power.

13.3 Fama-French-Type Factor Models

The multifactor models that currently occupy center stage are the three-factor models introduced by Fama and French (FF) and its close relatives.[18] The systematic factors in the FF model are firm size and book-to-market ratio (B/M) as well as the market index. These additional factors are empirically motivated by the observations, documented in Chapter 11, that historical-average returns on stocks of small firms and on stocks with high ratios of book equity to market equity (B/M) are higher than predicted by the security market line of the CAPM.

However, Fama and French did more than document the empirical role of size and B/M in explaining rates of return. They also introduced a general method to generate factor portfolios and applied their method to these firm characteristics. Exploring this innovation is a useful way to understand the empirical building blocks of a multifactor asset pricing model.

Suppose you find, as Fama and French did, that stock market capitalization (or "market cap") seems to predict alpha values in a CAPM equation. On average, the smaller the market cap, the greater the alpha of a stock. This finding would add size to the list of anomalies that refute the CAPM.

But suppose you believe that size varies with sensitivity to changes in future investment opportunities. Then, what appears as alpha in a single factor CAPM is really an extra-market source of risk in a multifactor CAPM. If this sounds far-fetched, here's a story: When investors anticipate a market downturn, they adjust their portfolios to minimize their exposure to losses. Suppose that small stocks generally are harder hit in down markets, akin to a larger beta in bad times. Then investors will avoid such stocks in favor of the less-sensitive stocks of larger firms. This would explain a risk premium to small size beyond the beta on contemporaneous market returns. An "alpha" for size may be instead an ICAPM risk premium for assets with greater sensitivity to deterioration in future investment opportunities.

[18]Eugene F. Fama and Kenneth R. French, "Common Risk Factors in the Returns on Stocks and Bonds," *Journal of Financial Economics* 33 (1993), pp. 3–56.

The FF innovation is a method to quantify the size risk premium. Recall that the distribution of corporate size is asymmetric: a few big and many small corporations. Since the NYSE is the exchange where bigger stocks trade, Fama and French first determine the median size of NYSE stocks. They use this median to classify all traded U.S. stocks (NYSE + AMEX + NASDAQ) as big or small and create one portfolio from big stocks and another from small stocks. Finally, each of these portfolios is value-weighted for efficient diversification.

As in the APT, Fama and French construct a zero-net-investment size-factor portfolio by going long the small- and going short the big-stock portfolio. The return of this portfolio, called SMB (small minus big), is simply the return on the small-stock portfolio minus the return on the big-stock portfolio. If size is priced, then this portfolio will exhibit a risk premium. Because the SMB is practically well diversified (on the order of 4,000 stocks), it joins the market-index portfolio in a two-factor APT model with size as the extra-market source of risk. In the two-factor SML, the risk premium on any asset should be determined by its loadings (betas) on the two factor portfolios. This is a testable hypothesis.

Fama and French use this approach to form both size and book-to-market ratio (B/M) factors. To create these two extra-market risk factors, they double-sort stocks by both size and B/M. They break the U.S. stock population into three groups based on B/M ratio: the bottom 30% (low), the middle 40% (medium), and the top 30% (high).[19] Now six portfolios are created based on the intersections of the size and B/M sorts: Small/Low; Small/Medium; Small/High; Big/Low; Big/Medium; Big/High. Each of these six portfolios is value weighted.

The returns on the Big and Small portfolio are:

$$R_S = \tfrac{1}{3}(R_{S/L} + R_{S/M} + R_{S/H}); \, R_B = \tfrac{1}{3}(R_{B/L} + R_{B/M} + R_{B/H})$$

Similarly, the returns on the high and low (Value and Growth[20]) portfolios are:

$$R_H = \tfrac{1}{2}(R_{SH} + R_{BH}); \, R_L = \tfrac{1}{2}(R_{SL} + R_{BL})$$

The returns of the zero-net-investment factors SMB (Small minus Big, i.e., Long Small and Short Big), and HML (High minus Low, i.e., Long High B/M and Short Low B/M) are created from these portfolios:

$$R_{SMB} = R_S - R_B; \, R_{HML} = R_H - R_L$$

We measure the sensitivity of individual stocks to the factors by estimating the factor betas from first-pass regressions of stock excess returns on the excess return of the market index as well as on R_{SMB} and R_{HML}. These factor betas should, as a group, predict the total risk premium. Therefore, the Fama-French three-factor asset-pricing model is[21]

$$E(r_i) - r_f = a_i + b_i[E(r_M) - r_f] + s_i E[\text{SMB}] + h_i E[\text{HML}] \tag{13.8}$$

[19]Fama and French could have experimented with optimal break points for the three B/M groups, but such an approach might quickly give way to data mining.

[20]High B/M stocks are called *value* assets because, for the large part, their market values derive from assets already in place. Low B/M are called *growth* stocks because their market values derive from expected growth in future cash flows. One needs to assume high growth to justify the prices at which the assets trade. At the same time, however, a firm that falls into hard times will see its market price fall and its B/M ratio rise. So some of the so-called value firms may actually be distressed firms. This subgroup of the value-firm portfolio may well account for the value premium of the B/M factor.

[21]We subtract the risk-free rate from the return on the market portfolio, but not from the SMB and HML returns because the SMB and HML factors are *zero-net-investment* portfolios. Hence their entire return already is a premium. There is no opportunity cost from giving up the risk-free investment to switch into these portfolios.

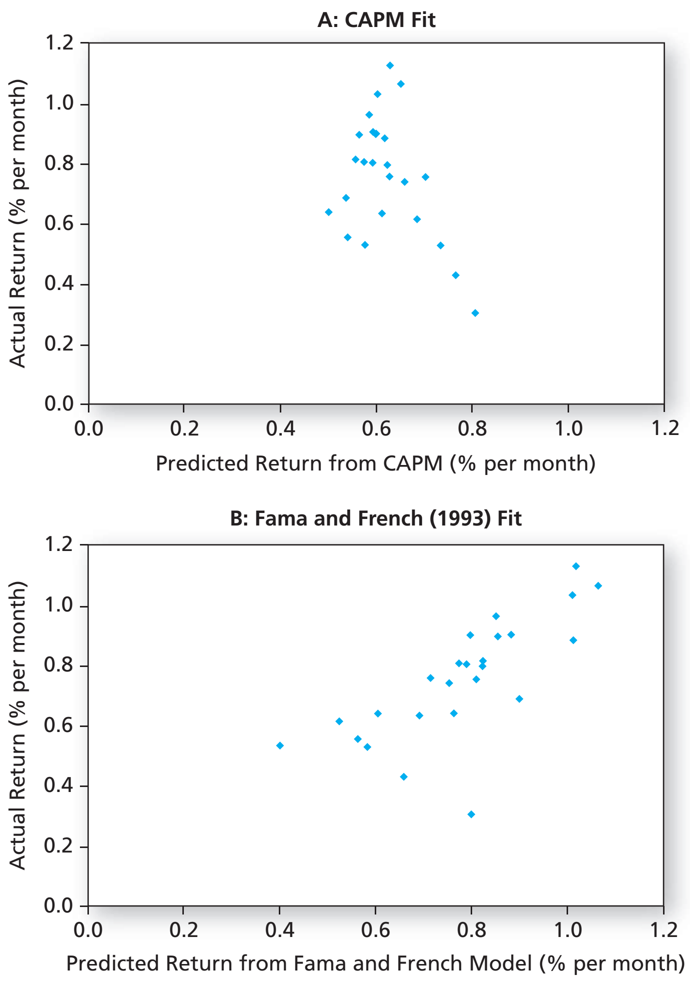

Figure 13.1 CAPM versus the Fama and French model. The figure plots the average actual returns versus returns predicted by CAPM and the FF model for 25 size and book-to-market double-sorted portfolios.

Source: Amit Goyal, "Empirical Cross Sectional Asset Pricing: A Survey," *Financial Markets and Portfolio Management* 26 (2012), pp. 3–38.

The coefficients b_i, s_i, and h_i are the betas (also called *loadings* in this context) of the stock on the three factors. If these are the only risk factors, excess returns on all assets should be fully explained by risk premiums due to these factor loadings. In other words, if these factors fully explain asset returns, the intercept of the equation should be zero.

Goyal[22] surveys asset pricing tests. He applies Equation 13.8 to the returns of 25 portfolios of all U.S. stocks sorted by size and B/M ratio. Figure 13.1 shows the average actual return of each portfolio over the period 1946–2010 against returns predicted by the CAPM (panel A) and by the FF three-factor model. In this test, the FF model provides a clear improvement over the CAPM.

Notice in panel A that the predicted returns are almost the same for all portfolios. This is indeed a weakness of tests with portfolios that are sorted on size and B/M, but not on beta. As a result, all portfolios have betas near 1.0. Adding a sort on beta to a 5 × 5 sort on size and B/M will raise the number of portfolios from 25 to 125. This is unwieldy. But advances in econometrics and computing power will allow these types of tests to advance.

Size and B/M as Risk Factors

Liew and Vassalou[23] show that returns on style portfolios (HML or SMB) seem to predict GDP growth, and thus may in fact capture some aspects of business cycle risk. Each bar in Figure 13.2 is the average difference in the return on the HML or SMB portfolio in years before good GDP growth versus in years with poor GDP growth. Positive values mean the portfolio does better in years prior to good macroeconomic performance. The predominance of positive values leads them to conclude that the returns on the HML and SMB portfolios are positively related to future

[22]Amit Goyal, "Empirical Cross Sectional Asset Pricing: A Survey," *Financial Markets and Portfolio Management* 26 (2012), pp. 3–38.

[23]J. Liew and M. Vassalou, "Can Book-to-Market, Size and Momentum Be Risk Factors That Predict Economic Growth?" *Journal of Financial Economics* 57 (2000), pp. 221–45.

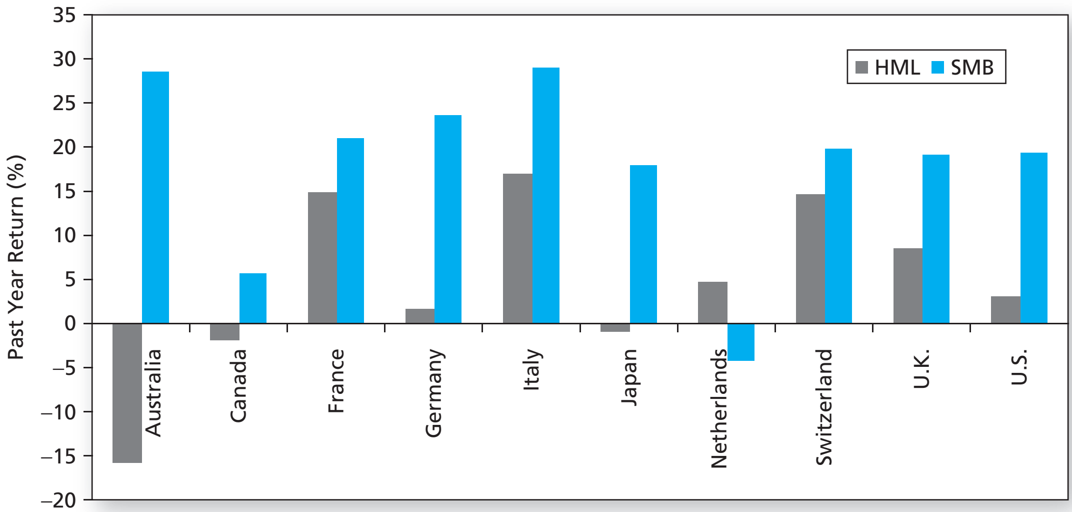

Figure 13.2 Difference in return to factor portfolios in year prior to above-average versus below-average GDP growth. Both SMB and HML portfolio returns tend to be higher in years preceding better GDP growth.

Source: J. Liew and M. Vassalou, "Can Book-to-Market, Size and Momentum Be Risk Factors That Predict Economic Growth?" *Journal of Financial Economics* 57 (2000), pp. 221–45. © 2000 with permission from Elsevier.

growth in the macroeconomy, and so may be proxies for business cycle risk. Thus, at least part of the size and value premiums may reflect rational rewards for greater risk exposure.

Petkova and Zhang[24] also try to tie the average return premium on value (high B/M) portfolios to risk premiums. Their approach uses a conditional CAPM. In the conventional CAPM, we treat both the market risk premium and firm betas as given parameters. In contrast, as we noted earlier in the chapter, the conditional CAPM allows both of these terms to vary over time, and possibly to co-vary. If a stock's beta is higher when the market risk premium is high, this positive association leads to a "synergy" in its risk premium, which is the product of its incremental beta and market risk premium.

What might lead to such an association between beta and the market risk premium? Zhang[25] focuses on irreversible investments. He notes that firms classified as value firms (with high book-to-market ratios) on average will have greater amounts of tangible capital. Investment irreversibility puts such firms more at risk for economic downturns because in a severe recession, they will suffer from excess capacity from assets already in place. In contrast, growth firms are better able to deal with a downturn by deferring investment plans. The greater exposure of high book-to-market firms to recessions will result in higher down-market betas. Moreover, some evidence suggests that the market risk premium also is higher in down markets, when investors are feeling more economic pressure and anxiety.

[24]Ralitsa Petkova and Lu Zhang, "Is Value Riskier than Growth?" *Journal of Financial Economics* 78 (2005), pp. 187–202.

[25]Lu Zhang, "The Value Premium," *Journal of Finance* 60 (2005), pp. 67–103.

The combination of these two factors might impart a positive correlation between the beta of high B/M firms and the market risk premium.

To quantify these notions, Petkova and Zhang attempt to fit both beta and the market risk premium to a set of "state variables," that is, variables that summarize the state of the economy. These are:

DIV = Market dividend yield.

DEFLT = Default spread on corporate bonds (Baa – Aaa rates).

TERM = Term structure spread (10-year–1-year Treasury rates).

TB = 1-month T-bill rate.

They estimate a first-pass regression, but first substitute these state variables for beta as follows:

$$\begin{aligned} r_{\text{HML}} &= \alpha + \beta r_{Mt} + e_i \\ &= \alpha + [\underbrace{b_0 + b_1\text{DIV}_t + b_2\text{DEFLT}_t + b_3\text{TERM}_t + b_4\text{TB}_t}_{=\ \beta_t\ \leftarrow\ \text{a } \textit{time-varying} \text{ beta}}]r_{Mt} + e_i \end{aligned}$$

The strategy is to estimate parameters b_0 through b_4 and then fit beta using the values of the four state variables at each date. In this way, they can estimate beta in each period.

Similarly, one can directly estimate the determinants of a time-varying market risk premium, using the same set of state variables:

$$r_{\text{Mkt},\,t} - r_{ft} = c_0 + c_1\text{DIV}_t + c_2\text{DEFLT}_t + c_3\text{TERM}_t + c_4\text{TB}_t + e_t$$

The fitted value from this regression is the estimate of the market risk premium.

Finally, Petkova and Zhang examine the relationship between beta and the market risk premium. They define the state of economy by the size of the premium. A peak is defined as the periods with the 10% lowest risk premiums; a trough has the 10% highest risk premiums. The results, presented in Figure 13.3, support the notion of a countercyclical value

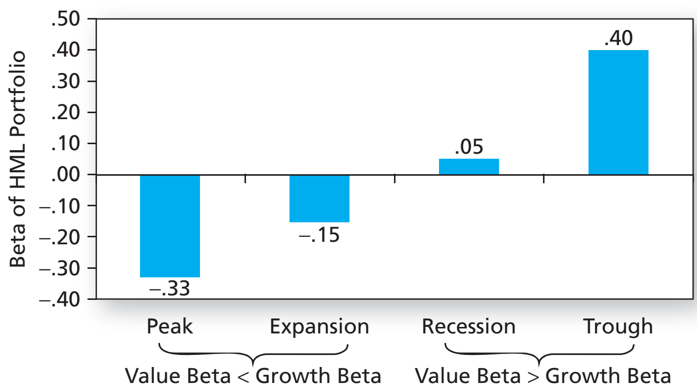

Figure 13.3 HML beta in different economic states. The beta of the HML portfolio is higher when the market risk premium is higher.

Source: Ralitsa Petkova and Lu Zhang, "Is Value Riskier than Growth?" *Journal of Financial Economics* 78 (2005), pp. 187–202. © 2005 with permission from Elsevier.

beta: The beta of the HML portfolio is negative in good economies, meaning that the beta of value stocks (high book-to-market) is less than that of growth stocks (low B/M), but the reverse is true in recessions. While the covariance between the HML beta and the market risk premium is not sufficient to explain by itself the average return premium on value portfolios, it does suggest that at least part of the explanation may be a rational risk premium.

Behavioral Explanations

On the other side of the debate, several authors make the case that the value premium is a manifestation of market irrationality. The essence of the argument is that analysts tend to extrapolate recent performance too far out into the future, and thus tend to overestimate the value of firms with good recent performance. When the market realizes its mistake, the prices of these firms fall. Thus, on average, "glamour firms," which are characterized by recent good performance, high prices, and lower book-to-market ratios, tend to underperform "value firms" because their high prices reflect excessive optimism relative to those lower book-to-market firms.

Figure 13.4, from a study by Chan, Karceski, and Lakonishok,[26] makes the case for overreaction. Firms are sorted into deciles based on income growth in the past 5 years. By construction, the growth rates uniformly increase from the first through the tenth decile. The book-to-market ratio for each decile at the *end* of the 5-year period (the dashed line) tracks recent growth very well. B/M falls steadily with growth over the past 5 years. This is evidence that *past* growth is extrapolated and then impounded in price. High past growth leads to higher prices and lower B/M ratios.

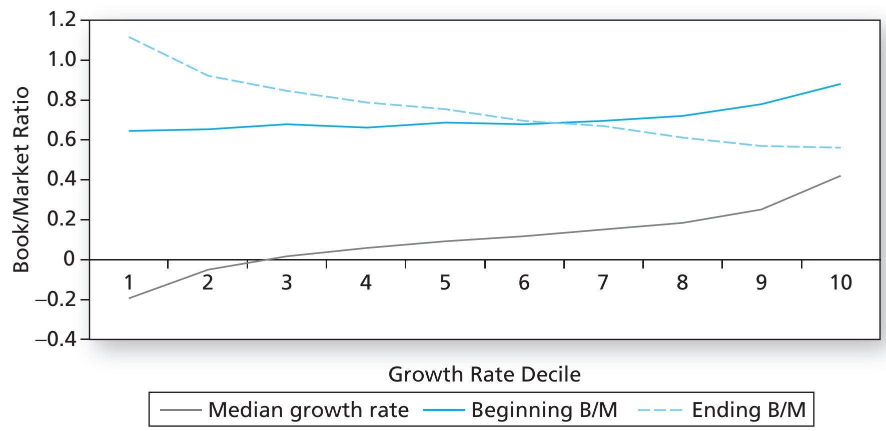

Figure 13.4 The book-to-market ratio reflects past growth, but not future growth prospects. B/M tends to fall with income growth experienced at the *end* of a 5-year period, but actually increases slightly with future income growth rates.

Source: L.K.C. Chan, J. Karceski, and J. Lakonishok, "The Level and Persistence of Growth Rates," *Journal of Finance* 58 (April 2003), pp. 643–84. Used with permission of John Wiley and Sons, via Copyright Clearance Center.

[26]L.K.C. Chan, J. Karceski, and J. Lakonishok, "The Level and Persistence of Growth Rates," *Journal of Finance* 58 (April 2003), pp. 643–84.

But B/M at the *beginning* of a 5-year period shows little or even a positive association with subsequent growth (the solid colored line), implying that market capitalization today is *inversely* related to growth prospects. In other words, the firms with lower B/M (glamour firms) experience no better or even worse average future income growth than other firms. The implication is that the market ignores evidence that past growth cannot be extrapolated far into the future. Book-to-market may reflect past growth better than future growth, consistent with extrapolation error.

More direct evidence supporting extrapolation error is provided by La Porta, Lakonishok, Shleifer, and Vishny,[27] who examine stock price performance when actual earnings are released to the public. Firms are classified as growth versus value stocks, and the stock price performance at earnings announcements for 4 years following the classification date is then examined. Figure 13.5 demonstrates that growth stocks underperform value stocks surrounding these announcements. We conclude that when news of actual earnings is released to the public, the market is relatively disappointed in stocks it has been pricing as growth firms.

Momentum: A Fourth Factor

Since the seminal Fama-French three-factor model was introduced, a fourth factor has come to be added to the standard controls for stock return behavior. This is a momentum factor. As we first saw in Chapter 11, Jegadeesh and Titman uncovered a tendency for good or bad performance of stocks to persist over several months, a sort of momentum property.[28] Carhart added this momentum effect to the three-factor model as a tool to

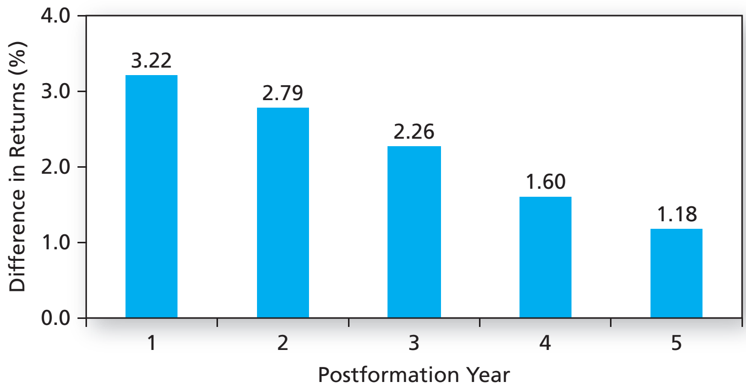

Figure 13.5 Value minus glamour returns surrounding earnings announcements, 1971–1992. Announcement effects are measured for each of 4 years following classification as a value versus a growth firm.

Source: R. La Porta, J. Lakonishok, A. Shleifer, and R.W. Vishny, "Good News for Value Stocks," *Journal of Finance* 52 (1997), pp. 859–874. Used with permission of John Wiley and Sons, via Copyright Clearance Center.

[27]R. La Porta, J. Lakonishok, A. Shleifer, and R.W. Vishny, "Good News for Value Stocks," *Journal of Finance* 52 (1997), pp. 859–874.

[28]Narasimhan Jegadeesh and Sheridan Titman, "Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency," *Journal of Finance* 48 (March 1993), pp. 65–91.

evaluate mutual fund performance.[29] The factor is constructed in the same way and is denoted by WML (winners minus losers). Versions of this factor take winners/losers based on 1–12 months of past returns. Carhart found that much of what appeared to be the alpha of many mutual funds could in fact be explained as due to their loadings or sensitivities to market momentum. The original Fama-French model augmented with a momentum factor has become a common four-factor model used to evaluate abnormal performance of a stock portfolio.

Of course, this additional factor presents further conundrums of interpretation. To characterize the original Fama-French factors as reflecting obvious sources of risk is already a bit of a challenge. A momentum factor seems even harder to position as reflecting a risk–return trade-off.

13.4 Liquidity and Asset Pricing

In Chapter 9 we saw that an important extension of the CAPM incorporates considerations of asset liquidity. Unfortunately, measuring liquidity is far from trivial. The effect of liquidity on an asset's expected return is composed of two factors:

1. Transaction costs that are dominated by the bid–ask spread that dealers set to compensate for losses incurred when trading with informed traders.
2. Liquidity *risk* resulting from covariance between *changes* in asset liquidity cost with both *changes* in market-index liquidity cost and with market-index rates of return.

Neither of these factors are directly observable and their effect on equilibrium rates of return is difficult to estimate.

Liquidity embodies several characteristics such as trading costs, ease of sale, necessary price concessions to effect a quick transaction, market depth, and price predictability. As such, it is difficult to measure with any single statistic. Popular measures of liquidity, or, more precisely, illiquidity, focus on the price impact dimension: What price concession might a seller have to offer in order to accomplish a large sale of an asset or, conversely, what premium must a buyer offer to make a large purchase?

One measure of illiquidity is employed by Pástor and Stambaugh, who look for evidence of price reversals, especially following large trades.[30] Their idea is that if stock price movements tend to be partially reversed on the following day, then we can conclude that part of the original price change was not due to perceived changes in intrinsic value (these price changes would not tend to be reversed), but was instead a symptom of price impact associated with the original trade. Reversals suggest that part of the original price change was a concession on the part of trade initiators who needed to offer higher purchase prices or accept lower selling prices to complete their trades in a timely manner. Pástor and Stambaugh use regression analysis to show that reversals do in fact tend to be larger when associated with higher trading volume—exactly the pattern that one would expect if part of the price move is a liquidity phenomenon. They run a first-stage regression of returns on lagged returns and trading volume. The coefficient on the latter term measures the tendency of high-volume trades to be accompanied by larger reversals.

[29] Mark M. Carhart, "On Persistence in Mutual Fund Performance," *Journal of Finance* 52 (March 1997), pp. 57–82.

[30] L. Pástor and R. F. Stambaugh, "Liquidity Risk and Expected Stock Returns," *Journal of Political Economy* 111 (2003), pp. 642–85.

Another measure of illiquidity, proposed by Amihud, also focuses on the association between large trades and price movements.[31] His measure is:

$$\text{ILLIQ} = \text{Monthly average of daily}\left[\frac{\text{Absolute value(Stock return)}}{\text{Dollar volume}}\right]$$

This measure of illiquidity is based on the price impact per dollar of transactions in the stock and can be used to estimate both liquidity cost and liquidity risk.

Finally, Sadka uses trade-by-trade data to devise a third measure of liquidity.[32] He begins with the observation that part of price impact, a major component of illiquidity cost, is due to asymmetric information. (Turn back to our discussion of liquidity in Chapter 9 for a review of asymmetric information and the bid–ask spread.) He then uses regression analysis to break out the component of price impact that is due to information issues. The liquidity of firms can wax or wane as the prevalence of informationally motivated trades varies, giving rise to liquidity risk.

Any of these liquidity measures can be averaged over stocks to devise measures of marketwide illiquidity. Given market illiquidity, we can then measure the "liquidity beta" of any individual stock (the sensitivity of returns to changes in market liquidity) and estimate the impact of liquidity risk on expected return. If stocks with high liquidity betas have higher average returns, we conclude that liquidity is a "priced factor," meaning that exposure to it offers higher expected return as compensation for the risk.

Pástor and Stambaugh conclude that liquidity risk is in fact a priced factor, and that the risk premium associated with it is quantitatively significant. They sort portfolios into deciles based on liquidity beta and then compute the average alphas of the stocks in each decile using two models that *ignore* liquidity: the CAPM and the Fama-French three-factor model. Figure 13.6 shows that the alpha computed under either model rises substantially across liquidity-beta deciles, clear evidence that when controlling for other factors, average return rises along with liquidity risk. Not surprisingly, the relationship between liquidity risk and alpha across deciles is more regular for the Fama-French model, as it controls for a wider range of other influences on average return.

Pástor and Stambaugh also test the impact of the liquidity beta on alpha computed from a four-factor model (that also controls for momentum) and obtain similar results. In fact, they suggest that liquidity risk factor may account for a good part of the apparent profitability of the momentum strategy.

Acharya and Pedersen use Amihud's measure to test for price effects associated with the average *level* of illiquidity as well as a liquidity risk premium.[33] They demonstrate that expected stock returns depend on the average level of illiquidity. (Figure 9.4 in Chapter 9 shows a similar result.) But Acharya and Pedersen demonstrate that stock returns depend on several liquidity betas as well: the sensitivity of individual stock illiquidity to market illiquidity; the sensitivity of stock returns to market illiquidity; and the sensitivity of stock illiquidity to market return. They conclude that adding these liquidity effects to the conventional CAPM increases our ability to explain expected asset returns.

[31]Yakov Amihud, "Illiquidity and Stock Returns: Cross-Section and Time-Series Effects," *Journal of Financial Markets* 5 (2002), pp. 31–56.

[32]Ronnie Sadka, "Momentum and Post-earnings Announcement Drift Anomalies: The Role of Liquidity Risk," *Journal of Financial Economics* 80 (2006), pp. 309–49.

[33]V. V. Acharya and L. H. Pedersen, "Asset Pricing with Liquidity Risk," *Journal of Financial Economics* 77 (2005), pp. 375–410.

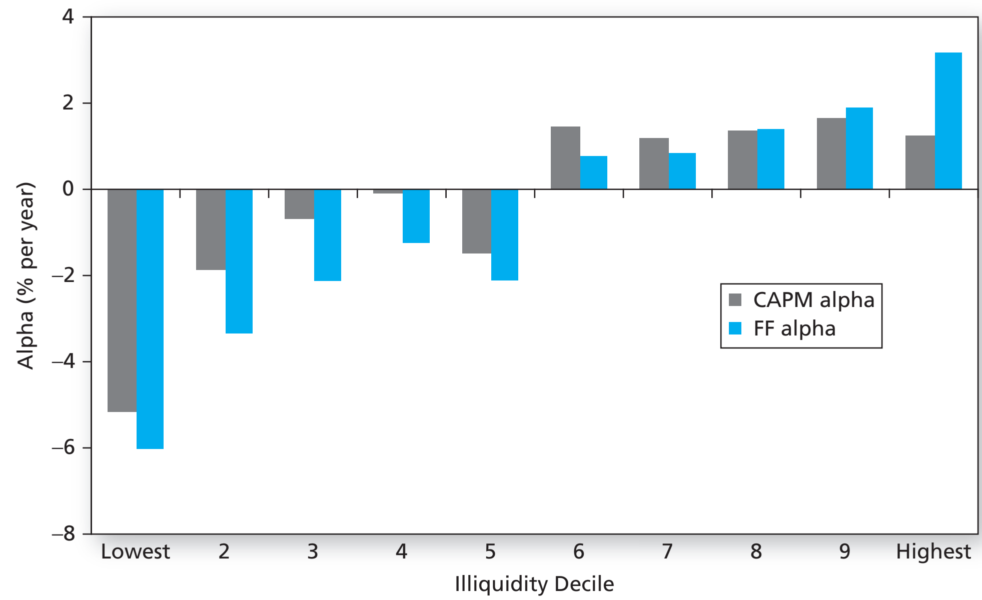

Figure 13.6 Alphas of value-weighted portfolios sorted on liquidity betas

Source: L. Pástor and R. F. Stambaugh, "Liquidity Risk and Expected Stock Returns," *Journal of Political Economy* 111 (2003), pp. 642–85, Table 4. Copyright © 2003, The University of Chicago Press.

13.5 Consumption-Based Asset Pricing and the Equity Premium Puzzle

In a classic article, Mehra and Prescott observed that historical excess returns on risky assets in the U.S. are too large to be consistent with economic theory and reasonable levels of risk aversion.[34] This observation has come to be known as the "equity premium puzzle." The debate about the equity premium puzzle suggests that forecasts of the market risk premium should be lower than historical averages. The question of whether past returns provide a guideline to future returns is sufficiently important to justify stretching the scope of our discussions of equilibrium in capital markets.

Consumption Growth and Market Rates of Return

The ICAPM is derived from a lifetime consumption/investment plan of a representative consumer/investor. Each individual's plan is set to maximize a utility function of lifetime consumption, and consumption/investment in each period is based on age and current wealth, as well as the risk-free rate and the market portfolio's risk and risk premium.

[34]Jarnish Mehra and Edward Prescott, "The Equity Premium: A Puzzle," *Journal of Monetary Economics,* March 1985.

The consumption model implies that what matters to investors is not their wealth per se, but their lifetime flow of consumption. There can be slippage between wealth and consumption due to variation in factors such as the risk-free rate, the market portfolio risk premium, or prices of major consumption items. Therefore, a better measure of consumer well-being than wealth is the consumption flow that such wealth can support.

Given this framework, the generalization of the basic CAPM is that instead of measuring security risk based on the covariance of returns with the market return (a measure that focuses only on wealth), we are better off using the covariance of returns with aggregate consumption. Hence, we would expect the risk premium of the market index to be related to that covariance as follows:

$$E(r_M) - r_f = A\text{Cov}(r_M, r_C) \tag{13.10}$$

where A depends on the average coefficient of risk aversion and r_C is the rate of return on a consumption-tracking portfolio constructed to have the highest possible correlation with growth in aggregate consumption.[35]

The first wave of attempts to estimate consumption-based asset pricing models used consumption data directly rather than returns on consumption-tracking portfolios. By and large, these tests found the CCAPM no better than the conventional CAPM in explaining risk premiums. The *equity premium puzzle* refers to the fact that using reasonable estimates of A, the covariance of consumption growth with the market-index return, $\text{Cov}(r_M, r_C)$, is far too low to justify observed historical-average excess returns on the market-index portfolio, shown on the left-hand side of Equation 13.10.[36] Thus, the risk premium puzzle says in effect that historical excess returns are too high and/or our inferences about risk aversion are too low.

Recent research improves the quality of estimation in several ways. First, rather than using consumption growth directly, it uses consumption-tracking portfolios. The available (infrequent) data on aggregate consumption is used only to construct the consumption-tracking portfolio. The frequent and accurate data on the return on these portfolios may then be used to test the asset pricing model. (On the other hand, any inaccuracy in the construction of the consumption-mimicking portfolios will muddy the relationship between asset returns and consumption risk.) For example, a study by Jagannathan and Wang focuses on year-over-year fourth-quarter consumption and employs a consumption-tracking portfolio.[37] Table 13.5, excerpted from their study, shows that the Fama-French factors are in fact associated with consumption betas as well as excess returns. The top panel contains familiar results: Moving across each row, we see that higher book-to-market ratios are associated with higher average returns. Similarly, moving down each column, we see that larger size generally implies lower average returns. The novel results are in the lower panel: A high book-to-market ratio is associated with higher consumption beta, and larger firm size is associated with lower consumption beta. The suggestion is that the explanatory power of the Fama-French factors for average returns may in fact reflect differences in consumption

[35]This equation is analogous to the equation for the risk premium in the conventional CAPM, i.e., that $E(r_M) - r_f = A\text{Cov}(r_M, r_M) = A\text{Var}(r_M)$. In the multifactor version of the ICAPM, however, the market is no longer mean-variance efficient, so the risk premium of the market index will not be proportional to its variance. The APT also implies a linear relationship between risk premium and covariance with relevant factors, but it is silent about the slope of the relationship because it avoids assumptions about utility.

[36]Notice that the conventional CAPM does not pose such problems. In the CAPM, $E(r_M) - r_f = A\text{Var}(r_M)$. A risk premium of .085 (8.5%) and a standard deviation of .20 (20%, or variance of .04) imply a coefficient of risk aversion of .085/.04 = 2.125, which is quite plausible.

[37]Ravi Jagannathan and Yong Wang, "Lazy Investors, Discretionary Consumption, and the Cross-Section of Stock Returns," *Journal of Finance* 62 (August 2006), pp. 1623–61.

Table 13.5

Annual excess returns and consumption betas

Size	Book-to-Market Low	Medium	High
Average annual excess returns* (%)			
Small	6.19	12.24	17.19
Medium	6.93	10.43	13.94
Big	7.08	8.52	9.5
Consumption beta*			
Small	3.46	4.26	5.94
Medium	2.88	4.35	5.71
Big	3.39	2.83	4.41

*Average annual excess returns on the 25 Fama-French portfolios from 1954 to 2003. Consumption betas estimated by the time series regression

$$R_{i,t} = \alpha_i + \beta_{i,c} g_{ct} + e_{i,t},$$

where $R_{i,t}$ is the excess return over the risk-free rate, and g_{ct} is annual consumption growth calculated using fourth-quarter consumption data.

Source: Ravi Jagannathan and Yong Wang, "Lazy Investors, Discretionary Consumption, and the Cross-Section of Stock Returns," *Journal of Finance* 62 (August 2006), pp. 1623–61.

risk of those portfolios. Figure 13.7 shows that the average returns of the 25 Fama-French portfolios are strongly associated with their consumption betas. Other tests reported by Jagannathan and Wang show that the CCAPM explains returns even better than the Fama-French three-factor model, which in turn is superior to the single-factor CAPM.

Moreover, the standard CCAPM focuses on a representative consumer/investor, thereby ignoring information about heterogeneous investors with different levels of wealth and consumption habits. To improve the model's power to explain returns, some newer studies allow for several classes of investors with differences in wealth and consumption behavior. For example, the covariance between market returns and consumption is far higher when we focus on the consumption risk of households that actually hold financial securities.[38] This observation mitigates the equity risk premium puzzle.

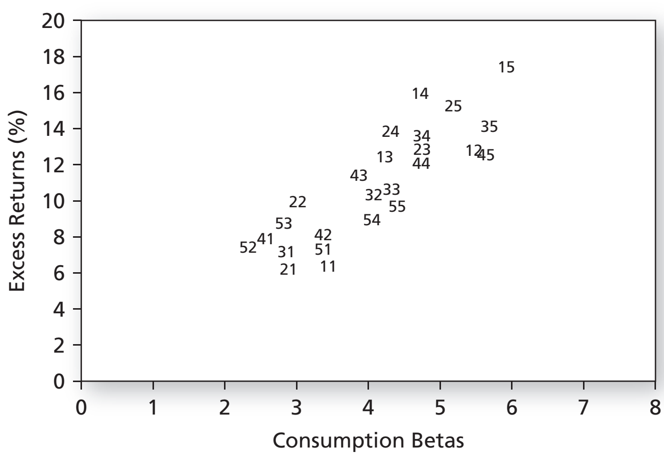

Figure 13.7 Cross section of stock returns: Fama-French 25 portfolios, 1954–2003

Annual excess returns and consumption betas. This figure plots the average annual excess returns on the 25 Fama-French portfolios and their consumption betas. Each two-digit number represents one portfolio. The first digit refers to the size quintile (1 = smallest, 5 = largest), and the second digit refers to the book-to-market quintile (1 = lowest, 5 = highest).

[38]C. J. Malloy, T. Moskowitz, and A. Vissing-Jørgensen, "Long-Run Stockholder Consumption Risk and Asset Returns," *Journal of Finance* 64 (December 2009), pp. 2427–80.

Expected versus Realized Returns

Fama and French offer another interpretation of the equity premium puzzle.[39] Using stock index returns from 1872 to 1999, they report the average risk-free rate, average stock market return (represented by the S&P 500 index), and resultant risk premium for the overall period and subperiods:

Period	Risk-Free Rate	S&P 500 Return	Equity Premium
1872–1999	4.87	10.97	6.10
1872–1949	4.05	8.67	4.62
1950–1999	6.15	14.56	8.41

The big increase in the average excess return on equity after 1949 suggests that the equity premium puzzle is largely a creature of modern times.

Fama and French suspect that estimating the risk premium from average realized returns may be the problem. They use the constant-growth dividend-discount model (see an introductory finance text or Chapter 18) to estimate expected returns and find that for the period 1872–1949, the dividend discount model (DDM) yields similar estimates of the *expected* risk premium as the average *realized* excess return. But for the period 1950–1999, the DDM yields a much smaller risk premium, which suggests that the high average excess return in this period may have exceeded the returns investors actually expected to earn at the time.

In the constant-growth DDM, the expected capital gains rate on the stock will equal the growth rate of dividends. As a result, the expected total return on the firm's stock will be the sum of dividend yield (dividend/price) plus the expected dividend growth rate, g:

$$E(r) = \frac{D_1}{P_0} + g \tag{13.11}$$

where D_1 is end-of-year dividends and P_0 is the current price of the stock. Fama and French treat the S&P 500 as representative of the average firm, and use Equation 13.11 to produce estimates of $E(r)$.

For any sample period, $t = 1, \ldots, T$, Fama and French estimate expected return from the sum of the dividend yield (D_t/P_{t-1}) plus the dividend growth rate ($g_t = D_t/D_{t-1} - 1$). In contrast, the *realized* return is the dividend yield plus the rate of capital gains ($P_t/P_{t-1} - 1$). Because the dividend yield is common to both estimates, the difference between the expected and realized return equals the difference between the dividend growth and capital gains rates. While dividend growth and capital gains were similar in the earlier period, capital gains significantly exceeded the dividend growth rate in modern times. Hence, Fama and French conclude that the equity premium puzzle may be due at least in part to unanticipated capital gains in the latter period.

Fama and French argue that dividend growth rates produce more reliable estimates of the capital gains investors actually expected to earn than the average of their realized capital gains. They point to three reasons:

1. Average realized returns over 1950–1999 exceeded the internal rate of return on corporate investments. If those average returns were representative of expectations, we would have to conclude that firms were willingly engaging in negative-NPV investments.

[39]Eugene Fama and Kenneth French, "The Equity Premium," *Journal of Finance* 57, no. 2 (2002).

2. The statistical precision of estimates from the DDM are far higher than those using average historical returns. The standard error of the estimates of the risk premium from realized returns greatly exceed the standard error from the dividend discount model (see the following table).
3. The reward-to-volatility (Sharpe) ratio derived from the DDM is far more stable than that derived from realized returns. If risk aversion remains the same over time, we would expect the Sharpe ratio to be stable.

The evidence for the second and third points is shown in the following table, where estimates from the dividend discount model (DDM) and from realized returns (Realized) are shown side by side.

	Mean Return		Standard Error		*t*-Statistic		Sharpe Ratio	
Period	DDM	Realized	DDM	Realized	DDM	Realized	DDM	Realized
1872–1999	4.03	6.10	1.14	1.65	3.52	3.70	0.22	0.34
1872–1949	4.35	4.62	1.76	2.20	2.47	2.10	0.23	0.24
1950–1999	3.54	8.41	1.03	2.45	3.42	3.43	0.21	0.51

Fama and French's study provides a simple explanation for the equity premium puzzle, namely, that observed rates of return in the recent half-century were unexpectedly high. It also implies that forecasts of future excess returns will be lower than past averages. (Coincidentally, their study was published in 1999, and so far appears prophetic in light of low subsequent average returns since then.)

Work by Goetzmann and Ibbotson lends support to Fama and French's argument.[40] Goetzmann and Ibbotson combine research that extends data on rates of return on stocks and long-term corporate bonds back to 1792. Summary statistics for these values between 1792 and 1925 are as follows:

	Arithmetic Average	Geometric Average	Standard Deviation
NYSE total return	7.93%	6.99%	14.64%
U.S. bond yields	4.17%	4.16%	4.17%

These statistics suggest a risk premium that is much lower than the historical average for 1926–2009 (much less 1950–1999), which is the period that produces the equity premium puzzle.[41] Thus, the period for which Fama and French claim realized rates were unexpected is actually relatively short in historical perspective.

Survivorship Bias

The equity premium puzzle emerged from long-term averages of U.S. stock returns. There are reasons to suspect that these estimates of the risk premium are subject to survivorship bias, as the United States has arguably been the most successful capitalist system in the world, an outcome that probably would not have been anticipated several decades ago.

[40]William N. Goetzmann and Roger G. Ibbotson, "History and the Equity Risk Premium," working paper, Yale University, October 18, 2005.

[41]The short-term risk-free rate is a lot more difficult to assess because short-term bonds in this period were quite risky and average rates exceeded the yields on long-term corporate bonds.

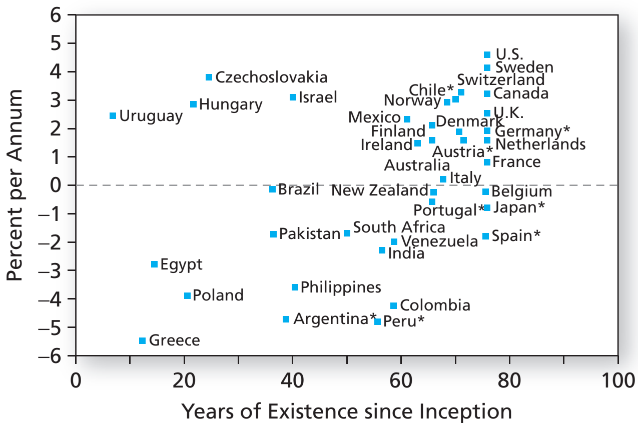

Figure 13.8 Real returns on global stock markets. The figure displays average real returns for 39 markets over the period 1921 to 1996. Markets are sorted by years of existence. The graph shows that markets with long histories typically have higher returns. An asterisk indicates that the market suffered a long-term break.

Jurion and Goetzmann assembled a database of capital appreciation indexes for the stock markets of 39 countries over the period 1921–1996.[42] Figure 13.8 shows that U.S. equities had the highest real return of all countries, at 4.3% annually, versus a median of .8% for other countries. Moreover, unlike the United States, many other countries have had equity markets that actually closed, either permanently or for extended periods of time.

The implication of these results is that using average U.S. data may impart a form of survivorship bias to our estimate of expected returns, because unlike many other countries, the United States has never been a victim of such extreme problems. Estimating risk premiums from the experience of the most successful country and ignoring the evidence from stock markets that did not survive for the full sample period will impart an upward bias in estimates of expected returns. The high realized equity premium obtained for the United States may not be indicative of required returns.

As an analogy, think of the effect of survivorship bias in the mutual fund industry. We know that some companies regularly close down their worst-performing mutual funds. If performance studies include only mutual funds for which returns are available during an entire sample period, the average returns of the funds that make it into the sample will be reflective of the performance of long-term survivors only. With the failed funds excluded from the sample, the average measured performance of mutual fund managers will be better than one could reasonably expect from the full sample of managers. Think back to the box in Chapter 11, "How to Guarantee a Successful Market Newsletter." If one starts many newsletters with a range of forecasts, and continues only the newsletters that turned out to have successful advice, then it will *appear* from the sample of survivors that the average newsletter had forecasting skill.

Extensions to the CAPM May Resolve the Equity Premium Puzzle

Constantinides argues that the standard CAPM can be extended to account for observed excess returns by relaxing some of its assumptions, in particular, by recognizing that consumers face uninsurable and idiosyncratic income shocks, for example, the loss of employment.[43] The prospect of such events is higher in economic downturns and this observation takes us a long way toward understanding the means and variances of asset returns as well as their variation along the business cycle.

In addition, life-cycle considerations are important and often overlooked. Borrowing constraints become important when placed in the context of the life cycle. The imaginary

[42]Philippe Jurion and William N. Goetzmann, "Global Stock Markets in the Twentieth Century," *Journal of Finance* 54, no. 3 (June 1999).

[43]George M. Constantinides, "Understanding the Equity Risk Premium Puzzle," in *Handbooks in Finance: Handbook of the Equity Risk Premium,* ed. Rajnish Mehra (Amsterdam: Elsevier, 2008), pp. 331–59.

"representative consumer" who holds all stock and bond market wealth does not face borrowing constraints. Young consumers, however, do face meaningful borrowing constraints. Constantinides traces their impact on the equity premium, the demand for bonds, and on the limited participation of many consumers in the capital markets. Finally, he shows that adding habit formation to the conventional utility function helps explain higher risk premiums than those that would be justified by the covariance of stock returns with aggregate consumption growth. He argues that integrating the notions of habit formation, incomplete markets, the life cycle, borrowing constraints, and other sources of limited stock market participation is a promising vantage point from which to study the prices of assets and their returns, both theoretically and empirically within the class of rational asset-pricing models.

Liquidity and the Equity Premium Puzzle

We've seen that liquidity risk is potentially important in explaining the cross section of stock returns. The illiquidity premium may be on the same order of magnitude as the market risk premium. Therefore, the common practice of treating the average excess return on a market index as an estimate of a risk premium per se is almost certainly too simplistic. Part of that average excess return is almost certainly compensation for *liquidity* risk rather than just the (systematic) *volatility* of returns. If this is recognized, the equity premium puzzle may be less of a puzzle than it first appears.

Behavioral Explanations of the Equity Premium Puzzle

Barberis and Huang explain the puzzle as an outcome of irrational investor behavior.[44] The key elements of their approach are loss aversion and narrow framing, two well-known features of decision making under risk in experimental settings. Narrow framing is the idea that investors evaluate every risk they face in isolation. Thus, investors will ignore low correlation of the risk of a stock portfolio with other components of wealth, and therefore require a higher risk premium than rational models would predict. Combined with loss aversion, investor behavior will generate large risk premiums despite the fact that traditionally measured risk aversion is low. (See Chapter 12 for more discussion of such behavioral biases.)

Models that incorporate these effects can generate a large equilibrium equity risk premium and a low and stable risk-free rate, even when consumption growth is smooth and only weakly correlated with the stock market. Moreover, they can do so for parameter values that correspond to plausible predictions about attitudes to independent monetary gambles. The analysis for the equity premium also has implications for a closely related portfolio puzzle, the stock market participation puzzle. They suggest some possible directions for future research.

The approach of Barberis and Huang, when accounting for heterogeneity of preferences, can explain why a segment of the population that one would expect to participate in the stock market still avoids it. Narrow framing also explains the disconnect between consumption growth and market rates of return. The assessment of stock market return in isolation ignores the limited impact on consumption via smoothing and other hedges. Loss aversion that exaggerates disutility of losses relative to a reference point magnifies this effect. The development of empirical literature on the tenets of these theories may determine the validity and implications of the equity premium puzzle.

[44]Nicholas Barberis and Ming Huang, "The Loss Aversion/Narrow Framing Approach to the Equity Premium Puzzle," in *Handbooks in Finance: Handbook of the Equity Risk Premium* ed. Rajnish Mehra (Amsterdam: Elsevier, 2008), pp. 199–229.

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SUMMARY

1. Although the single-factor expected return–beta relationship has not been confirmed by scientific standards, its use is already commonplace in economic life.
2. Early tests of the single-factor CAPM rejected the SML, finding that nonsystematic risk was related to average security returns.
3. Later tests controlling for the measurement error in beta found that nonsystematic risk does not explain portfolio returns but also that the estimated SML is too flat compared with what the CAPM would predict.
4. Roll's critique implied that the usual CAPM test is a test only of the mean-variance efficiency of a prespecified market *proxy* and therefore that tests of the linearity of the expected return–beta relationship do not bear on the validity of the model.
5. Tests of the mean-variance efficiency of professionally managed portfolios against the benchmark of a prespecified market index conform with Roll's critique in that they provide evidence on the efficiency of the market index. Empirical evidence suggests that most professionally managed portfolios are outperformed by market indexes, which corroborates the efficiency of those indexes and hence the CAPM.
6. Tests of the single-index model that account for human capital and cyclical variations in asset betas are far more consistent with the single-index CAPM and APT. These tests suggest that extra-market macroeconomic variables are not necessary to explain expected returns. Moreover, anomalies such as effects of size and book-to-market ratios disappear once these variables are accounted for.
7. The dominant multifactor models today are variants of the Fama-French model, incorporating market, size, value, momentum, and sometimes liquidity factors. Debate continues on whether returns associated with these extra-market factors reflect rational risk premia or behaviorally induced mispricing.
8. The equity premium puzzle originates from the observation that equity returns exceeded the risk-free rate to an extent that is inconsistent with reasonable levels of risk aversion—at least when average rates of return are taken to represent expectations. Fama and French show that the puzzle emerges primarily from excess returns over the last 50 years. Alternative estimates of expected returns using the dividend growth model instead of average returns suggest that excess returns on stocks were high because of unexpected large capital gains. The study suggests that future excess returns will be lower than realized in recent decades.
9. Early research on consumption-based capital asset pricing models was disappointing, but more recent work is far more encouraging. In some studies, consumption betas explain average portfolio returns as well as the Fama-French three-factor model. These results support Fama and French's conjecture that their factors proxy for more fundamental sources of risk.

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KEY TERMS

first-pass regression

second-pass regression

benchmark error

KEY EQUATIONS

First-pass regression equation: $r_{it} - r_{ft} = a_i + b_i(r_{Mt} - r_{ft}) + e_{it}$

Second-pass regression equation: $\overline{r_t - r_f} = \gamma_0 + \gamma_1 b_i$

Fama-French 3-factor model: $E(r_i) - r_f = a_i + b_i[E(r_M) - r_f] + s_i E[\text{SMB}] + h_i E[\text{HML}]$

PROBLEM SETS

1. Suppose you find, as research indicates, that in the cross-section regression of the CCAPM, the coefficients of factor loadings on the Fama-French model are significant predictors of average return factors (in addition to consumption beta). How would you explain this phenomenon?

Basic

2. Search the Internet for a recent graph of market volatility. What does this history suggest about the history of consumption growth?

The following annual excess rates of return were obtained for nine individual stocks and a market index:

Intermediate

excel
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		Stock Excess Returns (%)								
Year	Market Index	*A*	*B*	*C*	*D*	*E*	*F*	*G*	*H*	*I*
1	29.65	33.88	−25.20	36.48	42.89	−39.89	39.67	74.57	40.22	90.19
2	−11.91	−49.87	24.70	−25.11	−54.39	44.92	−54.33	−79.76	−71.58	−26.64
3	14.73	65.14	−25.04	18.91	−39.86	−3.91	−5.69	26.73	14.49	18.14
4	27.68	14.46	−38.64	−23.31	−0.72	−3.21	92.39	−3.82	13.74	0.09
5	5.18	15.67	61.93	63.95	−32.82	44.26	−42.96	101.67	24.24	8.98
6	25.97	−32.17	44.94	−19.56	69.42	90.43	76.72	1.72	77.22	72.38
7	10.64	−31.55	−74.65	50.18	74.52	15.38	21.95	−43.95	−13.40	28.95
8	1.02	−23.79	47.02	−42.28	28.61	−17.64	28.83	98.01	28.12	39.41
9	18.82	−4.59	28.69	−0.54	2.32	42.36	18.93	−2.45	37.65	94.67
10	23.92	−8.03	48.61	23.65	26.26	−3.65	23.31	15.36	80.59	52.51
11	−41.61	78.22	−85.02	−0.79	−68.70	−85.71	−45.64	2.27	−72.47	−80.26
12	−6.64	4.75	42.95	−48.60	26.27	13.24	−34.34	−54.47	−1.50	−24.46

3. Perform the first-pass regressions and tabulate the summary statistics.
4. Specify the hypotheses for a test of the second-pass regression for the SML.
5. Perform the second-pass SML regression by regressing the average excess return of each portfolio on its beta.
6. Summarize your test results and compare them to the results reported in the text.
7. Group the nine stocks into three portfolios, maximizing the dispersion of the betas of the three resultant portfolios. Repeat the test and explain any changes in the results.
8. Explain Roll's critique as it applies to the tests performed in Problems 3 to 7.
9. Plot the capital market line (CML), the nine stocks, and the three portfolios on a graph of average returns versus standard deviation. Compare the mean-variance efficiency of the three portfolios and the market index. Does the comparison support the CAPM?

Suppose that, in addition to the market factor that has been considered in Problems 3 to 9, a second factor is considered. The values of this factor for years 1 to 12 were as follows:

Year	% Change in Factor Value	Year	% Change in Factor Value
1	−9.84	7	−3.52
2	6.46	8	8.43
3	16.12	9	8.23
4	−16.51	10	7.06
5	17.82	11	−15.74
6	−13.31	12	2.03

10. Perform the first-pass regressions as did Chen, Roll, and Ross and tabulate the relevant summary statistics. (*Hint:* Use a multiple regression as in a standard spreadsheet package. Estimate the betas of the 12 stocks on the two factors.)
11. Specify the hypothesis for a test of a second-pass regression for the two-factor SML.
12. Do the data suggest a two-factor economy?
13. Can you identify a factor portfolio for the second factor?
14. Suppose you own your own business, which now makes up about half your net worth. On the basis of what you have learned in this chapter, how would you structure your portfolio of financial assets?

Challenge

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CFA® PROBLEMS

1. Identify and briefly discuss three criticisms of beta as used in the capital asset pricing model.
2. Richard Roll, in an article on using the capital asset pricing model (CAPM) to evaluate portfolio performance, indicated that it may not be possible to evaluate portfolio management ability if there is an error in the benchmark used.
   a. In evaluating portfolio performance, describe the general procedure, with emphasis on the benchmark employed.
   b. Explain what Roll meant by the benchmark error and identify the specific problem with this benchmark.
   c. Draw a graph that shows how a portfolio that has been judged as superior relative to a "measured" security market line (SML) can be inferior relative to the "true" SML.
   d. Assume that you are informed that a given portfolio manager has been evaluated as superior when compared to the Dow Jones Industrial Average, the S&P 500, and the NYSE Composite Index. Explain whether this consensus would make you feel more comfortable regarding the portfolio manager's true ability.
   e. Although conceding the possible problem with benchmark errors as set forth by Roll, some contend this does not mean the CAPM is incorrect, but only that there is a measurement problem when implementing the theory. Others contend that because of benchmark errors the whole technique should be scrapped. Take and defend one of these positions.
3. Bart Campbell, CFA, is a portfolio manager who has recently met with a prospective client, Jane Black. After conducting a survey market line (SML) performance analysis using the Dow Jones Industrial Average as her market proxy, Black claims that her portfolio has experienced superior performance. Campbell uses the capital asset pricing model as an investment performance measure and finds that Black's portfolio plots below the SML. Campbell concludes that Black's apparent superior performance is a function of an incorrectly specified market proxy, not superior investment management. Justify Campbell's conclusion by addressing the likely effects of an incorrectly specified market proxy on both beta and the slope of the SML.

SOLUTIONS TO CONCEPT CHECKS

1. The SCL is estimated for each stock; hence we need to estimate 100 equations. Our sample consists of 60 monthly rates of return for each of the 100 stocks and for the market index. Thus each regression is estimated with 60 observations. Equation 13.1 in the text shows that when stated in excess return form, the SCL should pass through the origin, that is, have a zero intercept.
2. When the SML has a positive intercept and its slope is less than the mean excess return on the market portfolio, it is flatter than predicted by the CAPM. Low-beta stocks therefore have yielded returns that, on average, were higher than they should have been on the basis of their beta. Conversely, high-beta stocks were found to have yielded, on average, lower returns than they should have on the basis of their betas. The positive coefficient on γ_2 implies that stocks with higher values of firm-specific risk had on average higher returns. This pattern, of course, violates the predictions of the CAPM.
3. *a.* According to Equation 13.5, γ_0 is the average return earned on a stock with zero beta and zero firm-specific risk. According to the CAPM, this should be the risk-free rate, which for the 1946–1955 period was 9 basis points, or .09% per month (see Table 13.1). According to the CAPM, γ_1 should equal the average market risk premium, which for the 1946–1955 period was 103 basis points, or 1.03% per month. Finally, the CAPM predicts that γ_3, the coefficient on firm-specific risk, should be zero.
   b. A positive coefficient on beta-squared would indicate that the relationship between risk and return is nonlinear. High-beta securities would provide expected returns more than proportional to risk. A positive coefficient on $\sigma(e)$ would indicate that firm-specific risk affects expected return, a direct contradiction of the CAPM and APT.

CHAPTER FOURTEEN

Bond Prices and Yields

IN THE PREVIOUS chapters on risk and return relationships, we treated securities at a high level of abstraction. We assumed implicitly that a prior, detailed analysis of each security already had been performed, and that its risk and return features had been assessed.

We turn now to specific analyses of particular security markets. We examine valuation principles, determinants of risk and return, and portfolio strategies commonly used within and across the various markets.

We begin by analyzing **debt securities.** A debt security is a claim on a specified periodic stream of income. Debt securities are often called *fixed-income securities* because they promise either a fixed stream of income or one that is determined according to a specified formula. These securities have the advantage of being relatively easy to understand because the payment formulas are specified in advance. Uncertainty about their cash flows is minimal as long as the issuer of the security is sufficiently creditworthy. That makes these securities a convenient starting point for our analysis of the universe of potential investment vehicles.

The bond is the basic debt security, and this chapter starts with an overview of the universe of bond markets, including Treasury, corporate, and international bonds. We turn next to bond pricing, showing how bond prices are set in accordance with market interest rates and why bond prices change with those rates. Given this background, we can compare the myriad measures of bond returns such as yield to maturity, yield to call, holding-period return, and realized compound rate of return. We show how bond prices evolve over time, discuss certain tax rules that apply to debt securities, and show how to calculate after-tax returns. Finally, we consider the impact of default or credit risk on bond pricing and look at the determinants of credit risk and the default premium built into bond yields. Credit risk is central to both collateralized debt obligations and credit default swaps, so we examine these instruments as well.