Katherine Schipper
and Rex Thompson
Carnegie-Mellon University

Common Stocks as Hedges against Shifts in the Consumption or Investment Opportunity Set*

This paper contains an investigation of the potential for using NYSE stocks as hedges against changes in the consumption-investment opportunity set. We perform this investigation under two characterizations of a multiperiod or generalized capital asset pricing model. We find sufficient cross-sectional dispersion in common stock return covariances with unanticipated changes in real GNP, the price level, and aggregate consumption that hedge portfolios offer meaningful hedging potential in the portfolio-formation period. The positive hedging potential persists out of the portfolio-formation period, but is strongly significant only for consumption.

I. Introduction

The purpose of this paper is to explore the potential of using common stocks as hedges against unanticipated shifts over time in investors' consumption or investment opportunity sets. The generalized or multiperiod capital asset pricing model (CAPM) developed in different forms by Merton (1973), Long (1974), Richard (1977), and Breeden (1979) forms the basis for this exploration. In this model, shifts in investors' consumption or investment opportunity sets are caused by changes in the stochastic elements of the state of the world that affect investor taste for wealth. The state of the world is defined in terms of the level of state variables so that unanticipated changes in the levels of the state variables imply or are associated with changes in the state of the world.

The analysis of this paper does not constitute a test of the generalized CAPM, because hedging potential is a necessary but not sufficient condition for the generalized CAPM to improve upon the traditional two-factor model. The existence of hedging potential is of interest in itself, how-

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ever, as long as some classes of investors are interested in hedging, even in the absence of a general market preference for this activity.

In this exploration, we limit our attention only to rate of return and industry classification data. These data constitute the information set from which we examine the possibilities investors have to form portfolios of common stocks with hedging potential. Results of the tests we perform suggest that it is possible to form portfolios of NYSE common stocks that are contemporaneous hedges against unanticipated changes in the variables we suggest as proxies for the state of the world. Attempts to form portfolios that are ex ante hedges are somewhat less successful, yet nonetheless encouraging.

In Section II we discuss the implications for hedging of the generalized CAPM in the forms suggested by Merton and Richard and by Breeden. The original form of Merton and Richard requires ex ante identification of state variables. In the form suggested by Breeden, aggregate consumption serves as a summary statistic for the state of the world (including the level of aggregate wealth) so the generalized model reduces to a very convenient form. However, aggregate consumption is difficult to measure accurately. Given the limitations of the data, we estimate hedging potential as it applies to both forms of the model. In Section III we discuss the data, their limitations, and our models of unanticipated changes in the state of the world. Sections IV–VI contain tests of the hedging potential of common stocks and industry portfolios. In Section VII we offer some conclusions.

II. The Generalized Capital Asset Pricing Model and Testable Implications

Multi-Beta Specification

The models developed by Merton (1973), Long (1974), and Richard (1977) are of the form

$$\alpha_j - r = \beta_{j1}(\alpha_m - r) + \beta_{j2}(\alpha_n - r). \tag{1}$$

These models are generalizations of the Sharpe-Lintner-Mossin CAPM given by (1′):

$$\alpha_j - r = \beta_{jm}(\alpha_m - r). \tag{1'}$$

In (1) and (1′),

α_j = expected real rate of return on asset j,[1]
α_m = expected real rate of return on the market portfolio,
α_n = expected real rate of return on a hedge portfolio constructed to have a covariance with each security's return

1. Long (1974) derives his model in nominal terms.

which is identical to the covariance between the unanticipated changes in the state variable of interest and the security's return,

r = the real risk-free rate of interest,

β_{j1}, β_{j2} = multiple regression coefficients. In the case of several state variables β_{j2} can be thought of as a vector of regression coefficients multiplying a vector of excess returns on hedge portfolios, one for each state variable.

Given the linear specification of the generalized CAPM of (1), the importance of a particular state variable in the asset pricing equation is determined by two factors: (1) the extent and nature of the correlation between asset returns and the returns on the hedge portfolio, and (2) the extent of the excess return expected (required), in equilibrium, on the hedge portfolio. In other words, the generalized models can theoretically improve upon the two-factor model if (1) asset returns are correlated with unanticipated changes in the investment or consumption opportunity set over the same or future periods, and (2) investors in the aggregate have significant risk preferences with respect to these changes in the opportunity set. Given the representation of the generalized CAPM in (1), an investigation of hedging considerations involves first the selection of likely candidates for state-of-the-world variables and second the estimation of the relationship between real returns to common stocks and unanticipated changes in the state-of-the-world variables.

In Section III, we select two candidates for state variables. These candidates have considerable economic appeal, although it is difficult to know for certain that we have identified the state-of-the-world variables most relevant to investors. The candidate variables we examine are the price level as measured by the Consumer Price Index (CPI) and real gross national product less corporate profits (GNP). Unanticipated changes in these two variables are selected as indicators of underlying shifts in the consumption and investment opportunity sets available in the economy.[2] Changes in real GNP are influenced by changes in technology and shifts in the relative demand for alternative consumption goods.[3] We use real GNP as a measure of the level of real eco-

2. The relationship between changes in the price level (inflation) and rates of return earned on comprehensive common stock indexes has been studied previously. See, for example, Lintner (1965), Fama and MacBeth (1974), Body (1976), Jaffe and Mandelker (1976), and Nelson (1976). These studies have not examined the existence of cross-sectional differences in correlation between individual security returns (and industry portfolio returns) and inflation.

3. It can also be argued that investors are potentially interested in hedging against unfavorable changes in real GNP because GNP contains the return to assets (such as human capital) which are not included in the market index. This line of reasoning, while helping to motivate an interest in GNP, is not in the spirit of the generalized CAPM, which assumes the existence of a true market portfolio.

nomic activity; as such we hypothesize that it reflects both the consumption and investment opportunity sets available in the economy. The results of Hodrick and Prescott (1978) are consistent with this line of intuition. They examine the contemporaneous correlation of detrended real GNP and various detrended macroeconomic aggregates. Except for measures of inflation, all of their macroeconomic aggregates have simple correlations greater than .50 with detrended real GNP. These results are summarized in table 1.

Single-Beta Specification

The assumption that the state of the world is captured by the level of real GNP and the price level is difficult to test directly. This is unfortunate, since the generalized CAPM in the form of (1) requires the ex ante specification of state variables. Breeden (1979) suggests an alternative specification which appears to avoid the issue of state-variable identification. He shows that changes in aggregate consumption can be used to infer the change in aggregate wealth and the change in utility resulting from shifts in the consumption-investment opportunity set. He demonstrates that under the assumption of a single consumption good, the generalized CAPM of (1) can be written alternatively as

$$\alpha_j - r = \beta_{jc}(\alpha_c - r), \tag{2}$$

where α_j = expected real rate of return on asset j,
α_c = expected real rate of return on a security or portfolio whose return is perfectly correlated with aggregate consumption,
β_{jc} = a traditional measure of beta except that the real rate of return on the market portfolio is replaced by the unanticipated change in aggregate real consumption,
r = the real risk-free rate of interest.

TABLE 1 Contemporaneous Correlation of Detrended Real GNP and Various Detrended Macroeconomic Aggregates, 1947–76

Variable	Correlation with Real GNP
Hours of work	.89
Consumer services	.70
Consumer nondurables	.71
Consumer durables	.68
Producer durables	.80
Durables	.81
Government spending	.69
Real M1	.66
Velocity of M1	.66
Real M2	.62
Velocity of M2	.42

SOURCE.—Taken from Hodrick and Prescott (1978).
NOTE.—Detrending was accomplished with a regression of the natural logarithm of the variable on a constant, a third-order polynomial in time, and three seasonal dummy variables. Data are quarterly.

The intuition behind this single-beta specification of the model is as follows: Individuals select their optimum investment portfolios and consumption levels such that at each moment in time their marginal utilities of consumption are equal to their indirect marginal utilities of wealth. In the absence of state-of-the-world considerations, increases in wealth (i.e., returns on the market portfolio) translate into changes in the level of consumption through the optimality conditions. At any instant in time individuals adjust their rates of consumption in response to changes in the level of their wealth. They could express their demand preferences for a given security either in terms of the security's covariance with the changes in their wealth or in terms of the security's covariance with changes in their consumption. Given that the investor taste for wealth (i.e., marginal utility of wealth) is influenced by other elements in the state of the world, changes in these elements also induce changes in consumption through the optimality conditions. At any instant in time, the covariance of a security's return with the market and all relevant state variables is summarized by the covariance of a security's return with consumption, so that for purposes of security pricing, changes in consumption summarize the changes in both wealth and the state of the world.[4]

If we knew the true β_{jc} from (2) and the true β_{jm} from the two-factor model of (1′), the two models should have the same power in explaining the cross-sectional variation in average returns to securities if there are no state variables for which securities are useful hedges (i.e., the β_{j2} in [1] are equal to zero for all securities for all state variables). If securities *are* useful hedges against relevant state variables, then the single-beta specification of the generalized model should have superior explanatory power, relative to the two-factor model, in cross-sectional tests. If we do not wish to examine the cross-sectional properties of security returns, there is one condition under which we can conclude that the generalized model is not a potential improvement over the two-factor model: the β_{jc}'s are identical across assets. Unfortunately, we would not predict that the β_{jc}'s are identical even if the two-factor model is a complete and correct specification of asset pricing, since in this case the β_{jm}'s of (1′) and the β_{jc}'s of (2) will be perfectly correlated.

4. In Breeden's model the covariance between a security's return and consumption is a weighted average of the covariance between the security's return and the market return and the covariance between that security's return and changes in the state of the world. The notion that an endogenous variable such as aggregate consumption should summarize the changes in the state variables driving the economy is very intuitive. In fact, any endogenous variable which is affected by the state variables summarizes their movement. Yet the assumption of stationarity of the covariance structure underlying security returns and state variables is not sufficient to generate stationary covariances between security returns and endogenous variables such as consumption. In general, one would expect these covariances to be nonstationary and vary with the level of aggregate wealth and the state of the world. In our empirical work, we assume stationarity, however.

To derive a more powerful test of the existence of hedging potential, the single-beta specification can be rewritten in a multi-beta form with consumption acting in place of the state variable in (1). This derivation is based on the fact that Breeden's consumption beta can be written as

$$\beta_{jc} = kV_{jm} + \sum_{s=1}^{S} c_s V_{js},$$

where V_{jm} is the covariance between the return to asset j and the market portfolio, V_{js} is the covariance between the return to asset j and the unanticipated change in state variable s, and k and the c_s are constants across the j assets.

The generalized model of (1) and the two-factor model of (1′) are equivalent if the V_{js}'s are scalar multiples of the V_{jm}'s (i.e., $V_{js} = qV_{jm}$ across j).[5] However, because of the linear relationship determining β_{jc}, if this scalar equality is true, then the *partial* correlations (holding the return to the market constant) between asset returns and unexpected changes in consumption are equal to zero. Furthermore, this hypothesis can be tested without ex ante identification of the relevant state variables. Thus, although consumption is not a state-of-the-world variable, the multi-beta form of Breeden's model permits the same kinds of tests to be applied to both consumption and the state variables. We will use the multi-beta form of Breeden's model in the tests which follow.

Outline of Tests

In the empirical analysis which follows, we examine two questions: (1) Using the multi-beta form of the generalized CAPM, is it possible to form a portfolio of common stocks which offers a hedge against unanticipated changes in the state-of-the-world variables real GNP and the price level? (2) Using consumption in the multi-beta form of the model, is it possible to form a hedge portfolio against unanticipated changes in consumption? We address these questions using returns to industry portfolios as well as returns to individual stocks. Before we can estimate and test regression coefficients, however, we must address several preliminary issues. These are discussed in Section III.

III. Empirical Tests: Preliminaries

Real versus Nominal Variables

Although investors are ultimately interested in real consumption, generalized CAPMs can be derived in either real or nominal terms. The

5. This point follows directly from equation (1). The multiple regression coefficient is

$$\beta_{j2} = \left(\frac{\sigma_m^2 \sigma_{j\Delta\tilde{S}} - \sigma_{m\Delta\tilde{S}}\sigma_{jm}}{\sigma_m^2 \sigma^2{}_{\Delta\tilde{S}} - \sigma_{m\Delta\tilde{S}}{}^2}\right),$$

where $\Delta\tilde{S}$ is the unanticipated change in the state of interest and the variances and covariances are of the variables defined in (1); $\beta_{j2} = 0$ (and the model collapses) whenever the numerator is zero. If $(\sigma_{j\Delta\tilde{S}}) = \theta \otimes (\sigma_{jm})$, then the numerator can be written as $\theta\sigma_m^2\sigma_{jm} - \theta\sigma_m^2\sigma_{jm}$ because $\sigma_m\Delta\tilde{S} = \theta\sigma_m^2$. It is not necessary that $\theta = 0$ (i.e., $\sigma_{m\Delta\tilde{S}} = 0$).

CAPMs derived using nominal variables (such as Long's) include terms which transform the model back into real variables through explicit inflation adjustments. Since generalized CAPMs in real terms need no such adjustment, they include inflation only as a potential state-of-the-world variable. To be consistent with models stated in real terms, we adjust common stock returns for inflation and measure consumption and GNP in real terms.

Data

The 521 firms on the Center for Research in Security Prices tape with no missing monthly data during the period 1953–75 and 20 common stock portfolios (industry indexes) grouped by two-digit SEC industrial classifications are analyzed.[6] The quarterly real return on a given industry portfolio or firm j is given by R_{jt} defined as follows:

$$R_{jt} = \left[\prod_{\tau=1}^{3} (1 + r_{j\tau})/\theta_{\tau} \right] - 1,$$

where θ_{τ} = ratio of the end-of-month to beginning-of-month Consumer Price Index (CPI), and $r_{j\tau}$ = nominal return to portfolio or firm j over the month τ of quarter t. In the case of portfolios, $r_{j\tau}$ is equal to the arithmetic average of the returns on all NYSE common stocks listed as being in that industry during that month. Table 2 indicates the number of securities in each industry portfolio, SEC codes, and betas for July 1954 to June 1975, our sample time period.

Quarterly measures of the macroeconomic aggregates were taken from the *Handbook of Cyclical Indicators*. Our consumption variable is defined as the sum of real expenditures on consumer services, consumer nondurables, and consumer durables. The treatment of expenditures on consumer durables is an important issue in empirical work related to consumption. One approach, followed by Sargent (1978), among others, is to substitute for expenditures on consumer durables some imputed service flow from the stock of durables. Another solution is to examine only nondurables and services (Hall 1978). Given the current state of disagreement about the treatment of consumer durables, we decided to conduct all our empirical tests on two measures of consumption, one including and one excluding expenditures on consumer durables. There was no qualitative difference in our results.

Preliminary Estimation Procedures

In deriving the generalized CAPM, Merton and Richard use a continuous time formulation which specifies that the rates of change in stock

6. Robert Stambaugh and the Center for Research in Security Prices at the University of Chicago provided us with the industry indexes. The indexes are fully described in Stambaugh (1978).

TABLE 2 Industry Portfolios

Name of Industry	SEC Codes	Firms, 12/65 (N)	Beta, 7/54–6/75
1. Mining	10–14	42	.80
2. Food and beverages	20	79	.86
3. Textile and apparel	22–23	47	1.14
4. Paper products	26	30	.89
5. Chemical	28	85	.87
6. Petroleum	29	34	.64
7. Stone, clay, and glass	32	38	.97
8. Primary metals	33	75	.92
9. Fabricated metal	34	37	1.03
10. Machinery	35	101	1.12
11. Appliances and electrical equipment	36	80	1.29
12. Transportation equipment	37	63	1.10
13. Miscellaneous manufacturing	38–39	44	1.20
14. Railroads	40	37	.94
15. Other transportation	41, 42, 44, 45, 47	33	1.20
16. Utilities	49	116	.53
17. Department stores	53	29	1.15
18. Other retail trade	50–52, 54–59	79	1.12
19. Banking, finance, real estate	60–67	73	.98
20. Miscellaneous	1, 4, 15–17, 21, 24 25, 27, 30, 31, 46, 48, 70, 72, 73, 75, 78, 79, 80, 82, 89, 99	126	1.12

SOURCE.—Except for last col., betas, these data are taken from table 6 of Stambaugh (1978).

prices and changes in the state variables follow diffusion processes, with the stochastic component distributed independently through time. The relevant measure of covariance from the point of view of hedging potential is the covariance between security returns and the stochastic (or unanticipated) portion of the change in the state-of-the-world variables. Similarly, in Breeden's formulation, the relevant covariance is between security returns and the ex ante unanticipated portion of the change in consumption. We separate the change in the state variables and consumption into anticipated and unanticipated portions by making one-step-ahead forecasts from simple time series and extrapolative models of the processes.

We define the unanticipated portion of the change in real GNP, real consumption, and the price level (i.e., inflation) as $\Delta\tilde{S}_\tau = \Delta S_\tau - \Delta\hat{S}_\tau$, where ΔS_τ is the realized change in time τ and $\Delta\hat{S}_\tau$ is its forecast.

In the case of GNP and consumption, the forecast of the change in τ is defined as

$$\Delta\hat{S}_\tau = \hat{\beta}_{o\tau} + \sum_{i=1}^{4} \hat{\beta}_{i\tau}\Delta S_{\tau-1} + \hat{\beta}_5 \cdot \tau,$$

where the $\hat{\beta}_{i\tau}$ are regression parameter estimates from a corresponding time series regression of changes in GNP or consumption on past changes and time. The parameter estimates for the forecast in time τ are based only on data prior to τ, so that the anticipations, $\Delta\hat{S}_{\tau}$, are estimated from continually updated models. The regression parameters for the last regression (τ = second quarter of 1975) are shown in table 3 along with summary statistics of the time series of forecast errors. Note that the forecast errors appear unbiased and serially uncorrelated although the explanatory power of the forecast regressions is small. For consumption, the forecast model is largely superfluous in terms of reducing the variance of the forecast error relative to the variance of the change in consumption itself.

Our motivation for using time series models for the macroeconomic aggregates GNP and consumption stems from the studies of Cooper (1972), Nelson (1972), and Cooper and Nelson (1975). Granger and Newbold (1977) review the work and conclude that, without the expert judgment of an econometrician to "adjust" the output of the model, large structural equation models forecast rather poorly compared with simple time series models. Hall (1978) arrives at a similar conclusion. There are fewer references to forecasting models of *changes* in macroeconomic aggregates, and the explanatory power of the forecast models is much lower. The errors generated from forecasts of the

TABLE 3 **Forecast Models for Changes in Real GNP and Real Consumption**

	Anticipation Regression for 1975II	
	GNP*	Consumption*
Constant	2.90 (1.90)	1.77 (1.80)
β_1	.45 (4.48)	.10 (1.04)
β_2	.11 (.94)	.23 (2.24)
β_3	.08 (.62)	.06 (.57)
β_4	−.12 (−1.05)	−.15 (−1.35)
β_5	.002 (.02)	.03 (1.66)
R_2	.26	.11
D-W	1.98	1.99
Summary of forecast errors from the anticipation regressions:		
Mean of forecast errors	.03 (.03)	−.08 (−.14)
Serial correlation of forecast errors:†	.04 (.37)	.08 (.73)

NOTE.—Numbers in parentheses are t-statistics.

*GNP and consumption are measured in billions of 1972 dollars. If ΔS indicates the first difference of GNP (or consumption), the following regression provides our estimates of anticipated and unanticipated ΔS, using quarterly data from 3/54 to 2/75:

$$\Delta S_t = \alpha + \sum_{i=1}^{4} \beta_i \Delta S_{t-i} + \beta_5 \text{ time} + e_t.$$

†Serial correlation is measured by the slope coefficient in the OLS regression of the forecast errors on themselves, lagged once.

changes are highly correlated with the errors generated from forecasts of the levels, however.

We use the 91-day treasury bill rate of interest as our forecast of the rate of inflation. As pointed out in Fama (1975), the difference between the realized rate of inflation and the nominal, riskless rate of interest should be perfectly correlated with the unanticipated rate of inflation if the capital market is information efficient and the required (expected) real rate of interest is constant. While the evidence is more consistent with the hypothesis that the real rate of interest is not constant over time, including the time series of past rates of inflation in our forecasts had little effect on the time series properties of the forecast error (which we call the unanticipated rate of inflation). Given our specification of the unanticipated rate of inflation, it is probably more precise to consider it both the result of shifts in the real rate of interest and the result of unanticipated inflation. The mean of the unanticipated inflation series can be interpreted as the negative of the average real rate of interest over the period. The statistical properties of the series (except for the switch in the sign of the mean) are virtually identical to those discussed in Fama (1975) for the 3-month real rate of interest.

It is also important to note that the wage and price controls of the early seventies distort the CPI as a measure of consumer prices over this period. Our estimate of unanticipated inflation is much less precise after 1971, and this fact should be kept in mind when the empirical results of our tests are interpreted.

IV. Initial Parameter Estimation and Tests of Significance

In this section we test the joint hypothesis that the multiple regression coefficients, β_{j2} in (1), are identically equal to zero for all of the industry portfolios and firms in our sample. While the equilibrium relationship of (1) is stated in terms of expected rates of return on individual securities (or portfolios of securities), the market portfolio and hedge portfolio, it is important to note that the hypothesis $\beta_{j2} = 0$ can be tested without knowledge of the hedge portfolio or its rate of return. If we assume multivariate normality of security returns and stationarity of the relevant stochastic processes, then, by construction of the hedge portfolio, the vector of β_{j2} coefficients from the multiple regressions

$$R_{jt} = \beta_{jo} + \beta_{j1}R_{mt} + \beta_{j2}\Delta\tilde{S}_t + \epsilon_{jt}, \qquad t = 1,T, \tag{3}$$

where R_{jt} = the realized return on security or portfolio j in t,
R_{mt} = the realized return on the market portfolio in t,
$\Delta\tilde{S}_t$ = the unanticipated change in the state variable or consumption in t,

ϵ_{jt} = an independent error term,
$\beta_{jo}, \beta_{j1}, \beta_{j2}$ = multiple regression coefficients,

is identical (up to a multiplicative scalar) to the vector of coefficients one would obtain were the hedge portfolio returns substituted for the unanticipated changes in the state variable.[7] The estimated parameters from (3) are the parameters on which the tests of this section are based. The forecast errors estimated in the previous section are used as our unanticipated changes in the state variables and consumption.

Under the null hypothesis, $\beta_{j2} = 0$ for all j. This hypothesis is tested under the assumption of multivariate normality of asset returns and two assumptions regarding the cross-sectional covariance matrix of error terms from equation (3). Under the assumption of cross-sectional independence of residuals (i.e., a diagonal covariance matrix), the following test statistic has asymptotically a χ^2 distribution with J degrees of freedom (see Theil 1971):

$$-2 \ln \left[\prod_{j=1}^{J} \frac{L_j(\hat{\omega})}{L_j(\hat{\Omega})} \right], \tag{4}$$

where $\dfrac{L_j(\hat{\omega})}{L_j(\hat{\Omega})}$ = the likelihood ratio for asset j;

= the square root of the sum of squared errors unconstrained divided by the constrained sum of squared errors, raised to the power T (T is the number of quarterly time series observations);

J = the number of assets, either 20 in the case of industry portfolios, or 521 in the case of individual firms.

If the constraint that all $\hat{\beta}_{j2}$'s = 0 is a particularly binding one, the statistic in (4) will be large relative to its expected value under the null hypothesis. The χ^2 statistics computed from the likelihood ratios are reported in table 4 for both the industry portfolios and the 521 individual stocks. Except in the case of the price level, these statistics are significant at the .05 level or better.

Table 4 also contains results from a more general test of the null hypothesis. If the true covariance matrix of error terms were known, the following test statistic has a χ^2 distribution with J degrees of freedom under the null hypothesis (see Theil 1971):

$$Q = (r - R\hat{\beta})' \{R[X'(\Sigma^{-1} \otimes I)X]^{-1} R'\}^{-1} (r - R\hat{\beta}), \tag{4'}$$

7. The denominators of the two multiple regression coefficients are different because the variance of return to the hedge portfolio is not constrained to equal the variance of the unanticipated change in the state.

where

$$r = \underset{J\times 1}{0}\,; R = \underset{J\times J}{I} \otimes [001];\ \underset{3J\times 1}{\hat{\beta}} = \begin{bmatrix} \hat{\beta}_{10} \\ \hat{\beta}_{11} \\ \hat{\beta}_{12} \\ \vdots \\ \hat{\beta}_{J0} \\ \hat{\beta}_{J1} \\ \hat{\beta}_{J2} \end{bmatrix}$$

$$\underset{J\times J}{\sum} = \text{covariance matrix of error terms}$$

$$X = \underset{J\times J}{I} \otimes \bar{X};\ \bar{X} = \underset{T\times 3}{\begin{bmatrix} 1 & R_{m1} & \Delta\tilde{S}_1 \\ \vdots & \vdots & \vdots \\ 1 & R_{mT} & \Delta\tilde{S}_T \end{bmatrix}}.$$

Since Σ is unknown, we replaced it with its maximum likelihood estimate. Our test statistic is therefore asymptotically (over T) χ^2. It is

TABLE 4 **Multi-Beta Specifications Using GNP, the Price Level, and Consumption, over the Time Period 1954III–1975II**

	Consumption	Variable Price Level	GNP	All Three*	Market Model
	A. χ^2 Tests of the Joint Hypothesis $\beta_{j2} = 0$ for 19 Industry Portfolios†				
Likelihood ratio test, assuming diagonal covariance matrix of residuals	35.4	19.7	68.4	136.5	335
Asymptotic χ^2 *test*, assuming full covariance matrix of residuals	56.3	38.7	48.5	146.2	258
	B. χ^2 Tests of the Joint Hypothesis $\beta_{j2} = 0$ for 521 Stocks‡				
Likelihood ratio test, assuming diagonal covariance matrix of residuals‡	658	568	807	2,084	7,091

*When all three variables are considered together, there are 57 df. The .05 level of significance is 79.1; the .01 level is 88.4.

†The statistics for portfolios are distributed asymptotically χ^2 with 19 df. The .05 level of significance is 30.14; the .01 level is 36.19.

‡Statistics for individual stocks are distributed asymptotically χ^2 with 521 df. The .05 level of significance is 575; the .01 level is 598.

computationally impractical to estimate and invert Σ for the 521 stocks, so this statistic is reported for the industry portfolios only. Further, to avoid a near singular estimate of the covariance matrix, one portfolio, miscellaneous (no. 20), was excluded from the computations.

As reported in table 4, when industry portfolios are considered, the null hypothesis is rejected at the .01 level of significance whenever the assumption of independence of return disturbances is relaxed to allow for a full covariance matrix of disturbances. Under the assumption of a diagonal covariance matrix, it is also rejected at the .01 level for GNP and for all three variables together, and at the .05 level for consumption. The null hypothesis is not rejected for the price level, under the assumption of a diagonal covariance matrix. When individual stocks are considered under the assumption of a diagonal covariance matrix of residuals, the null hypothesis is rejected at the .01 level for consumption and GNP, but not for the price level. These results indicate that the null hypothesis of zero β_{j2} coefficients is improbable.

Table 5 gives the β_{j2} estimates for the industry portfolios, computed over the entire 21-year period, and their t-statistics, computed under the assumption of a diagonal covariance matrix of returns. From table 5, we see that about half the $\hat{\beta}_{j2}$'s are positive. For GNP and consumption, but not for the price level, several $\hat{\beta}_{j2}$'s have t-statistics greater than 2.0 in magnitude. The statistically significant correlation reported in this section implies the existence of hedge portfolios. In the next section we form these portfolios and test for the amount of hedging they provide.

V. Construction of the Hedge Portfolios and Contemporaneous Hedging

The hedge portfolios underlying the generalized CAPM are constructed to have covariance with each security's return which is identical to the covariance between the changes in the state of the world and each security's return. If the covariance matrix of returns and the vector of covariances with the unanticipated changes in a particular state-of-the-world variable or consumption are known then the hedge portfolio is the vector X where

$$\begin{aligned} \underline{\Omega \mathrm{X}} &= \underline{\gamma} \quad \text{or} \\ \underline{\mathrm{X}} &= \Omega^{-1}\underline{\gamma}, \end{aligned} \tag{5}$$

where Ω = the covariance matrix of returns, and $\underline{\gamma}$ = the vector of covariances with unanticipated changes in a particular state-of-the-world variable or consumption. The $\underline{\mathrm{X}}$ is the portfolio which theoretically should be combined with the market portfolio for hedging purposes. Note that if a portfolio whose returns are perfectly correlated

TABLE 5 Estimated Coefficients from the Regression $R_{jt} = \beta_{j0} + \beta_{j1} R_{mt} + \beta_{j2} \Delta\tilde{S}_t + \epsilon_{jt}$, $t = 1,84$, for 20 Industry Portfolios

	Consumption			Price Level			GNP		
Portfolio Number	$\hat{\beta}_{j2}$	t	Long (+) or Short (−) in Hedge Portfolio	$\hat{\beta}_{j2}$	t	Long (+) or Short (−) in Hedge Portfolio	$\hat{\beta}_{j2}$	t	Long (+) or Short (−) in Hedge Portfolio
1.	−.0032	−1.4	−	.02	.0	+	−.0005	− .5	+
2.	−.0036	−2.8	−	1.24	1.0	+	−.0016	−2.8	−
3.	.0009	.4	+	.06	.0	+	.0002	.2	+
4.	.0008	.3	+	− .66	− .3	+	−.0010	−1.0	+
5.	.0020	1.4	−	− .39	− .3	−	.0004	.6	−
6.	−.0051	−1.9	−	.67	.3	+	−.0010	− .8	−
7.	−.0014	− .8	−	1.73	1.2	+	−.0002	− .3	−
8.	.0047	2.1	+	1.46	.7	+	.0007	.6	−
9.	−.0024	−2.1	−	.90	.9	−	−.0002	− .3	−
10.	.0010	.7	+	1.64	1.4	−	.0012	2.1	+
11.	.0024	.8	+	−2.70	−1.1	+	.0011	.8	+
12.	.0025	1.6	+	− .70	− .5	+	.0015	2.3	+
13.	.0007	.3	−	−1.01	− .5	−	.0004	.4	−
14.	.0053	2.2	+	1.91	.9	−	.0022	2.1	+
15.	−.0001	− .0	−	.60	.3	−	−.0014	−1.3	−
16.	−.0024	−1.3	−	−1.80	−1.2	−	−.0013	−1.6	−
17.	−.0009	− .5	−	.70	.5	+	−.0007	− .9	−
18.	−.0015	− .8	−	− .40	− .3	−	.0002	.3	+
19.	−.0029	−2.5	+	− .08	− .1	−	−.0006	−1.1	+
20.*	−.0011	−1.1	N.A.	−1.14	−1.3	N.A.	−.0005	−1.2	N.A.

*The twentieth industry (miscellaneous) is not included in the hedge portfolio.

with unanticipated changes in the state variable exists, $\underline{X}$ will have this property.

Since Ω and $\underline{\gamma}$ are not known, we replaced them with their maximum likelihood estimates (the sample covariances). The resulting estimate of the vector $\underline{X}$ is consistent as the number of time series observations used to calculate the sample covariances becomes infinite. In small samples it is biased because of an errors-in-variables problem. To minimize this problem we have used as many observations as possible in estimating the vector $\underline{X}$.

The positions (long or short) of each industry index in the hedge portfolios are given in table 5. The actual portfolio weights are scaled by their cross-sectional sum in the results reported throughout the remaining sections of the paper. The explanatory power of the models is not altered by scaling the weights, and the relationships can then be interpreted as those between standard portfolios (with weights summing to one or minus one).

Hedge portfolios are not, in general, perfectly correlated with the unanticipated changes in the state-of-the-world variables. The amount of correlation reflects the extent to which the asset universe (in this case the NYSE) can be used to hedge against changes in the state. In table 6 the contemporaneous relationships between the hedge portfolios and the state variables and consumption are presented.

Table 6 contains results of the multiple regressions

$$R_{nt} = \gamma_o + \gamma_1 R_{mt} + \gamma_2 \Delta\tilde{S}_t + \epsilon_t, \qquad t = 1{,}84, \tag{6}$$

and

$$R_{nt} = \gamma_o + \gamma_2 \Delta\tilde{S}_t + e_t, \qquad t = 1{,}84, \tag{7}$$

where R_{nt} = the real rate of return to the hedge portfolio in t,
R_{mt} = real rate of return on the equally weighted NYSE index,
$\Delta\tilde{S}_t$ = unanticipated change in the state variable (or consumption),
ϵ_t = an orthogonal error term,
$\gamma_o, \gamma_1, \gamma_2$ = regression parameters.

In part A, results for hedge portfolios constructed from the 19 industry indexes are presented. Part B contains results for hedge portfolios constructed from the 521 individual stocks and will be discussed shortly. For comparison, part C contains simple correlations between the market index and the unanticipated changes in the state variables and consumption.

In part A, the explanatory power of all the regressions is impressive. In particular, the contribution of the state variable or consumption, as judged by t-values, indicates that, ex post, it is possible to form hedge

TABLE 6 **Contemporaneous Relationship between the Returns to Hedge Portfolios and Unanticipated Changes in the State of the World**

	Consumption		Price Level		GNP	
	A. Hedge Portfolios Based on Industry Indexes (84 Observations)					
γ_1	...	.80	...	−1.08	...	.42
t_1	...	2.91	...	−4.63	...	1.86
γ_2	.04	.04	39.56	31.13	.02	.02
t_2	7.32	6.69	6.76	5.62	7.09	6.82
R^2	.40	.45	.36	.49	.38	.41
D-W	1.81	1.73	2.10	1.86	1.74	1.78
	B. Hedge Portfolios Based on 521 Stocks (Odd Quarters)					
γ_1	...	.14	...	− .07	...	− .07
t_1	...	.28	...	− .69	...	− .22
γ_2	.21	.21	30.23	29.79	.05	.05
t	15.26	15.05	14.57	13.62	13.18	12.97
R^2	.85	.85	.84	.84	.81	.81
D-W	1.54	1.55	1.78	1.75	1.80	1.81
	Hedge Portfolios Based on 521 Stocks (Even Quarters)					
γ_1	...	2.56	...	− .31	...	1.06
t_1	...	1.93	...	−1.95	...	2.15
γ_2	.16	.14	34.97	32.10	.04	.03
t_2	7.76	6.65	8.99	7.93	7.10	6.07
R^2	.60	.64	.67	.70	.56	.60
D-W	2.02	2.01	2.37	2.38	1.89	2.04
	C. Correlation between the Market Index and Unanticipated Changes in the State of the World					
α_1	.005		−8.50		.0018	
t	2.33		−3.44		1.42	

NOTE.—In parts A and B, statistics are from the regressions $R_{nt} = \gamma_0 + \gamma_1 R_{mt} + \gamma_2 \Delta\tilde{S} + \epsilon_t$ and $R_{nt} = \gamma_0 + \gamma_2 \Delta\tilde{S} + e_t$. In part C, statistics are from the regression $R_{mt} = \alpha_0 + \alpha_1 \Delta\tilde{S}_t + \epsilon_t$.

portfolios with significant hedging potential. The lowest t-statistic is 5.6. Judging from the modest correlation between the market index and the state variables (as seen in part C), the t-statistics are reliable indicators of the contribution of the state variable in the multiple regressions.

Because of the size of the covariance matrix for the individual stocks, the exact hedge portfolio was not constructed. Instead, an approximation was obtained through the following procedure: (1) β_{j2} estimates from equation (3) were obtained using the odd quarters in the sample, that is, 42 observations. These estimates were used to rank the 521 stocks and assign them to one of 20 portfolios in descending order by size of β_{j2}. (2) The median (tenth) portfolio was dropped. (3) The remaining 19 portfolios were used as underlying assets similar to the industry indexes.

Hedge portfolios were constructed from these 19 intermediate portfolios, their covariance matrix, and covariances with the state variables. Hedge portfolios were constructed for both the even quarters and the odd quarters. Part B contains the results of the multiple regressions of these hedge portfolios on the market index and the state variables and consumption. Note the increased explanatory power over the industry index hedge portfolios during the odd quarters (i.e., the quarters used to form the intermediate portfolios). During the even quarters the significance of the hedging potential is about the same as with the industry indexes.[8] The implication is that the $\hat{\beta}_{j2}$'s of the intermediate portfolios regress toward the mean in the even quarters (out of sample) and have approximately the same cross-sectional distribution of $\hat{\beta}_{j2}$'s as the industry indexes. Within the intermediate portfolio formation period (the odd quarters), the cross-sectional distribution of $\hat{\beta}_{j2}$'s offers a bigger spread and thus better hedging potential. This regression phenomenon indicates that much of the ex post apparent hedging potential of the individual stocks is due to within-sample estimation error and is hard to predict ex ante, using past values of $\hat{\beta}_{j2}$.

The conclusion to be drawn from table 6 in conjunction with the general statistical significance of the individual $\hat{\beta}_{j2}$'s in table 4 is that a reasonable amount of hedging potential exists in NYSE stocks. Ex post, utilization of the sample coefficients yields a hedge portfolio which has over 30% of the variance of its return explained by movements in the state variable or consumption. In other words, if one had perfect foresight regarding the sample estimates of the $\hat{\beta}_{j2}$ coefficients, a significant hedge against the state variables and consumption could have been constructed.

Preliminary tests of stability of the $\hat{\beta}_{j2}$ coefficients indicate, on the other hand, that although in large time series samples the coefficients are statistically significant, it is sometimes difficult to identify a hedge portfolio, ex ante, based on past estimates of the $\hat{\beta}_{j2}$'s. These issues are discussed in Section VI.

VI. Stability of the Hedge Portfolio and the Individual Parameter Estimates

Individual Parameter Estimates

In order for investors to utilize the hedging potential of common stocks, it is necessary for them to predict, ex ante, the weights comprising the hedge portfolios. Since these weights are functions of the

8. Hedge portfolios from the industry indexes were constructed using only even quarters and only odd quarters. The t-values for the state variables for the separate periods yield the same general conclusions.

$\hat{\beta}_{j2}$'s, stability over time in these coefficients would allow past estimates to be used as ex ante predictors of the future. To investigate this possibility, the 21-year sample was broken into 3 time periods of 7 years each: third quarter 1954 to second quarter 1961; third quarter 1961 to second quarter 1968; and third quarter 1968 to second quarter 1975. Regression parameters were estimated in each time period and the following cross-sectional regressions run:

$$\hat{\beta}_{j2t} = \alpha_0 + \alpha_1 \hat{\beta}_{j2t-1} + \epsilon_j, \qquad j = 1{,}521 \text{ or } j = 1{,}20, \tag{8}$$

where $\hat{\beta}_{j2t}$ is the multiple regression coefficient from equation (3) for period $t\,(t = 1{,}2$, or 3). The results are reported in table 7. Part A contains results for the industry indexes and part B for the individual stocks. For comparison, cross-sectional regressions of the beta coefficients from the market model are also reported.

In all of the regressions, care should be exercised in the interpretation of the slope coefficient. Because of estimation error in the independent variable (i.e., the $\hat{\beta}_{j2}$'s and market model betas), the slope coefficient will be attenuated toward zero even if the "true" relationship between the β_{j2}'s has a slope coefficient of unity. In this case, however, we are interested in measuring the degree of stability, over time, in the estimated coefficients.

From part B of table 7, it appears that there may be some stability over time for $\hat{\beta}_{j2}$'s of individual stock returns with unanticipated changes in real GNP. The association is not very strong, however,

TABLE 7 **The Stability of Regression Coefficients**

	Consumption	Price Level	GNP	Market Model
		A. 20 Industry Portfolios		
Period 2 on 1:				
α_1 (t)	.51(3.46)	−.56(−.84)	.16(.41)	.58(5.03)
R^2	.37	0	0	.56
Period 3 on 2:				
α_1 (t)	−.25(−1.68)	.11(.69)	−.07(−.47)	.77(2.87)
R^2	.09	0	0	.28
		B. 521 Common Stocks		
Period 2 on 1:				
α_1 (t)	.20(4.43)	−.01(−.14)	−.07(−.76)	.42(13.84)
R^2	.03	0	0	.27
Period 3 on 2:				
α_1 (t)	−.01(−.48)	.02(.74)	.06(3.04)	.51(14.25)
R^2	0	0	.016	.28

NOTE.—Summary statistics from the cross-sectional regression $\hat{\beta}_{j2t} = \alpha_0 + \alpha_1\hat{\beta}_{j2t-1} + e_j, j = 1{,}521$ or $j = 1{,}20$. In this regression, $\hat{\beta}_{j2t}$ is the regression coefficient of the jth industry portfolio (or firm) in period t on the unanticipated portion of the change in GNP, price level, or consumption. Period 1 is 3/54–2/61, period 2 is 3/61–2/68, period 3 is 3/68–2/75. Quarterly data are used.

since at best the model explains less than 2% of the variance in the $\hat{\beta}_{j2}$'s. The relationship for GNP appears across only 2 of the 3 possible time periods, and the sign of the across-time-periods correlation coefficient reverses as we move from the period 1–2 correlation to the period 2–3 correlation.

The relationship for GNP disappears completely, however, when we look at the industry portfolios (part A). The association is not statistically significant at any reasonable level, across any or all time periods considered. It could be, therefore, that the association found between periods 2 and 3 for individual firms is spurious, that is, due to industry commonalities affecting error terms cross-sectionally. It is interesting that the signs of the $\hat{\alpha}_1$'s reverse as we move from industry portfolios to individual stocks.

Results of cross-sectional tests based on the multi-beta specification of the consumption model indicate the existence of some stability in the regression coefficients. The results for the consumption models are puzzling, however, for several reasons. First, there appears to be a strong relationship between regression coefficients in periods 1 and 2 when industry portfolios are considered, but this relationship does not appear between 2 and 3, nor is it as strong when we consider individual stocks. Second, the sign changes as we move from the period 1–2 correlations to the period 2–3 correlations, and the magnitude of $\hat{\alpha}_1$ drops sharply.

At this point it is worth noting again that the true covariance between the endogenous variable consumption and security returns would be expected to vary with the level of aggregate wealth and the state of the world. This could provide an explanation for our results. On the other hand, measurement error is probably the source of much of the instability. We draw this conclusion based on the tests in the next section, which reduce the measurement error problem in the estimation of the consumption betas.

In contrast, note the significance of the market model regressions. Despite the reputed lack of stability in market model beta estimates, their stability overshadows whatever modest stability exists in the $\hat{\beta}_{j2}$'s.

Performance of the Hedge Portfolios Out of Sample

The results in Section V and table 6 indicate that within the sample period used to construct them, the hedge portfolios offer significant hedging potential. Table 8 contains the results of a test to verify the existence of hedging potential out of the sample period used to construct the hedge portfolios. The intent is to determine whether it is possible to construct a hedge portfolio based on parameter estimates from one time period which hedges against changes in its state variable in another time period.

TABLE 8 Noncontemporaneous Relationship between the Returns to Hedge Portfolios and Unanticipated Changes in the State of the World

	Consumption		Price Level		GNP	
γ_1	...	.76	...	−1.59	...	.80
t_1	...	1.48	...	−5.43	...	2.80
γ_2	.05	.04	1.25	.28	.006	.005
t_2	4.50	3.82	.65	.04	1.75	1.63
R^2	.20	.21	.005	.29	.04	.13
D-W	1.91	1.83	1.99	1.90	1.86	1.93

NOTE.—Statistics from the regressions $R_{nt} = \gamma_o + \gamma_1 R_{mt} + \gamma_2 \Delta\tilde{S}_t + e_t$ and $R_{nt} = \gamma_o + \gamma_2 \Delta\tilde{S}_t + e_t$. Hedge portfolios based on industry indexes (84 observations). The return on the hedge portfolio is computed in quarter t (t = 1,84). The hedge portfolio is formed from the other 83 quarters of data. Thus, each quarter in turn is "held out" from portfolio formation.

The problem with tests which involve hold-out samples is that efficiency is lost in the parameter estimation phase of the test. Information contained in the hold-out sample is not utilized. On the other hand, verification of hedging potential out of sample is important for an investor actually interested in forming an operational hedge portfolio.

To use as much information as possible in the parameter estimation phase without completely eliminating the hold-out sample, we adopted the following procedure for our out-of-sample tests:

1. For each of the 84 quarters in our sample period construct a hedge portfolio based on parameter estimates from the remaining 83 time series observations. In other words, estimate the sample covariances between the unanticipated change in a state variable (or consumption) and the returns to the industry indexes, and also estimate the covariance matrix of returns among the industry indexes in each of the 84 overlapping time periods of 83 quarters each. Each quarter is thus "held out" in turn.

2. Using the portfolio weights comprising the hedge portfolios formed in step (1), calculate the return to the hedge portfolio in the single quarter which is not used in the parameter estimation phase, that is, the "hold-out" quarter. This step generates 84 out-of-sample returns to 84 separate hedge portfolios, and although the portfolio weights are highly correlated across portfolios, the weights comprising any individual portfolio are independent of the return earned in the quarter which is withheld during the estimation phase.

3. Estimate the out-of-sample hedging potential by fitting equations (6) and (7) with the 84 out-of-sample portfolio returns as the independent variables. If the hedge portfolio weights do not persist out of sample, the multiple regression coefficients on the state variables (or consumption) in (6) should be zero and the regression coefficients in (7) should be approximately equal to those in part C of table 6 for the

market index. The results of these tests are contained in table 8.[9] Note the sharp contrast with the in-sample results reported in part A of table 6. While all three out-of-sample return vectors are positively correlated with unanticipated changes in their respective state variables or consumption, the marginal significance level of the relationship is not impressive for GNP or the price level. For GNP, the marginal significance level of the multiple regression coefficient on the state variable is close to .05 for a one-tailed test (t = 1.63) and close to .06 for the single-variable regression (t = 1.75). Inflation hedging is less impressive with t-statistics below unity. The consumption hedge has much better performance with t-statistics above 3.8. These results are weaker, however, than the in-sample tests, which produced t-statistics in excess of 6.6 (reported in table 6).

There are several interesting features of the results in table 8 as they relate to the results of the previous sections. Of the three variables we consider, inflation is the most difficult to hedge against, out of sample, and this is consistent with the low χ^2 statistics for the test of the joint hypothesis that the underlying β_{j2} coefficients in equation (3) are equal to zero for inflation (table 4). Inflation also has the poorest in-sample hedging results, although the difference between inflation and the other variables is more pronounced in table 8 than in table 6.

Both GNP and inflation have generally lower cross-sectional stability in their β_{j2} coefficient estimates than consumption, as evidenced by the results in table 7. This relative lack of stability manifests itself in relatively poorer out-of-sample hedging potential.

One conclusion to be drawn from the tests of stability is that, while the $\hat{\beta}_{j2}$ coefficients differ significantly across industries in a statistical sense (e.g., the results in table 4), estimation error nearly destroys the usefulness of the parameter estimates out of sample. Further, as the number of time series observations is decreased during parameter estimation, the severity of the estimation-error problem increases. Attempts to use larger hold-out samples than one observation (e.g., half the data) meet with virtually no success.

When the entire data set is used, estimation error does not result in a complete failure to reject the null hypothesis of no hedging potential, particularly against unanticipated changes in consumption and GNP. The out-of-sample tests and tests of coefficient stability lead to the conclusion, however, that additional information besides the past his-

9. Out-of-sample tests are reported for the industry portfolios only. It is computationally impractical to perform the steps outlined above for the 521 individual firms. Intermediate portfolios formed on the basis of coefficients estimated with half of the data (rather than 83 observations), as in table 6, do not contain enough information to generate statistically significant out-of-sample hedging ability.

tory of rate-of-return covariability should be sought by investors attempting actually to construct a hedge portfolio.

VII. Conclusions

Our examination of the potential to use portfolios of NYSE stocks as hedges against changes in the state of the world is based on two alternative characterizations of investor demand for hedging. The first characterization requires the ex ante identification of the state variables of greatest interest to investors. We select real GNP and the price level as candidate state variables and find the following:

1. Over the time period examined (third quarter 1954 to second quarter 1975), it is possible to reject at the .05 level the hypothesis that real rates of return to individual NYSE common stocks and industry portfolios have cross-sectionally identical associations with unanticipated changes in real GNP.
2. The association between real returns and unanticipated changes in the price level (i.e., unanticipated inflation) is more nearly constant across securities and industries. Using a maximum-likelihood estimate of the cross-sectional covariance matrix of error terms, however, we are able to reject (at the .01 level) the hypothesis that returns to all industries have the same association with unanticipated inflation.
3. Hedge portfolios formed on the basis of estimated covariances between asset returns and unanticipated changes in the two state variables have a high degree of in-sample correlation with these unanticipated changes.
4. Out of sample, while the hedge portfolio returns are positively correlated with the unanticipated changes in the state variables, this correlation is not statistically significant at the .05 level, although, in the case of GNP, this correlation is significant at the .06 level.

It is not possible to claim that we have examined the only relevant state variables in the economy. On the other hand, our results indicate the possibility, in principle, of forming portfolios of NYSE stocks which hedge against unanticipated changes in macroeconomic indicators of shifts in the consumption-investment opportunity set. In practice, however, it appears that additional information besides the past history of return variability will have to be used in the portfolio formation process.

The second characterization of investor demand for hedging uses changes in aggregate consumption as a summary statistic for investor reaction to unspecified changes in the state of the world that affect their taste for current consumption versus future wealth. Within this framework it is not necessary to specify, a priori, the relevant state variables in the economy, and our results are very encouraging. We find the following: (1) The hypothesis that real returns to all stocks and industries have the same association with unanticipated changes in aggregate consumption can be rejected at very high levels of confidence (well above .99). (2) Based on estimated sample covariances between asset returns and unanticipated changes in consumption, it is possible to form hedge portfolios whose returns are significantly positively correlated with the unanticipated changes in consumption both in and out of the portfolio formation period. This last result indicates that investors who desire to hold a portfolio of securities which has higher returns when aggregate consumption is unexpectedly high should be able to do so with a weighted combination of NYSE stocks. The existence of this hedging potential leads naturally to the question of whether hedge portfolios command a return premium in the marketplace relative to, say, the returns predicted by the traditional two-factor asset pricing model. If they do, then investors can be characterized as having aggregate risk preferences with respect to hedging against uncertainties in the consumption-investment opportunity set. This research constitutes a logical extension to the current paper.

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