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# Uncovering the Risk–Return Relation in the Stock Market

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# UNCOVERING THE RISK–RETURN RELATION IN THE STOCK MARKET

## **Abstract**

There is an ongoing debate about the apparent weak or negative relation between risk (conditional variance) and expected returns in the aggregate stock market. We develop and estimate an empirical model based on the ICAPM that separately identifies the two components of expected returns—the risk component and the component due to the desire to hedge changes in investment opportunities. The estimated coefficient of relative risk aversion is positive, statistically significant, and reasonable in magnitude. However, expected returns are driven primarily by the hedge component. The omission of this component is partly responsible for the existing contradictory results.

The return on the market portfolio plays a central role in the capital asset pricing model (CAPM), the financial theory widely used by both academics and practitioners. However, the intertemporal properties of stock market returns are not yet fully understood.<sup>1</sup> In particular, there is an ongoing debate in the literature about the relation between stock market risk and return and the extent to which stock market volatility moves stock prices. This paper provides new evidence on the risk-return relation by estimating a variant of Merton's (1973) intertemporal capital asset pricing model (ICAPM).

In his seminal paper, Merton (1973) shows that the conditional excess market return,  $E_{t-1}r_{M,t} - r_{f,t}$ , is a linear function of its conditional variance,  $\sigma_{M,t-1}^2$ , (the risk component) and its covariance with investment opportunities,  $\sigma_{MF,t-1}$ , (the hedge component), i.e.,

$$E_{t-1}r_{M,t} - r_{f,t} = \left[ \frac{-J_{WW}W}{J_W} \right] \sigma_{M,t-1}^2 + \left[ \frac{-J_{WF}}{J_W} \right] \sigma_{MF,t-1}, \quad (1)$$

where  $J(W(t), F(t), t)$  is the indirect utility function of the representative agent with subscripts denoting partial derivatives,  $W(t)$  is wealth, and  $F(t)$  is a vector of state variables that describe investment opportunities.<sup>2</sup>  $\frac{-J_{WW}W}{J_W}$  is a measure of relative risk aversion, which is usually assumed to be constant over time. If people are risk averse, then this quantity should be positive.

Under certain conditions, Merton (1980) argues that the hedge component is negligible and the conditional excess market return is proportional to its conditional variance.<sup>3</sup> Since Merton's work, this specification has been subject to dozens of empirical investigations, but these papers have drawn conflicting conclusions on the sign of the coefficient of relative risk aversion. In general, however, despite widely differing specifications and estimation techniques, most studies find a weak or negative relation. Examples include French, Schwert and Stambaugh (1987), Campbell (1987), Glosten, Jagannathan and Runkle (1993), Whitelaw (1994), and more recent papers, including Goyal and Santa-Clara (2003), Lettau and Ludvigson (2003) and Brandt and Kang (2004). Notable exceptions are concurrent papers by Bali and Peng (2004) and Ghysels, Santa-Clara and Valkanov (2004) that document a positive and significant relation. Bali and Peng (2004) use intraday data to estimate the conditional variance and study the risk-return tradeoff at a daily frequency, in contrast to much of the literature which uses lower frequency returns. Ghysels, Santa-Clara and Valkanov (2004) use functions of long lags of squared daily returns to proxy for the monthly conditional variance. However, neither paper focuses on the hedge component and its interaction with the risk component as we do in this study.

The failure to reach a definitive conclusion on the risk-return relation can be attributed to two factors. First, neither the conditional expected return nor the conditional variance are directly observable; certain restrictions must be imposed to identify these two variables. Instrumental variable models and autoregressive conditional heteroscedasticity (ARCH) models are the two most commonly used identification methods. In general, empirical results are sensitive to the restrictions imposed by these models. For example, Campbell (1987) finds that the results depend on the choice of instrumental variables. Specifically, the nominal risk-free rate is negatively related to the expected return and positively related to the variance, and “these two results together give a perverse negative relationship between the conditional mean and variance for common stock” (Campbell (1987, p.391)). In the context of ARCH models, if the conditional distribution of the return shock is changed from normal to student-t, the positive relation found by French, Schwert and Stambaugh (1987) disappears (see Baillie and DeGennaro (1990)).

Second, there are no theoretical restrictions on the sign of the correlation between risk and return. Backus and Gregory (1993) show that in a Lucas exchange economy, the correlation can be positive or negative depending on the time series properties of the pricing kernel. This result suggests that the hedge component can be a significant pricing factor and can have an important effect on the risk-return relation. In general, the risk-return relation can be time-varying as observed by Whitelaw (1994). The theory, however, still requires a positive *partial* relation between stock market risk and return. The more relevant empirical issue is to disentangle the risk component from the hedge component.

Scruggs (1998) presents some initial results on the decomposition of the expected excess market return into risk and hedge components. Assuming that the long-term government bond return represents investment opportunities, he estimates equation (1) using a bivariate exponential GARCH model and finds that the coefficient of relative risk aversion is positive and statistically significant. However, his approach has some weaknesses. For example, he assumes that the conditional correlation between stock returns and bond returns is constant, but Ibbotson Associates (1997) provide evidence that it actually changes sign over time in historical data. After relaxing this assumption, Scruggs and Glabadanidis (2003) fail to replicate the earlier results. Of course, this latter result does not imply a rejection of equation (1); rather, it challenges the assumption that bond returns are perfectly correlated with investment opportunities.

In contrast, we develop an empirical specification based on Merton’s (1973) ICAPM and Campbell and Shiller’s (1988) log-linearization method and implement estimation using instrumental variables.<sup>4</sup> Instead of working with the ex ante excess return, which is not directly observable, we decompose the ex post excess return into five components: the risk component and the hedge component, which together make up expected returns, revisions in these two components, which measure unexpected returns due to shocks to expected returns, and a residual component reflecting unexpected returns due to revisions in cash flow and interest rate forecasts. We explicitly model the volatility feedback effect,<sup>5</sup> and we also control for innovations in the hedge component. Therefore, we explain part of the unexpected return on a contemporaneous basis and improve the efficiency of the estimation and the identification of the risk and hedge components of expected returns.

Another innovation relative to previous work is that we use monthly volatility implied by S&P 100 index option prices as an instrumental variable for the conditional market variance.<sup>6</sup> Implied volatility is a powerful predictor of future volatility, subsuming the information content of other predictors in some cases (see, for example, Christensen and Prabhala (1998) and Fleming (1998)). Implied volatility is therefore an efficient instrumental variable and improves the precision of the estimation.

We get three important and interesting results from estimating the model with the implied volatility data. First, the coefficient of relative risk aversion is positive and precisely estimated, e.g., 4.93 with a standard error of 2.14 in our fully specified model. Second, we find that expected returns are primarily driven by changes in investment opportunities, not by changes in stock market volatility. The two together explain 6.8% of the total variation in stock market returns, while the latter alone explains less than 1% of the variation. Moreover, other than for two short episodes associated with severe market declines, the variance of the estimated hedge component is larger than that of the risk component. Third, the risk and hedge components are negatively correlated. Thus the omitted variables problem caused by estimating equation (1) without the hedge component can cause a severe downward bias in the estimate of relative risk aversion.

One concern is that the implied volatility data only start in November 1983. In order to check the robustness of our results, we also estimate the model with longer samples of monthly and quarterly data, in which the conditional market variance is estimated with lagged financial variables. The results from this empirical exercise are also more readily compared to those in the

existing literature. Similar results are found in this longer dataset. For the monthly data, the point estimate of the coefficient of relative risk aversion is 2.05 with a standard error of 2.98. In spite of the longer sample, the standard error is higher due to the imprecision associated with estimating the conditional variance using financial variables rather than implied volatility. For the quarterly data, the estimate of relative risk aversion is 7.75 with a standard error of 2.79. In both cases, expected returns are driven primarily by changes in investment opportunities.

These analyses allow us to explain the counter-intuitive and contradictory evidence in the current literature. The primary issue is a classical omitted variables problem. Because the omitted variable, the hedge component, is large and negatively correlated with the included variable, the risk component, the coefficient is severely downward biased and can even be driven negative. In addition, the conditional variance is often measured poorly, thus generating large standard errors and parameter estimates that can vary substantially across specifications. Finally, controlling for the effect of shocks to expected returns on unexpected returns (i.e., the volatility feedback effect and the analogous effect of innovations in the hedge component) can increase the efficiency of our estimation, sometimes substantially. However, the results suggest that care must be taken when including these effects since misspecification and estimation error can cause the inclusion of these components to degrade the performance of the model in some cases.

The remainder of the paper is organized as follows. Section I presents a log-linear model of stock returns that decomposes ex post returns. The data are discussed in Section II. The empirical investigation is conducted in Section III, and Section IV concludes the paper.

## I. Theory

### A. A Log-Linear Asset Pricing Model

We first derive an asset pricing model based on Merton's ICAPM and Campbell and Shiller's (1988) log-linearization method. The log-linear approximation provides both tractability and accuracy.

As in Campbell and Shiller (1988), the continuously compounded market return  $r_{M,t+1}$  is defined as

$$r_{M,t+1} = \log(P_{M,t+1} + D_{M,t+1}) - \log(P_{M,t}), \quad (2)$$

where  $P_{M,t+1}$  is the price at the end of period  $t+1$  and  $D_{M,t+1}$  is the dividend paid out during

period  $t+1$ . Throughout this paper, we use upper case to denote the level and lower case to denote the log. In addition, the subscript  $M$  will be suppressed for notational convenience.

Using a first-order Taylor expansion around the steady state of the log dividend price ratio  $\overline{d-p}$ , equation (2) can be rewritten as a first-order difference equation for the stock price,

$$r_{t+1} \approx k + \rho p_{t+1} - p_t + (1 - \rho)d_{t+1}, \quad (3)$$

where

$$\rho = \frac{1}{1 + \exp(\overline{d-p})}, \quad (4)$$

$$k = -\log(\rho) - (1 - \rho) \log\left(\frac{1}{\rho} - 1\right), \quad (5)$$

and  $\rho$  is set equal to 0.997 for monthly data and 0.98 for quarterly data as in Campbell, Lo and MacKinlay (1997, Chapter 7). Henceforth for simplicity we replace the approximation sign in equation (3) with an equals sign. Although in general the approximation error may not be negligible, Campbell, Lo and MacKinlay (1997, Chapter 7) provide evidence that it is very small in our context.

Solving equation (3) forward and imposing the appropriate transversality condition, we get an accounting identity for the price that also holds ex ante. Substituting this equation back into (3), we get the standard decomposition of the ex post stock return into two parts—the expected return and the shocks to the return (see, e.g., Campbell, Lo and MacKinlay (1997, Chapter 7)). For the excess market return,  $e_{t+1} \equiv r_{t+1} - r_{f,t+1}$ , where  $r_{f,t+1}$  is the nominal risk-free rate, this decomposition can be rewritten as

$$\begin{aligned} e_{t+1} = & E_t e_{t+1} - \left[ E_{t+1} \sum_{j=1}^{\infty} \rho^j e_{t+1+j} - E_t \sum_{j=1}^{\infty} \rho^j e_{t+1+j} \right] \\ & - \left[ E_{t+1} \sum_{j=1}^{\infty} \rho^j r_{f,t+1+j} - E_t \sum_{j=1}^{\infty} \rho^j r_{f,t+1+j} \right] \\ & + \left[ E_{t+1} \sum_{j=0}^{\infty} \rho^j \Delta d_{t+1+j} - E_t \sum_{j=0}^{\infty} \rho^j \Delta d_{t+1+j} \right], \end{aligned} \quad (6)$$

where  $\Delta d_{t+1+j}$  is dividend growth. Unexpected excess returns are made up of three components—revisions in future expected excess returns, revisions in the risk-free rate forecasts, and revisions in cash flow forecasts.



Merton's ICAPM (equation (1)) provides the model for expected excess returns

$$E_t e_{t+1} = \gamma \sigma_t^2 + \lambda \sigma_{MF,t}, \quad (7)$$

where  $\frac{-J_{WWW}}{J_W} = \gamma$  (the coefficient of relative risk aversion) and  $\frac{-J_{WF}}{J_W} = \lambda$ , which are both assumed to be constant over time. Substituting equation (7) into equation (6) and noting that  $E_t e_{t+1+j} = E_t[E_{t+j} e_{t+1+j}]$  by iterated expectations, we get

$$e_{t+1} = \gamma \sigma_t^2 + \lambda \sigma_{MF,t} - \eta_{\sigma,t+1} - \eta_{F,t+1} - \eta_{f,t+1} + \eta_{d,t+1}, \quad (8)$$

where

$$\eta_{\sigma,t+1} = E_{t+1} \sum_{j=1}^{\infty} \rho^j \gamma \sigma_{t+j}^2 - E_t \sum_{j=1}^{\infty} \rho^j \gamma \sigma_{t+j}^2, \quad (9)$$

$$\eta_{F,t+1} = E_{t+1} \sum_{j=1}^{\infty} \rho^j \lambda_{t+j} \sigma_{MF,t+j} - E_t \sum_{j=1}^{\infty} \rho^j \lambda_{t+j} \sigma_{MF,t+j}, \quad (10)$$

$$\eta_{f,t+1} = E_{t+1} \sum_{j=1}^{\infty} \rho^j r_{f,t+1+j} - E_t \sum_{j=1}^{\infty} \rho^j r_{f,t+1+j}, \quad (11)$$

$$\eta_{d,t+1} = E_{t+1} \sum_{j=0}^{\infty} \rho^j \Delta d_{t+1+j} - E_t \sum_{j=0}^{\infty} \rho^j \Delta d_{t+1+j}. \quad (12)$$

The first two terms in equation (8) capture the expected excess return. The third and fourth terms explicitly write out the unexpected return due to shocks to the risk component and hedge component of expected returns, respectively. The remaining terms are shocks to risk-free rate forecasts and cash flow forecasts.

## B. Modeling the Risk and Hedge Components of Returns

The empirical implementation of equation (8) requires further specification of the risk and hedge components of returns. By imposing a specific time series model on these components, we can also reduce the shocks to these components, which are written in equation (8) as infinite sums, to more manageable closed-form terms.

First consider the risk component of expected returns and the shock to this component. To construct an empirical model of the conditional variance, we project the realized variance,  $v_{t+1}^2$ , on to a vector of state variables,  $Z_t$ , i.e.,

$$v_{t+1}^2 = \omega_0 + \omega_1 Z_t + \zeta_{t+1} \quad (13)$$

The fitted value from the estimation is used as a proxy for the conditional market variance,<sup>7</sup> i.e.,

$$\hat{\sigma}_t^2 = \omega_0 + \omega_1 Z_t \quad (14)$$

For the longer sample period we use one lag of realized volatility in addition to a set of financial predictor variables as the state variables. For periods during which we have implied volatility data, we also add this variable to  $Z_t$ . Discussion of the computation of the realized variance and the choice of state variables is postponed until Section II.

In order to calculate the innovation in the risk component and its effect on unexpected returns we need to compute the shock to this conditional variance, which, in turn, requires specifying a process for the state variables. Following Campbell and Shiller (1988), among others, we assume that the state variables,  $Z_{t+1}$ , follow a vector autoregressive (VAR) process with a single lag:<sup>8</sup>

$$Z_{t+1} = B_0 + B_1 Z_t + \varepsilon_{Z,t+1} \quad (15)$$

Because  $Z_t$  includes the realized variance, the VAR process in equation (15) subsumes equation (13). Given this law of motion,

$$\eta_{\sigma,t+1} = \rho\gamma\omega_1(I - \rho B_1)^{-1}\varepsilon_{Z,t+1} \quad (16)$$

where  $I$  is an identity matrix with the same dimension as the vector  $Z_t$  (see the Appendix for details). Note that the unexpected return due to revisions in the risk component is a linear function of the shocks to the state variables that define the conditional variance. This term generates the volatility feedback effect in equation (8), i.e., returns are negatively related to contemporaneous innovations in the conditional variance.

There are several ways to estimate the hedge component ( $\lambda\sigma_{MF,t}$ ) in equation (8). Scruggs (1998) uses a bivariate exponential GARCH model, in which he assumes that the long-term government bond return is perfectly correlated with investment opportunities. Following Campbell (1996), we model the hedge component as a linear function of a vector of state variables,  $X_t$ , i.e.,

$$\widehat{\lambda\sigma}_{MF,t} = \phi_0 + \phi_1 X_t. \quad (17)$$

This formulation needs some explanation since, in the stock return predictability literature, it is used to model total expected returns not just the component of expected returns due to hedging

demands. The danger is that we may mistakenly attribute part of the risk component to the hedge component, i.e., we will not be able to identify the two components separately. We avoid this problem by ensuring that our proxy for conditional volatility subsumes most of the information about the risk component that is contained in the state variables in equation (17). In particular, we specify the hedge component state variables,  $X_t$ , as a subset of the conditional variance state variables,  $Z_t$ . Therefore, the process of projecting realized variance on these variables guarantees that we have extracted all the (linear) information about future volatility that they contain. The residual predictive power that these variables have for expected returns should be due only to the hedge component.

One advantage of equation (17) is that it allows us to calculate the revision term for the hedge component,  $\eta_{F,t+1}$  in equation (8), directly as in Campbell and Shiller (1988), Campbell (1991) and Campbell and Ammer (1993). By controlling for this component of returns, we can potentially increase the efficiency of the estimation and the precision with which we estimate the coefficients. Specifically, again assuming a VAR(1) for the state variables,<sup>9</sup>

$$X_{t+1} = A_0 + A_1 X_t + \varepsilon_{X,t+1}, \quad (18)$$

the revision to the hedge component is

$$\eta_{F,t+1} = \rho\phi_1(I - \rho A_1)^{-1}\varepsilon_{X,t+1}, \quad (19)$$

where  $I$  is an identity matrix with the same dimension as the vector  $X_t$ . This result is analogous to the result in equation (16), with the minor exception that the shock to the risk component includes the coefficient of relative risk aversion,  $\gamma$ , as an additional multiplicative factor. As for the risk component, innovations to the hedge component are a linear function of the shocks to the state variables.

After substituting equations (14), (16), (17), and (19) into equation (8), we obtain the model that is estimated in this paper:

$$\begin{aligned} e_{t+1} = & \gamma[\omega_0 + \omega_1 Z_t] + [\phi_0 + \phi_1 X_t] - \rho\gamma\omega_1(I - \rho B_1)^{-1}\varepsilon_{Z,t+1} - \rho\phi_1(I - \rho A_1)^{-1}\varepsilon_{X,t+1} \\ & - \eta_{f,t+1} + \eta_{d,t+1}. \end{aligned} \quad (20)$$

This equation captures the six components of excess market returns: expected returns due to the risk and hedge components, unexpected returns due to shocks to these components of expected

returns, and shocks to cash flow and risk-free rate forecasts. The risk and risk revision terms are linear functions of the estimated lagged conditional variance and the contemporaneous shock to the state variables that define this conditional variance, respectively. The hedge and hedge revision terms are written in terms of the lagged state variables and the shocks to these variables, respectively. The shocks to the cash flow and risk-free rate forecasts are not written out explicitly, and they form the regression residual in the specification that we estimate.

## II. Data Description

The model is estimated with three sets of data. The first dataset utilizes the volatility implied by S&P 100 index (OEX) option prices as an instrument for the conditional market variance and covers the period November 1983 to May 2001. The implied volatility series only starts in 1983, so we also use two other datasets over longer sample periods (July 1962 to May 2001 for monthly data and 1952Q1 to 2002Q3 for quarterly data) that adopts commonly used financial variables as instruments to estimate the conditional market variance.

The implied volatility series is a combination of the data constructed by Christensen and Prabhala (1998) and the VIX data calculated by the CBOE. Christensen and Prabhala (1998) compute non-overlapping monthly implied volatility data for the S&P 100 index spanning the period November 1983 to May 1995. It is important to note that the S&P 100 index option contract expires on the third Saturday of each month. Christensen and Prabhala compute implied volatility based on a contract that expires in twenty-four days. The sampling month is thus different from the calendar month; moreover, some trading days are not included in any contract. For example, the implied volatility for October 1987 is calculated using the option price on September 23, 1987 for the option that expires on October 17, 1987. For November 1987, it is based on the option price on October 28, 1987 for the option that expires on November 21, 1987. Thus, trading days between October 17, 1987, and October 28, 1987, including the October 19, 1987 stock market crash, are not included in any contract. We extend this series to May 2001 by using the VIX, which is a calendar month implied volatility series constructed from options with expiration dates that straddle the relevant month end.<sup>10</sup>

One alternative to splicing these two series is to use the VIX series from its inception in January

1986. We do not pursue this alternative for two reasons. First, the Christensen and Prabhala series starts in November 1983, providing an extra two years of data. Second, and more important, the Christensen and Prabhala series is likely to have less measurement error. Christensen and Prabhala use a single option maturity for each observation, and we match our realized variance to this maturity date. In contrast, in the VIX series each data point is actually an average of implied volatilities from options with less than a month to maturity and options with more than a month to maturity. This maturity mismatch induces measurement errors. Consistent with this intuition, rerunning the analysis using just the VIX series produces similar results except that the predictive power of implied volatility for realized variance is lower and the resulting estimates of the coefficient of relative risk aversion are less precise. Apart from the measurement error problem, there appear to be no significant differences between the two series; therefore, we use the merged series in the results that we report.<sup>11</sup>

The monthly excess market return and realized variance are constructed from daily excess market returns. We use daily value-weighted market returns (VWRET) from CRSP as daily market returns. The daily risk-free rate data are not directly available. Following Nelson (1991) and others, we assume that the risk-free rate is constant within each month and calculate the daily risk-free rate by dividing the monthly short-term government bill rate (from Ibbotson Associates (1997) or CRSP) by the number of trading days in the month. The daily excess market return is the difference between the daily risk-free rate and the daily market return.

The realized monthly market variance is defined as<sup>12</sup>

$$v_t^2 = \sum_{k=1}^{\tau_t} e_{t,k}^2 + 2 \sum_{k=1}^{\tau_t-1} e_{t,k} e_{t,k+1}, \quad (21)$$

where  $\tau_t$  is the number of days to expiration of the option contract in month  $t$ , when we are using the Christensen and Prabhala (1998) implied volatility data, or the number of days in the calendar month otherwise, and  $e_{t,k}$  is the daily excess market return. Equation (21) assumes a mean daily return of zero; however, adjusting the variance for the realized mean daily return over the month has no appreciable affect on the results. Equation (21) also adjusts for the first order autocorrelation in daily returns induced by non-synchronous trading in the stocks in the index (as in French, Schwert and Stambaugh (1987)).<sup>13</sup> The monthly excess market return is the sum of daily excess market returns, and quarterly returns and realized market variances are defined analogously.

For the longer sample period we estimate the conditional market variance by projecting realized variance on its own lag and two predetermined variables: (1) the consumption-wealth ratio (CAY) (see Lettau and Ludvigson (2001)), and (2) the stochastically detrended risk-free rate (RREL). The latter variable is defined as

$$\text{RREL}_t = r_{f,t} - \frac{1}{12} \sum_{k=1}^{12} r_{f,t-k}. \quad (22)$$

The risk-free rate is taken from Ibbotson Associates (1997) or CRSP, and the consumption-wealth ratio is computed and supplied by Martin Lettau.<sup>14</sup> For both sample periods we use the same two state variables, the consumption-wealth ratio and the detrended risk-free rate, to estimate the hedge component of returns.<sup>15</sup>

It is worth noting that the cointegrating vector used in computing the consumption-wealth ratio is estimated over the full sample. This methodology has been questioned, particularly in the context of out-of-sample predictability. Our focus is on understanding the economics of the in-sample risk-return tradeoff, and we can see no apparent reason why the use of the full sample cointegrating vector will spuriously affect the estimation of this relation. The reason to go with the full sample estimate is that it greatly reduces the estimation error. Moreover, we obtain similar results with a less parsimonious specification that has more instrumental variables.

Finally, we employ three additional variables as instruments in order to calculate overidentifying restrictions tests for various models. The natural choice is a set of variables that has been shown to predict returns and/or volatility, and we use the default spread (i.e., the yield spread between Baa-rated and Aaa-rated bonds), the dividend yield, and the term spread (i.e., the yield spread between long-term and short-term Treasury securities).

### III. Empirical Results

#### A. Econometric Strategy

We simultaneously estimate equations (15) and (20) using GMM:

$$Z_{t+1} = B_0 + B_1 Z_t + \varepsilon_{Z,t+1} \quad (23)$$

$$\begin{aligned} e_{t+1} &= \gamma[\omega_0 + \omega_1 Z_t] + [\phi_0 + \phi_1 X_t] \\ &\quad - \rho\gamma\omega_1(I - \rho B_1)^{-1}\varepsilon_{Z,t+1} - \rho\phi_1(I - \rho A_1)^{-1}\varepsilon_{X,t+1} + \epsilon_{t+1}. \end{aligned} \quad (24)$$

Recall that equation (23) subsumes both equations (13) and (18) because both the realized variance and the hedge component state variables are included in the vector  $Z_t$ . Thus the parameters  $\omega_0$  and  $\omega_1$  are rows of  $B_0$  and  $B_1$ , respectively,  $A_1$  is a submatrix of  $B_1$ , and  $\varepsilon_{X,t+1}$  is a subvector of  $\varepsilon_{Z,t+1}$ . Throughout we first estimate an unrestricted VAR and then reestimate the model zeroing out the statistically insignificant coefficients from the first stage. This procedure has no meaningful effect on the estimation of the model in equation (24), but it has the distinct advantage of highlighting the key interactions between the variables.

For estimating equations (23), we use the standard OLS moment conditions. The only subtlety is in formulating the moment conditions for equation (24). Note that theory does not imply that the terms  $\varepsilon_{Z,t+1}$  and  $\varepsilon_{X,t+1}$  are orthogonal to the contemporaneous regression error  $\epsilon_{t+1}$ ; therefore, these variables should not be used as instruments. Using a constant,  $X_t$  and the fitted conditional variance ( $\omega_0 + \omega_1 Z_t$ ) as instruments is sufficient to identify the free parameters. The two shocks are functions of the fitted residuals from equation (23), the estimated parameters  $B_1$ ,  $A_1$ ,  $\omega_0$  and  $\omega_1$  also come from this equation, and  $\rho$  is set to 0.997 (see Section I).  $\gamma$ ,  $\phi_0$  and  $\phi_1$  are identified by equation (24). What then is the value of including the two terms that represent shocks to the two components of expected returns? First, by reducing the amount of unexplained variation, they should improve the efficiency of the estimation and the accuracy with which the parameters of interest can be estimated. Second, these terms also depend on the parameters, and thus imposing the theoretical restrictions implied by the model may also help to pin down these parameters.

In order to understand what is driving our results relative to the existing literature and to understand the gains from imposing the additional restrictions on the revision terms, we also estimate restricted versions of the model that exclude various terms in equation (24). Specifically, we consider the following 5 cases:

$$1: \quad e_{t+1} = \phi_0 + \gamma[\omega_0 + \omega_1 Z_{t-1}] + \epsilon_{t+1} \quad (25)$$

$$2: \quad e_{t+1} = \phi_0 + \gamma[\omega_0 + \omega_1 Z_{t-1}] - \rho\gamma\omega_1(I - \rho B_1)^{-1}\varepsilon_{Z,t+1} + \epsilon_{t+1} \quad (26)$$

$$3: \quad e_{t+1} = \phi_0 + \phi_1 X_t + \epsilon_{t+1} \quad (27)$$

$$4: \quad e_{t+1} = \gamma[\omega_0 + \omega_1 Z_{t-1}] + [\phi_0 + \phi_1 X_t] + \epsilon_{t+1} \quad (28)$$

$$5: \quad e_{t+1} = \gamma[\omega_0 + \omega_1 Z_{t-1}] + [\phi_0 + \phi_1 X_t] - \rho\gamma\omega_1(I - \rho B_1)^{-1}\varepsilon_{Z,t+1} + \epsilon_{t+1} \quad (29)$$

Model 6 is the full model in equation (24). In each case, we use the set of instruments corresponding

to the independent variables in the GMM estimation, i.e., a constant, plus  $X_t$  and/or the fitted conditional variance. For example, in Model 1 there are two parameters to be estimated ( $\phi_0$  and  $\gamma$ ) and we use two instruments (the conditional variance and a constant). Model 2 is similar, except that the inclusion of the revision term should help to identify  $\gamma$ . In Model 3 we use a constant and the vector of variables  $X_t$  as instruments, and the remaining models use the full set of instruments. Thus, all the models are exactly identified. We also reestimate Models 1-3 using the full set of instruments and test the resulting overidentifying restrictions. For example, the overidentified version of Model 1 also uses the vector of variables  $X_t$  as instruments. Finally, we reestimate Models 4-6 using three additional state variables as instruments (the default spread, the term spread, and the dividend yield) and compute the resulting overidentifying restrictions test.

## B. Estimation with Implied Volatility Data

It is well known that we can predict stock market volatility with variables such as the nominal risk-free rate, the consumption-wealth ratio and lagged realized variance (see, for example, Campbell (1987), French, Schwert and Stambaugh (1987) and Lettau and Ludvigson (2003)).<sup>16</sup> To test the information content of implied volatility, we regress the realized variance on the implied variance from S&P100 options,  $V_t^2$ , and these additional variables, i.e.,

$$v_t^2 = a_0 + a_1 X_{t-1} + a_2 v_{t-1}^2 + a_3 V_{t-1}^2 + \zeta_t. \quad (30)$$

We estimate equation (30), and restricted versions thereof, with GMM, and the parameter estimates and heteroscedasticity consistent standard errors are reported in Table I.

We first exclude implied volatility in order to verify the predictive power of the other variables in our sample period. Both the consumption-wealth ratio and lagged variance enter significantly, with the signs of the coefficients consistent with the existing literature, and the explanatory power is substantial, with an  $R^2$  of 27%. The risk-free rate does not have any marginal explanatory power, but this may be specific to our sample period. When the implied variance is added to the specification, it is highly significant, and the  $R^2$  increases to 39%. The consumption-wealth ratio remains significant at the 10% level, but the magnitude of the coefficient is reduced by approximately a factor of two.<sup>17</sup> Finally, we also report estimates from a regression of realized variance on the implied variance alone. The  $R^2$  declines slightly to 37%, but it is clear that implied

Insert

Table I

here.



variance is the best single predictor and that little is lost by excluding the other explanatory variables. Consequently, we select the implied variance as the single explanatory variable in the variance equation. Of equal importance, these results imply that we will be able to separately identify the two components of expected returns. The explanatory variables used for the hedge component (i.e., the consumption-wealth ratio and the risk-free rate) will pick up little of the risk component because they have limited marginal explanatory power for future variance, after controlling for the predictive power of implied volatility. Including the additional variables in the model for conditional variance has no meaningful effect on the later estimation of the full model; therefore, for ease of exposition we ignore them.

If implied variance is a conditionally unbiased predictor of future variance, then in Table I the intercept in the last regression should be equal to zero and the coefficient on implied variance should be equal to one. However, an extensive literature has documented positive intercepts and slopes less than unity in similar regressions (see Poon and Granger (2002) for a survey of this literature). This bias may be related to the market price of volatility risk (see, e.g., Bollerslev and Zhou (2004)). In addition, if the S&P 100 differs in an economically significant way from the value-weighted CRSP index, then the parameter estimates may also differ from zero and one. This is almost certainly the case since the realized variance of the S&P 100 index is larger than the realized variance of the CRSP value-weighted portfolio, most likely because the S&P 100 is not a well-diversified portfolio. Table I shows that while the estimated coefficient is positive, it is significantly less than one, and the intercept is significantly positive, although it is small. Thus, while implied volatility may be informationally efficient relative to other variables it is not conditionally unbiased. As a result, we use the fitted value from this estimation as our proxy for conditional variance in the estimation of the full model.

Table II reports results from the estimation of equations (23)-(24) using monthly implied volatility data for the January 1983 to May 2001 period. The results for the conditional variance process, estimated using the implied volatility data, are shown in the first line of Panel A, which is just the last line of Table I. The estimated processes for the state variables for both the risk and hedge components are shown in regressions 2 through 4 in the same panel. For implied volatility, the AR(1) coefficient is positive and significant at the 1% level, as expected, although the estimated degree of persistence is not very large. Both the remaining state variables, the consumption-wealth

Insert  
Table II  
here.

ratio and the relative T-bill rate, are quite persistent. Over this sample none of the state variables show statistically significant predictive power for their counterparts, so we have zeroed out these coefficients for ease of presentation and interpretation. The results that follow are not sensitive to this choice.

The results from the estimation of the model for returns are reported in Panel B. Recall that we estimate six different specifications—five restricted models given in equations (25)-(29) and the full specification given in equation (24). In addition, we estimate both an exactly identified and an overidentified specification for the each model. Model 1 is the standard risk-return model estimated in much of the literature, i.e., a regression of returns on a measure of the conditional variance. However, in contrast to many existing results, we find a coefficient that is positive, albeit statistically insignificant, and reasonable in magnitude.<sup>18</sup> If the hedge component is unimportant or orthogonal to the risk component, the coefficient value of 2.5 represents an estimate of the coefficient of relative risk aversion of the representative agent; although, this estimate may be biased downwards slightly due to measurement error in the conditional variance. The absence of a hedge component also implies that the constant in the regression should be zero—a hypothesis that cannot be rejected at the 10% significance level. However, the  $R^2$  of the regression of less than 1% is very small, and adding the consumption-wealth ratio and risk-free rate as instruments yields a convincing rejection of the overidentifying restrictions. Even though the model can be rejected with these additional instruments, the estimate for relative risk aversion is larger and significant at the 5% level.

Model 2 attempts to refine the specification by controlling for the effect of shocks to the risk component on unexpected returns, i.e., the volatility feedback effect. Adding this term leaves the parameter estimates unchanged in the exactly identified specification because it is orthogonal to the estimated conditional variance by construction. Nevertheless, the estimation does provide some corroborating evidence for the existence of a risk component in that the  $R^2$  increases to 20%. It is not necessarily surprising that the  $R^2$  from model 2 greatly exceeds that from model 1. We know from extensive empirical investigations that expected returns are a small component of returns, and therefore the explanatory power of model 1 (and models 3 and 4 to come) is sure to be relatively small. In contrast, model 2 (and models 5 and 6 to come) exploit the correlation between innovations in the state variables that describe expected returns and unexpected returns.

Nevertheless, the model does put structure on the way that this correlation is exploited. Specifically, a fixed function of the innovations (based on parameters estimated in a separate set of equations) is added to the righthand side of the regression. If the correlation is of the wrong sign or the shocks are of the wrong magnitude, adding this term can reduce the  $R^2$ . In any case, these particular results should be interpreted with caution since the overidentified model can still be rejected at the 10% significance level.

These initial results suggest two conclusions. First, sample period issues aside, improving the quality of the proxy for conditional variance, in our case using implied volatility, seems to help in recovering the theoretically justified positive risk-return relation. In concurrent work, Bollerslev and Zhou (2004) find a similar result using implied volatility. Ghysels, Santa-Clara and Valkanov (2004) also present evidence consistent with this conclusion using functions of daily squared returns data to form a better proxy for conditional variance. They get a positive and significant coefficient when regressing monthly returns on this measure over a longer sample period. Second, while there is some evidence of a positive risk-return relation, statistical power is weak, and the model can be rejected. Thus, controlling for the hedge component of expected returns may be important.

Model 3 estimates the standard return predictability regression from the literature using our two state variables. In our case, however, we interpret this regression as an estimation of the hedge component of expected returns without controlling for the risk component. The signs of the coefficients, positive on the consumption-wealth ratio and negative on the relative T-bill rate, are consistent with the results in the literature, as is the  $R^2$  of just over 3%. The consumption-wealth ratio is significant at the 5% level, and the predictive power is substantially greater than that found for the risk component in model 1. However, using the estimated conditional variance as an additional instrument leads to a rejection of the model at the 5% level.

Under the ICAPM, both models 1 and 3 are misspecified since theoretically both the risk and hedge components should enter the model for expected returns. Model 4 combines these two terms, and the results are positive. First and foremost, estimated risk aversion is now 5.6 and it is significant at the 1% level. The risk-return relation is highly statistically significant and of a reasonable magnitude—a reversal of the weak and/or negative results in the literature. One natural explanation is that Model 1, and more generally similar specifications in the literature, suffer from a classical omitted variables problem, i.e., they do not control for the hedge component

of expected returns. The effect of an omitted variable on the estimated coefficient of the included variable depends on the covariance of this variable with the included variable. In this case, if the covariance is negative, i.e., the risk and hedge components are negatively correlated, then the coefficient on conditional variance, when this term is included alone, will be biased downwards. Second, including the risk component also helps in identifying the hedge component; the coefficient on the consumption-wealth ratio is now more significant. Third, the joint explanatory power of the two components exceeds the sum of the individual explained variations from the separate regressions—the  $R^2$  increases to 6.8%. Fourth, the results give us added confidence that we are correctly identifying the risk and hedge components. The hedge component is positively related to CAY, while the conditional variance is negatively related to CAY (see Table I). Finally, the model cannot be rejected using the dividend yield, default spread and term spread as additional instruments.

While model 4 is theoretically well-specified, it is possible that our identification of the components of returns can be improved by controlling for the effects of shocks to expected returns on contemporaneous unexpected returns. This issue is addressed by models 5 and 6. These models trade off efficiency and potential specification error via the inclusion of innovations in expected returns. Which model provides the best tradeoff is largely an empirical question. In model 5, we add the shock to the risk component of expected returns. The results are not dramatically different from those of model 4, but a couple of observations are worth making. First, including the shock to the conditional variance can effect both the estimate of relative risk aversion and the hedge component. In this case,  $\gamma$  drops from 5.6 to 4.4 for the just identified specifications, and the coefficients on both the state variables are closer to zero. Second, controlling for some of the variation of unexpected returns can increase the efficiency of the estimation. In this case, the  $R^2$  increases from 6.8% to 23.0%, and the standard errors on the coefficients drop by between 1% and 29%. As with model 4, model 5 cannot be rejected using the three additional instruments.

Finally, model 6 also includes the shock to the hedge component in the regression. The estimated coefficients for both the exactly identified and the overidentified specifications are similar to those from model 5 and the  $R^2$ s are marginally higher. However, the standard errors are larger, although relative risk aversion still remains significant at the 5% level for the overidentified specification. These results are somewhat disappointing because if the hedge component is persistent (see Panel

A) and explains expected returns (see Panel B, model 3), then shocks to the hedge component should explain a significant fraction of unexpected returns. Moreover, the denominator of CAY includes financial wealth (i.e., the level of the stock market) and thus innovations in CAY are negatively correlated with returns almost by construction. As such, the fact that the  $R^2$  does not increase more is testament to the strength of the theoretical restrictions imposed on the innovation term. The most likely explanation for these results is that the monthly consumption-wealth ratio is mismeasured. The monthly series is computed from the quarterly series via interpolation. Mismeasurement will not have a large adverse effect on the estimation of the hedge component because the consumption-wealth ratio and expected returns are persistent. However, the shock to the hedge component is unpredictable by definition, and mismeasurement of the consumption-wealth ratio could easily lead to a substantial degradation in the quality of the shock to this variable. Evidence to this effect is contained in the estimation with quarterly data that is discussed later.

In order to better illustrate the omitted variables problem and to gain some economic understanding of the results, we construct the fitted risk and hedge components of expected returns using the parameter estimates from the overidentified specification of model 6. However, given the similarities between the parameter estimates for all four specifications of models 5 and 6, all of these models generate the same conclusions. The two series are plotted in Figure 1 along with the NBER business cycle peaks and troughs (shaded bars represent recessions, i.e., the period between the peak of the cycle and the subsequent trough). In general, the hedge component is more variable than the risk component of expected returns, although the sample variance of the latter is larger due to two spikes in implied volatility in November 1987 and September-October 1998 (following steep declines in the market). The two series are negatively correlated, with a sample correlation of -0.41; thus, omitting the hedge component causes the coefficient on the risk component to be biased downwards. The magnitude of this bias depends on the covariance between the hedge component and the included variable (i.e., the conditional variance) relative to the variance of the included variable times its true coefficient (i.e., the true coefficient of relative risk aversion). In this sample, the covariance is -4.13 while the product of the estimated value of  $\gamma$  (from the overidentified specification of model 6) times the variance of the implied variance is 14.56. The bias is not sufficient to reverse the sign of the estimated coefficient in models 1 and 2, but it is substantial.

From an economic standpoint, the hedge component appears to exhibit some countercyclical

variation (i.e., it increases over the course of recessions), but there are only two recessions in the sample, one of which is only partially within the sample period, so this interpretation is extremely casual. The risk component exhibits little or no apparent business cycle patterns, although, as noted above, variation in this series is dominated by increases in implied volatility following large market declines. Of some interest, the hedge component is negative for substantial periods of time, implying that at these times the stock market serves as a hedge against adverse shifts in investment opportunities.

### C. Estimation with Financial State Variables

The results of Section III.B go a long way to resurrecting the positive risk-return relation, but the analysis suffers from two problems: (i) the sample period is relatively short, and (ii) it relies on implied volatility data that are not available in all periods or across all markets. Consequently, we now turn to an analysis that constructs conditional variance estimates from ex post variance computed using daily returns and conditioning variables that include lagged realized variance and our two state variables, the consumption-wealth ratio and the relative T-bill rate.

Before proceeding to the full estimation, we first examine the variance process more closely by estimating a regression of realized variance on two lags plus the two state variables:

$$v_t^2 = a_0 + \sum_{i=1}^2 a_{1,i} v_{t-i}^2 + \sum_{k=1}^2 a_{2,k} X_{k,t-1} + \zeta_t. \quad (31)$$

Realized stock market variance shoots up to 0.0755 in October 1987 and returns to a more normal level soon thereafter. The crash has a confounding effect on the estimation of equation (31), which is reported in Table III. Although the first lag of the market variance is the dominant explanatory variable in the pre-crash (9/62-9/87) sub-sample and to a lesser extent in the post-crash (1/88-5/01) sub-sample (the first two regressions reported in Table III, respectively), the second lag of market variance is also equally economically and more statistically significant in the full sample (the third regression). Not surprisingly, the  $R^2$  of this third regression is also much lower (5% versus 30% and 28% in the subsamples), and the sum of the coefficients on the lagged variance terms is also much lower (0.26 versus 0.61 and 0.48). Basically, including the crash significantly degrades the predictive power of the regression over all the other months because this one observation dominates the sample in a OLS context. To reduce the impact of the October 1987 market crash, we somewhat arbitrarily

set the realized stock market variance of October 1987 to 0.0190 basis points, the second largest realization in our sample.<sup>19</sup> The corresponding results are shown in the fourth regression in Table III. The coefficients and explanatory power look similar across the subperiods and the full sample after this adjustment, and the coefficient on the second lag of realized variance is relatively small but statistically significant (at the 1% level) in the full sample. However, this second lag does not add much to the explanatory power, as demonstrated by the fifth regression, which excludes this term. The  $R^2$  drops only 3%, from 25% to 22%. Of some interest, the consumption-wealth ratio is a significant predictor of future variance in all but the pre-crash regression, entering with a negative coefficient. Consequently, our final specification for the conditional variance has the consumption-wealth ratio and a single lag of the realized variance, where the October 1987 variance is adjusted as described above.

Table IV reports results for the estimation of the full system in equations (23)-(24) using monthly data over the period September 1962 to May 2001. The estimation of the variance process is reported in the first line of Panel A. Other than the substantial degree of explained variation, the key result is that the conditional variance is negatively and significantly related to the consumption-wealth ratio. Panel A also reports the estimation of the process for the two state variables. The results are comparable, although not identical, to those estimated over the shorter sample period in Table II. Again, both variables exhibit strong persistence and cross-variable predictability is limited.

Panel B reports the major results of interest, i.e., the estimates from the six models in Section III.A and also estimated using the implied volatility data in Section III.B. Models 1 and 2 contain only the risk component (the conditional variance) plus, in the latter case, the innovation in this component of expected returns. The effects of the omitted variable, i.e., the hedge component, and measurement issues in the conditional variance are clear. The coefficient on the conditional variance is predominantly negative and the standard error is large. The negative coefficient is consistent with previous studies that have documented a negative risk-return relation over similar sample periods (e.g., Whitelaw (1994)). The fact that the standard error is 50% or more larger than in the shorter sample period (which uses implied volatility) is testament to the value of finding better proxies for the conditional variance. Not surprisingly, using the consumption-wealth ratio and risk-free rate as additional instruments generates rejections of the model at all conventional

levels.

When both components are estimated together, as in model 4, the coefficient on the conditional variance is still negative for the exactly identified specification, and the standard error is still high for both specifications. Moreover, the estimated risk component of expected returns is small; the  $R^2$  of 3.6% in model 4 is no higher than that of model 3 which excludes the risk component. In contrast, the hedge component appears to be identified well, with the coefficients on both state variables significant at least the 5% level. It is interesting to note that the hedge component, in contrast to the conditional variance, is positively related to the consumption-wealth ratio. Thus, we get the negative covariance between the hedge and risk components that exacerbates the omitted variable problem in models 1 and 2 and also aids in separate identification of the two components of expected returns.

Adding shocks to the risk component of expected returns in model 5 has almost no effect on the results. In contrast, the innovation in the hedge component, included in model 6, causes a slight improvement in the  $R^2$ , and the imprecise estimate of the relative risk aversion is of a reasonable magnitude. Given that neither the risk nor hedge components of expected returns are identified very well due to estimation error and possible misspecification, it is not totally surprising that the shocks to these components provide little assistance.

The results in Tables II and IV are not directly comparable because they cover different sample periods. Consequently, as a robustness check, we reestimate the models in Table IV using the sample period in Table II and report the results in Table V. The Table V results confirm those of Table IV. Of course, the processes for CAY and RREL are identical to those in Table II, as is model 3 (without the overidentifying restrictions). Of primary interest, the estimate of  $\gamma$  is negative over the shorter sample period when only the risk component is included, and the sign is reversed when controlling for the hedge component. Again, the estimate of relative risk aversion is reasonable in magnitude but statistically insignificant at conventional levels. As before, the innovations in the risk and hedge components do not dramatically improve the fit of the model. In other words, the qualitative nature of the results in Table IV are preserved in the subsample covered by the implied volatility data in Table II. Thus, we have confidence that the evidence in Table II is not sample specific.

Finally, we reestimate the six models using quarterly data over the sample period 1952Q3-



2002Q3 and report the results in Table VI. The quarterly frequency may produce better results because the monthly CAY series may be subject to measurement error as mentioned above, the predictive ability for returns of variables such as the consumption-wealth ratio tends to increase at longer horizons (Lettau and Ludvigson (2001)), and longer lags of realized variance can be useful in predicting returns (Ghysels, Santa-Clara, and Valkanov (2004)).

Insert

The results at the quarterly horizon confirm those of Table IV, but there is superior identification of the coefficient of relative risk aversion. The variance process and the process for the other state variables in Panel A exhibit the same features. Models 1 and 2 show that the standard risk-return regression generates a negative coefficient, as it does at the monthly frequency. In fact, the overidentified specifications generate estimates that are negative and statistically significant. However, these models are strongly rejected using the consumption-wealth ratio and risk-free rate as additional instruments, indicating the serious misspecification problem caused by omitting the hedge component.

Table VI  
here.

In model 3, the hedge component shows increased explanatory power relative to the monthly frequency (with  $R^2$ s of 13.1% for both specifications versus 3.6% in Table IV) consistent with the return predictability literature. The majority of the additional explained variation comes from an increase in the coefficient on the consumption-wealth ratio from 0.39 in Table IV to 1.94 in Table VI. However, the model can be rejected at the 5% level using the conditional variance as an additional instrument. More important, putting the risk and hedge components together in model 4 has a sizable effect on both terms. That is, the effect of omitting either term is more dramatic than in the monthly data.  $\gamma$  increases to 6.3 (significant at the 5% level), the coefficient on CAY increases by almost 50%, and the  $R^2$ s climb to over 15%. The ability of the state variables in the hedge component to help identify the risk component is further evidence that their predictive power is not spurious. Moreover, this theoretically well-specified model cannot be rejected using the three additional financial predictors as instruments.

Inclusion of the innovation to the risk component in model 5 degrades the fit of the model, although the parameter estimates are largely unaffected and the estimate of relative risk aversion remains significant in the overidentified specification. This comparatively weak performance appears to be attributable to instability in the relation between the conditional variance and the consumption-wealth ratio over the longer sample period. Excluding this variable from the vari-

ance process in Panel A of Table VI improves the fit of model 5, but the parameter estimates are relatively unaffected.

In contrast, adding the innovation in the hedge component in model 6 improves the fit substantially. The  $R^2$ s increase to 42.9% and 44.7% for the just identified and overidentified specifications, respectively, the standard errors fall, and the model produces reasonable estimates of  $\gamma$  of 6.5 and 7.7, which are statistically significant at the 5% level. One important lesson is that controlling for the shocks to expected returns is only useful when these innovations are measured with reasonable accuracy.

Figure 2 plots the fitted risk and hedge components (from the overidentified specification of model 6) over the longer sample period, with the NBER business cycle peaks and troughs marked as in Figure 1. Several observations are in order. First, the hedge component is much more variable than the risk component of expected returns. The variances differ by a factor of approximately 5. Second, the correlation between the risk and hedge components is -0.55, which generates a severe omitted variables problem when the latter is excluded. The covariance between the hedge component and the conditional variance of -4.95 is larger than the value of 4.84 for  $\gamma$  times the variance of the conditional variance. Thus, the omitted variables bias is sufficient to drive the estimate of relative risk aversion negative in models 1 and 2.

From an economic standpoint, the countercyclical variation in the hedge component is much clearer than in the shorter sample period. The hedge component reaches its lowest values at business cycle peaks and its highest values at business cycle troughs. This result is not terribly surprising given the dependence of the hedge component on the consumption-wealth ratio, which is known to be a business cycle variable. Nevertheless, our decomposition allows us to give this variation a clear interpretation as variation in the ability of the stock market to hedge shifts in investment opportunities. Specifically, stocks appear to provide this hedge at the peak of the cycle, but not at the trough, when investors require compensation for holding an asset that covaries positively with investment opportunities. The hedge component can take on a negative value for extended periods, and because it sometimes dominates the risk component the total fitted expected excess return is also negative for certain periods. From a theoretical standpoint this result is possible (e.g., see Whitelaw (2000)), but it may not be intuitively plausible. However, it is important to keep in mind that these fitted values have associated standard errors, which may be quite large given the

Insert  
Figure 2  
here.

standard errors of the coefficient estimates. Moreover, while the linear specification of the hedge component appears to be a reasonable approximation, it is most likely to break down for extreme values of the independent variables and thus be less accurate for extreme fitted expected returns.

There are two important conclusions to be drawn from an analysis of the results in Tables II, IV, and VI. First, correcting for the omission of the hedge component in the model of expected returns can help to restore the positive partial risk-return relation that has been so difficult to find in the literature. This omitted variables problem is especially severe because the hedge component is negatively correlated with the risk component of expected returns and is more volatile. Second, superior proxies for conditional variance, such as implied volatility from option prices, also make identification of this relation much easier.

## IV. Conclusion

In this paper, we estimate a variant of Merton's (1973) intertemporal capital asset pricing model, and we find a positive relation between stock market risk and return. The estimated coefficient of relative risk aversion is reasonable in magnitude (between 1.6 and 7.7 depending on the sample period, frequency, and precise specification of the model); therefore, the power utility function appears to describe the data fairly well. The conflicting results found in previous studies are due, in large part, to the fact that they do not adequately distinguish the risk component of expected returns from the hedge component. Specifically, omitting the hedge component from the estimation causes a large downward bias in the estimate of relative risk aversion due to the negative correlation between these series.

Although stock market volatility is positively priced, in most cases it only explains a small fraction of return variation. Expected returns are driven primarily by changes in the ability of the stock market to hedge shifts in investment opportunities. Many existing economic theories can explain neither why the investment opportunity set moves so dramatically nor the macroeconomic forces behind this variation. Some recent research tries to fill this gap. For example, Campbell and Cochrane (1999) address changing investment opportunities in a habit formation model. In their model, when consumption approaches the habit level, the agent becomes extremely risk averse and demands a large expected return. Guo (2004) studies an infinite horizon heterogeneous agent

model in which only one type of agent holds stocks. If there are borrowing constraints and idiosyncratic labor income shocks, shareholders require a large equity premium when their borrowing constraints are close to binding. The investment opportunities are therefore determined by shareholders' liquidity conditions.<sup>20</sup> In contrast, Whitelaw (2000) generates large changes in investment opportunities by modeling the underlying economy as a two-regime process. Because regimes are persistent, regime shifts represent large movements in investment opportunities with corresponding changes in required returns.

The focus of this paper is on understanding risk and expected returns at the market level in a time series context; however, a significant piece of the empirical asset pricing literature focuses on the cross-section of expected returns across individual securities or portfolios. Interestingly, the importance of hedging changes in the investment opportunity set at the aggregate level is also likely to have strong implications in the cross-section. In particular, if volatility is not the primary source of priced risk at the market level, then the dynamic CAPM will not hold and market betas will not be the correct proxies for expected returns in the cross-section. Clearly, this issue warrants further investigation from both an empirical and theoretical standpoint.

## Appendix: Derivation of Equation (16)

The estimated conditional market variance (equation (14)) is

$$\hat{\sigma}_t^2 = \omega_0 + \omega_1 Z_t \quad (\text{A1})$$

where the state variables follow the process

$$Z_{t+1} = B_0 + B_1 Z_t + \varepsilon_{Z,t+1} \quad (\text{A2})$$

as in equation (15). The revision of the risk component is defined as:

$$\begin{aligned} \eta_{\sigma,t+1} &= E_{t+1} \sum_{j=1}^{\infty} \rho^j \gamma \sigma_{t+j}^2 - E_t \sum_{j=1}^{\infty} \rho^j \gamma \sigma_{t+j}^2 \\ &= \sum_{j=1}^{\infty} \rho^j \gamma (E_{t+1}[\sigma_{t+j}^2] - E_t[\sigma_{t+j}^2]) \\ &= \sum_{j=1}^{\infty} \rho^j \gamma [E_{t+1}(\omega_0 + \omega_1 Z_{t+j}) - E_t(\omega_0 + \omega_1 Z_{t+j})] \\ &= \sum_{j=1}^{\infty} \rho^j \gamma \omega_1 [E_{t+1} Z_{t+j} - E_t Z_{t+j}]. \end{aligned} \quad (\text{A3})$$

The process for the state variables implies

$$E_t Z_{t+j} = (I - B_1^j)(I - B_1)^{-1} B_0 + B_1^j Z_t \quad (\text{A4})$$

Therefore

$$\begin{aligned} \eta_{\sigma,t+1} &= \sum_{j=1}^{\infty} \rho^j \gamma \omega_1 [(I - B_1^{j-1})(I - B_1)^{-1} B_0 + B_1^{j-1} Z_{t+1} - (I - B_1^j)(I - B_1)^{-1} B_0 - B_1^j Z_t] \\ &= \sum_{j=1}^{\infty} \rho^j \gamma \omega_1 B_1^{j-1} [Z_{t+1} - B_1 Z_t - B_0] \\ &= \rho \gamma \omega_1 (I - \rho B_1)^{-1} \varepsilon_{Z,t+1} \end{aligned} \quad (\text{A5})$$

which is equation (16).

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## Footnotes

<sup>1</sup>The expected stock market return was long considered to be constant until relatively recent work documenting the predictability of market returns (e.g., Fama and French (1989)). It is now well understood that time-varying expected returns are consistent with rational expectations. See Campbell and Cochrane (1999) and Guo (2003) for recent examples of this literature.

<sup>2</sup>Strictly speaking, equation (1) is the discrete time version of Merton's ICAPM (see Long [1974]). In addition, the equation holds for the aggregate wealth portfolio for which we use the market portfolio as a proxy.

<sup>3</sup>Specifically, if the optimal consumption function of the representative agent is much less sensitive to the state variables that describe investment opportunities than to wealth or if the variance of the change in wealth is much larger than the variance of the change in the state variables, then this approximation will be reasonable (see footnote 12 in his paper).

<sup>4</sup>French, Schwert and Stambaugh (1987) argue that full information maximum likelihood estimators such as GARCH are generally more sensitive to model misspecification than instrumental variable estimators.

<sup>5</sup>Pindyck (1984, 1988), Poterba and Summers (1986), French, Schwert and Stambaugh (1987), Campbell and Hentschel (1992) and Wu (2001) all emphasize the importance of the volatility feedback effect in detecting the risk-return relation.

<sup>6</sup>Part of the implied volatility data are constructed by Christensen and Prabhala (1998) and are kindly provided to us by N. Prabhala.

<sup>7</sup>This type of specification has a long history in the literature. For example, French, Schwert and Stambaugh (1987) use a time series model of realized variance to model the conditional variance. Numerous papers since then have employed predetermined financial variables as additional predictors.

<sup>8</sup>Extending the VAR to longer lags is conceptually straightforward, but it adds nothing to the intuition from the model.

<sup>9</sup>Since  $X_t$  is a subset of  $Z_t$ , equation (18) is inconsistent with equation (15) unless the additional variables do not enter equation (18). In implementing this procedure we guarantee consistency by zeroing out the statistically insignificant coefficients throughout. Consequently, equation (18) is

subsumed by equation (15)

<sup>10</sup>See the CBOE web site (<http://www.cboe.com>) for details and the historical data series.

<sup>11</sup>Restricting the sample to the November 1983 to May 1995 subperiod spanned by the Christensen and Prabhala series also produces qualitatively similar results.

<sup>12</sup>See Anderson, Bollerslev, Diebold and Labys (2003) and the references therein for a discussion of the theory of quadratic variation and the conditions under which realized variance is an unbiased and efficient predictor of return volatility.

<sup>13</sup>In our sample, the first order autocorrelation of daily returns is 13.9% and all higher order autocorrelations are essentially zero.

<sup>14</sup>See his web site, <http://pages.stern.nyu.edu/~mlettau/>, for details.

<sup>15</sup>An earlier version of the paper used a somewhat different set of four instrumental variables for both the variance and the hedge component of returns: (1) RREL, (2) the yield spread between Baa-rated and Aaa-rated bonds, (3) the yield spread between 6-month commercial paper and 3-month Treasury bills, and (4) the dividend yield. The results are qualitatively similar, and the new specification is more parsimonious.

<sup>16</sup>Other variables such as the commercial paper–Treasury spread and longer lags of realized variance have a small amount of marginal predictive power over and above CAY and RREL in our sample. However, the results are invariant to including these additional variables and we restrict the set of variables for parsimony.

<sup>17</sup>Note that throughout the paper significance levels are based on two-sided tests. To the extent that one-sided tests are appropriate in some cases, the relevant significance level is half of that reported.

<sup>18</sup>The standard errors are computed via GMM and are asymptotic. Given the sample size, there is some question as to whether asymptotic standard errors are appropriate. This question is impossible to answer definitively, but we also compute small sample standard errors using a block bootstrap methodology. The resulting standard errors on the state variables are actually slightly lower than those reported in Table II, but the standard errors on  $\gamma$  are somewhat higher.

<sup>19</sup>Campbell et al (2000) suggest this type of adjustment to the crash variance, although a similar result could be achieved by dropping this observation from the sample. There may be other reasons to exclude the October 19, 1987 market crash from the sample. Schwert (1990b) shows it is unusual

in many ways, and Seyhun (1990) argues that it is not explained by the fundamentals. It is not predicted by the option data used in this paper.

<sup>20</sup>Aiyagari and Gertler (1999) and Allen and Gale (1994) emphasize the liquidity effect on stock market volatility.

Table I: The Efficiency of Implied Volatility

We estimate equation (30) and restricted versions thereof over the period from January 1984 to May 2001. Heteroscedasticity consistent standard errors are reported in parentheses. Coefficients that are significant at the 1%, 5% and 10% levels are marked by \*\*\*, \*\* and \*, respectively. <sup>a</sup>The constant has been scaled by a factor of 100 for presentation purposes.

	Const.	CAY <sub><i>t</i>-1</sub>	RREL <sub><i>t</i>-1</sub>	<i>v</i> <sub><i>t</i>-1</sub> <sup>2</sup>	<i>V</i> <sub><i>t</i></sub> <sup>2</sup>	<i>R</i> <sup>2</sup>
<i>v</i> <sub><i>t</i></sub> <sup>2</sup>	0.020*** (0.006)	-0.043*** (0.013)	0.246 (0.186)	0.394*** (0.091)		0.274
<i>v</i> <sub><i>t</i></sub> <sup>2</sup>	0.011* (0.006)	-0.023* (0.014)	0.045 (0.163)	0.105 (0.122)	0.420*** (0.101)	0.386
<i>v</i> <sub><i>t</i></sub> <sup>2</sup>	0.057*** <sup>a</sup> (0.019)				0.530*** (0.073)	0.365

Table II: Estimation Results with Implied Volatility

For Panel A we estimate the processes in equation (23) with statistically insignificant coefficients zeroed out. For Panel B we estimate the model in equation (24) and various restricted versions thereof (see Section III.A). In each case, the equations are estimated jointly via GMM over the period from January 1984 to May 2001. Heteroscedasticity consistent standard errors are reported in parentheses. Coefficients that are significant at the 1%, 5% and 10% levels are marked by \*\*\*, \*\* and \*, respectively. The last two columns provide the degrees of freedom, test statistic, and p-value (in brackets) for the overidentifying restrictions test (see Section III.A for details). <sup>a</sup>The constant has been scaled by a factor of 100 for presentation purposes.

Panel A: The Conditional Variance Process and the Processes for the State Variables

	Const.	$v_t$	$V_t^2$	CAY <sub>t</sub>	RREL <sub>t</sub>	$R^2$
$v_{t+1}^2$	0.057*** <sup>a</sup> (0.019)		0.530*** (0.073)			0.365
$V_{t+1}^2$	0.001*** (0.000)		0.641*** (0.118)			0.411
CAY <sub>t+1</sub>	0.063*** (0.016)			0.859*** (0.035)		0.738
RREL <sub>t+1</sub>	-0.002 <sup>a</sup> (0.003)				0.846*** (0.045)	0.702

Panel B: The Model

	Const.	$\gamma$	CAY	RREL	$R^2$	DF	$\chi^2$
Model 1	0.003 (0.004)	2.485 (1.909)			0.008	0	
Model 1	0.004 (0.004)	3.842** (1.918)			0.008	2	9.411 [0.009]
Model 2	0.003 (0.004)	2.485 (1.909)			0.203	0	
Model 2	0.001 (0.003)	4.571*** (1.705)			0.203	2	4.974 [0.083]
Model 3	-0.211** (0.097)		0.493** (0.215)	-4.706 (3.500)	0.034	0	
Model 3	-0.221** (0.097)		0.513** (0.214)	-4.395 (3.505)	0.034	1	4.778 [0.029]
Model 4	-0.334*** (0.103)	5.623*** (1.885)	0.744*** (0.266)	-5.767 (3.503)	0.068	0	
Model 4	-0.327*** (0.101)	5.919*** (1.731)	0.727*** (0.222)	-5.616* (3.382)	0.068	3	0.298 [0.960]
Model 5	-0.191** (0.084)	4.350*** (1.623)	0.426** (0.188)	-5.161 (3.426)	0.230	0	
Model 5	-0.201** (0.083)	3.656*** (1.352)	0.453** (0.184)	-4.279 (3.221)	0.227	3	1.038 [0.792]
Model 6	-0.189** (0.085)	4.311 (2.692)	0.424** (0.193)	-2.875 (3.794)	0.248	0	
Model 6	-0.144** (0.060)	4.928** (2.142)	0.322** (0.133)	-3.462 (3.066)	0.278	3	0.831 [0.842]

Table III: Variance Predictability Regressions

We estimate equation (31) for various subsamples. Heteroscedasticity consistent standard errors are reported in parentheses. Coefficients that are significant at the 1%, 5% and 10% levels are marked by \*\*\*, \*\* and \*, respectively. <sup>b</sup>The market variance of October 1987 is adjusted as discussed in Section III.C.

Subperiod		Const.	CAY <sub>t-1</sub>	RREL <sub>t-1</sub>	$v_{t-1}^2$	$v_{t-2}^2$	$R^2$
9/62-9/87	$v_t^2$	0.004 (0.003)	-0.009 (0.006)	-0.009 (0.087)	0.441*** (0.117)	0.172** (0.067)	0.298
1/88-5/01	$v_t^2$	0.015** (0.007)	-0.032** (0.015)	0.141 (0.185)	0.268*** (0.094)	0.213** (0.098)	0.278
9/62-5/01	$v_t^2$	0.012*** (0.004)	-0.023** (0.009)	0.016 (0.093)	0.151* (0.077)	0.113** (0.056)	0.048
9/62-5/01 <sup>b</sup>	$v_t^2$	0.007*** (0.002)	-0.015** (0.006)	0.015 (0.078)	0.360*** (0.066)	0.207*** (0.047)	0.252
9/62-5/01 <sup>b</sup>	$v_t^2$	0.008*** (0.003)	-0.015*** (0.006)	-0.014 (0.084)	0.453*** (0.067)		0.219

Table IV: Estimation Results with Financial State Variables

For Panel A we estimate the processes in equation (23) with statistically insignificant coefficients zeroed out. For Panel B we estimate the model in equation (24) and various restricted versions thereof (see Section III.A). In each case, the equations are estimated jointly via GMM over the period from September 1962 to May 2001. Heteroscedasticity consistent standard errors are reported in parentheses. Coefficients that are significant at the 1%, 5% and 10% levels are marked by \*\*\*, \*\* and \*, respectively. The last two columns provide the degrees of freedom, test statistic, and p-value (in brackets) for the overidentifying restrictions test (see Section III.A for details).

Panel A: The Conditional Variance Process and the Processes for the State Variables

	Const.	$v_t^2$	CAY <sub>t</sub>	RREL <sub>t</sub>	$R^2$
$v_{t+1}^2$	0.008*** (0.003)	0.454*** (0.067)	-0.015*** (0.006)		0.219
CAY <sub>t+1</sub>	0.066*** (0.011)		0.851*** (0.026)		0.726
RREL <sub>t+1</sub>	0.002** (0.001)		-0.004** (0.002)	0.813*** (0.056)	0.672

Panel B: The Model

	Const.	$\gamma$	CAY	RREL	$R^2$	DF	$\chi^2$
Model 1	0.008 (0.006)	-1.459 (3.039)			0.001	0	
Model 1	0.011* (0.006)	-2.917 (3.233)			0.001	2	15.130 [0.001]
Model 2	0.008 (0.006)	-1.468 (3.066)			0.001	0	
Model 2	0.004 (0.004)	1.455 (2.182)			0.030	2	14.500 [0.001]
Model 3	-0.166*** (0.058)		0.390*** (0.133)	-5.827*** (2.117)	0.036	0	
Model 3	-0.166*** (0.058)		0.391*** (0.132)	-5.812*** (2.097)	0.036	1	0.003 [0.958]
Model 4	-0.164** (0.068)	-0.160 (3.051)	0.387** (0.148)	-5.832*** (2.132)	0.036	0	
Model 4	-0.175*** (0.065)	0.657 (2.777)	0.408*** (0.142)	-5.637*** (2.105)	0.035	3	0.925 [0.819]
Model 5	-0.164** (0.067)	-0.161 (3.070)	0.387*** (0.147)	-5.827*** (2.115)	0.035	0	
Model 5	-0.167** (0.065)	-0.084 (2.898)	0.392*** (0.143)	-5.716*** (2.110)	0.035	3	0.978 [0.807]
Model 6	-0.182** (0.070)	1.597 (3.482)	0.421*** (0.153)	-5.474** (2.326)	0.040	0	
Model 6	-0.179*** (0.066)	2.053 (2.979)	0.412*** (0.145)	-2.816 (1.851)	0.067	3	4.272 [0.234]

Table V: Estimation Results with Financial State Variables–11/83-5/01 Subsample

For Panel A we estimate the processes in equation (23) with statistically insignificant coefficients zeroed out. For Panel B we estimate the model in equation (24) and various restricted versions thereof (see Section III.A). In each case, the equations are estimated jointly via GMM over the period from January 1984 to May 2001. Heteroscedasticity consistent standard errors are reported in parentheses. Coefficients that are significant at the 1%, 5% and 10% levels are marked by \*\*\*, \*\* and \*, respectively. The last two columns provide the degrees of freedom, test statistic, and p-value (in brackets) for the overidentifying restrictions test (see Section III.A for details). <sup>a</sup>The constant has been scaled by a factor of 100 for presentation purposes.

Panel A: The Conditional Variance Process and the Processes for the State Variables

	Const.	$v_t^2$	CAY <sub>t</sub>	RREL <sub>t</sub>	$R^2$
$v_{t+1}^2$	0.020*** (0.006)	0.390*** (0.090)	-0.043*** (0.013)		0.269
CAY <sub>t+1</sub>	0.063*** (0.016)		0.859*** (0.035)		0.738
RREL <sub>t+1</sub>	-0.002 <sup>a</sup> (0.003)			0.846*** (0.045)	0.702

Panel B: The Model

	Const.	$\gamma$	CAY	RREL	$R^2$	DF	$\chi^2$
Model 1	0.013** (0.005)	-2.029 (2.639)			0.004	0	
Model 1	0.014*** (0.005)	-1.564 (2.448)			0.003	2	5.851 [0.054]
Model 2	0.013** (0.005)	-2.083 (2.730)			0.032	0	
Model 2	0.019*** (0.005)	-4.984* (2.470)			0.052	2	5.008 [0.082]
Model 3	-0.211** (0.097)		0.493** (0.215)	-4.706 (3.500)	0.034	0	
Model 3	-0.207** (0.097)		0.485** (0.214)	-4.941 (3.493)	0.034	1	0.900 [0.343]
Model 4	-0.303** (0.146)	3.070 (3.247)	0.687** (0.316)	-4.486 (3.516)	0.039	0	
Model 4	-0.305** (0.143)	2.950 (3.272)	0.690** (0.308)	-3.706 (3.342)	0.039	3	1.047 [0.790]
Model 5	-0.308* (0.156)	3.202 (3.616)	0.697** (0.336)	-5.183 (3.773)	0.001	0	
Model 5	-0.194* (0.114)	-0.566 (1.993)	0.457* (0.249)	-4.368 (3.314)	0.047	3	1.801 [0.615]
Model 6	-0.311** (0.143)	3.419 (3.390)	0.704** (0.309)	-1.428 (3.683)	0.122	0	
Model 6	-0.287** (0.134)	4.116 (3.037)	0.647** (0.289)	-1.856 (3.064)	0.131	3	0.495 [0.920]



Table VI: Estimation Results with Financial State Variables–Quarterly Data

For Panel A we estimate the processes in equation (23) with statistically insignificant coefficients zeroed out. For Panel B we estimate the model in equation (24) and various restricted versions thereof (see Section III.A). In each case, the equations are estimated jointly via GMM over the period 1952Q4–2002Q3. Heteroscedasticity consistent standard errors are reported in parentheses. Coefficients that are significant at the 1%, 5% and 10% levels are marked by \*\*\*, \*\* and \*, respectively. The last two columns provide the degrees of freedom, test statistic, and p-value (in brackets) for the overidentifying restrictions test (see Section III.A for details). <sup>a</sup>The constant has been scaled by a factor of 100 for presentation purposes.

Panel A: The Conditional Variance Process and the Processes for the State Variables

	Const.	$v_t^2$	CAY <sub>t</sub>	RREL <sub>t</sub>	$R^2$
$v_{t+1}^2$	0.003*** (0.000)	0.423*** (0.088)	-0.095*** (0.027)		0.231
CAY <sub>t+1</sub>	-0.002 <sup>a</sup> (0.048)		0.833*** (0.038)		0.693
RREL <sub>t+1</sub>	-0.001 <sup>a</sup> (0.014)		-0.022** (0.009)	0.711*** (0.081)	0.527

Panel B: The Model

	Const.	$\gamma$	CAY	RREL	$R^2$	DF	$\chi^2$
Model 1	0.024 (0.016)	-1.379 (3.107)			0.002	0	
Model 1	0.057*** (0.013)	-8.712*** (2.420)			0.004	2	16.893 [0.000]
Model 2	0.025 (0.018)	-1.547 (3.435)			0.080	0	
Model 2	0.071*** (0.013)	-10.658*** (2.382)			0.184	2	10.931 [0.004]
Model 3	0.017*** (0.005)		1.945*** (0.399)	-5.599*** (1.994)	0.131	0	
Model 3	0.014*** (0.005)		1.946*** (0.399)	-5.240*** (1.989)	0.131	1	3.947 [0.047]
Model 4	-0.018 (0.017)	6.273** (3.082)	2.709*** (0.573)	-5.158** (1.962)	0.154	0	
Model 4	-0.014 (0.016)	6.187** (2.883)	2.446*** (0.523)	-6.210*** (1.904)	0.152	3	4.615 [0.202]
Model 5	-0.024 (0.027)	7.375 (4.880)	2.822*** (0.727)	-6.091** (2.402)	0.001	0	
Model 5	-0.018 (0.019)	6.433** (3.235)	2.522*** (0.565)	-6.902** (2.177)	0.006	3	2.563 [0.464]
Model 6	-0.019 (0.019)	6.515** (3.258)	2.779*** (0.586)	-3.216 (2.107)	0.429	0	
Model 6	-0.027 (0.017)	7.746** (2.795)	2.970*** (0.587)	-3.091* (1.740)	0.447	3	2.903 [0.407]

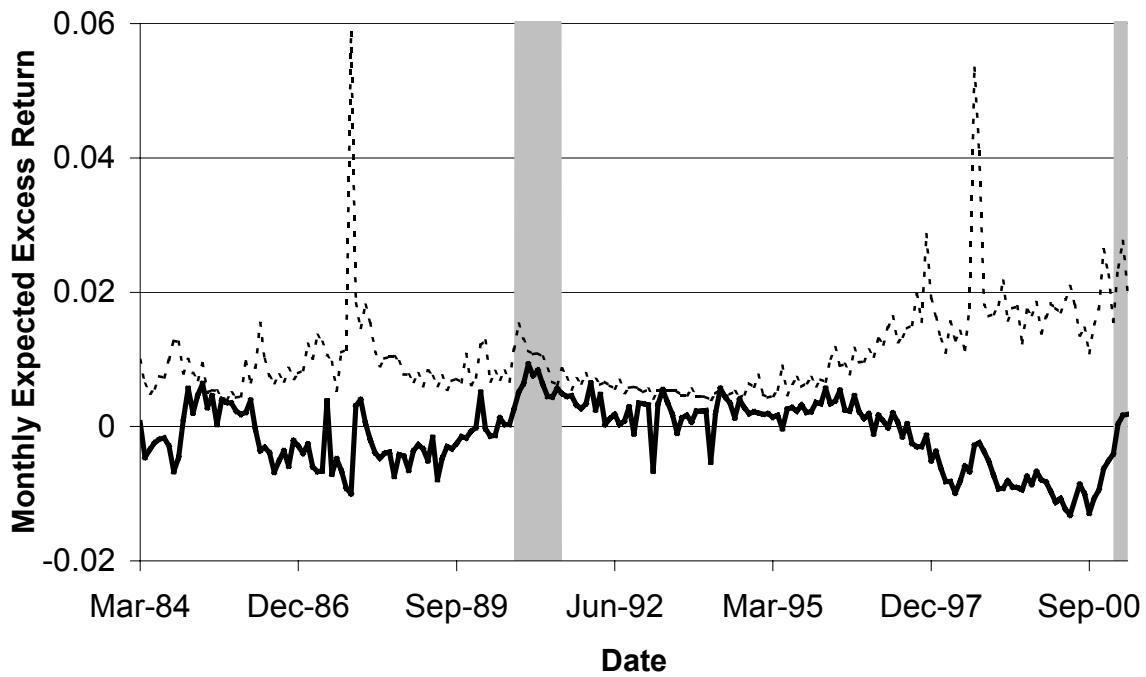


Figure 1: The Components of Expected Returns using Implied Volatility  
The risk (dashed line) and hedge (solid line) components of monthly expected excess returns for the period 3/84 to 5/01, using the implied volatility data. The estimation results are reported in Table II, Panel C, Model 6, overidentified specification. Recessions are marked as shaded bars.

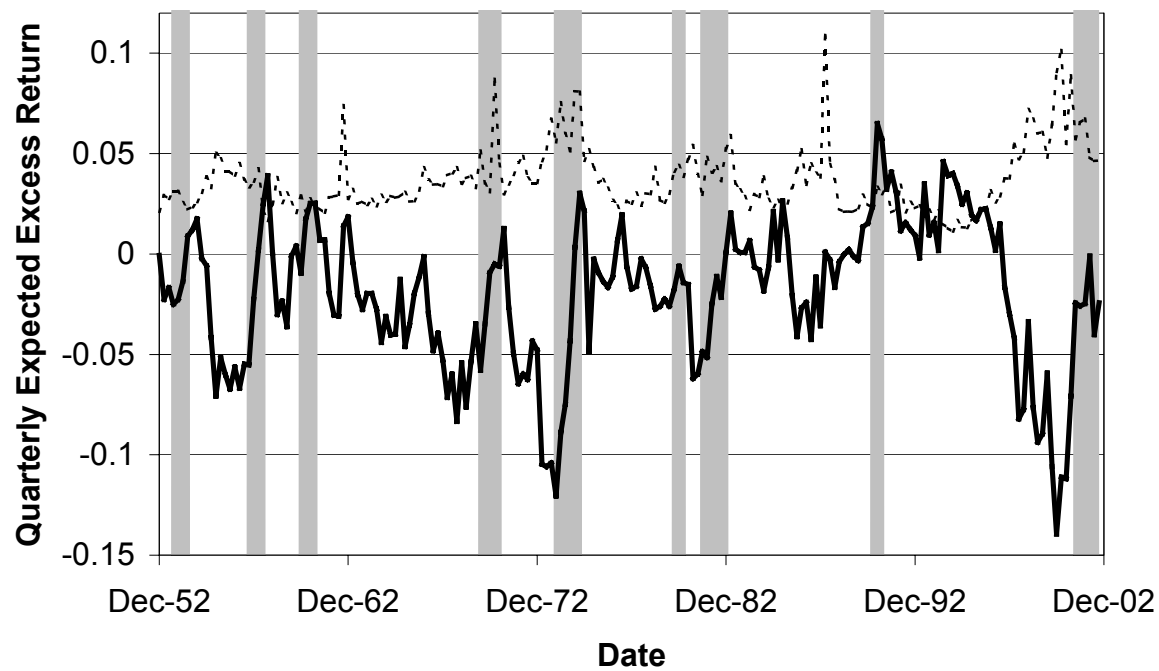


Figure 2: The Components of Expected Returns using Financial State Variables

The risk (dashed line) and hedge (solid line) components of quarterly expected excess returns for the period 1952Q2 to 2002Q3, using instrumental variables to estimate the conditional variance. The estimation results are reported in Table VI, Panel B, Model 6, overidentified specification. Recessions are marked as shaded bars.