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Evidence from the Stock Market

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Does Aggregate Relative Risk Aversion Change Countercyclically over Time? Evidence from the Stock Market

Abstract

Using a semiparametric estimation technique, we show that the risk-return tradeoff and the Sharpe ratio of the stock market increases monotonically with the consumption-wealth ratio (CAY) across time. While early studies have commonly interpreted such a finding as evidence of the countercyclical variation in aggregate relative risk aversion (RRA), we argue that it mainly reflects changes in investment opportunities for two reasons. First, we fail to reject the null hypothesis of constant RRA after controlling for CAY as a proxy for the hedge against changes in the investment opportunity set. Second, by contrast with habit formation models but consistent with ICAPM, we find that loadings on the conditional stock market variance scaled by CAY are *negatively* priced in the cross-sectional regressions. For illustration, we replicate the countercyclical stock market risk-return tradeoff using simulated data from Guo's (2004) limited stock market participation model, in which RRA is constant and CAY is a proxy for shareholders' liquidity conditions.

Keywords: Habit Formation, Time-Varying Risk Aversion, Countercyclical Sharpe Ratio, Limited Stock Market Participation, Illiquidity Premium, ICAPM, Conditional CAPM, Nonparametric and Semiparametric Models

JEL Classification: G12, C14

1. Introduction

In Merton's (1973) intertemporal capital asset pricing model (ICAPM), the conditional excess stock market return, $E_t r_{M,t+1}$, is determined by its conditional variance, $\sigma_{M,t}^2$, and its conditional covariance, $\sigma_{MF,t}$, with the state variable(s), *F*:

$$(1) \qquad E_t r_{M,t+1} = \gamma_t \sigma_{M,t}^2 + \lambda_t \sigma_{MF,t},$$

where γ_t and λ_t are the prices of risk. Equation (1) nests two main explanations of stock return predictability. First, the price of the market risk, γ_t, is a function of aggregate relative risk aversion (RRA), which changes across time countercyclically in habit formation models (e.g., Constantinides (1990), Campbell and Cochrane (1999), Brandt and Wang (2003), and Menzly et al. (2004)).[1] Second, the quantity of risk, as measured by $\sigma_{M,t}^2$ and $\sigma_{MF,t}$, exhibits a strong countercyclical pattern in the data (e.g., French et al. (1987), Schwert (1989), Scruggs (1998), and Guo and Whitelaw (2006)).

Recent studies provide tentative empirical evidence for both hypotheses. Lettau and Ludvigson (2001a) find that the consumption-wealth ratio (CAY), which is the error term from the cointegration relation among consumption, wealth, and labor income, is a strong predictor of stock market returns. One possible explanation is that, in Campbell and Cochrane's (1999) habit formation model, the scaled stock price, e.g., CAY, moves closely with time-varying RRA. To test this idea, Lettau and Ludvigson (2001b) estimate a variant of the conditional CAPM by

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[1] The coefficient γ_t is equal to RRA in the representative agent model with power utility function. Appendix A shows that, in Campbell and Cochrane's (1999) habit formation model, these two measures are closely related to each other in a complex manner but they are not identical. We thank Sydney Ludvigson for suggesting this clarification. Time-varying RRA is also consistent with a few other hypotheses. In Chan and Kogan's (2002) heterogeneous-agent model, aggregate RRA changes with the wealth distribution, although individual agents have constant RRA. Ang et al. (2005) and Post and Levy (2005) argue that investors may be risk averse for losses but (locally) risk-seeking for gains, and such a behavior can generate a potentially complex time-varying pattern of RRA. Many works in the loss aversion literature (e.g., Benartzi and Thaler (1995)) also endorse the idea that investors maintain an asymmetric attitude towards gains versus losses.

using CAY as the conditioning variable and find that their model performs substantially better than the unconditional CAPM, in which RRA is constant. By contrast, in Campbell's (1993) ICAPM, γ_t and λ_t are constant across time, and the scaled stock price can serve as an instrumental variable for the hedge component, $\sigma_{MF,t}$, in equation (1).[2] Consistent with this hypothesis, Guo and Whitelaw (2006) uncover a significantly positive risk-return tradeoff in the stock market after controlling for CAY as a proxy for the hedge component.

This paper provides the first attempt to evaluate the relative importance of these two hypotheses in explaining stock price movement over the post-World War II period. We first estimate equation (1) using the semiparametric smooth (or varying) coefficient model considered in Cai et al. (2000) and Li et al. (2002), in which γ_t depends nonlinearly on CAY in a nonparametric manner.[3] Figure 1 summarizes the two main findings. First, the solid line shows that γ_t increases monotonically with CAY in the conditional CAPM specification, and the relation is statistically significant at the 1% level. Second, the countercyclical variation in γ_t reflects an omitted variable problem. The dashed line shows that the positive relation between γ_t and CAY is attenuated dramatically and becomes insignificant at the 40% level after we also control for CAY as a proxy for the hedge component.

[2] There are two types of shocks in Campbell's ICAPM—the discount-rate shock and the cash-flow shock. Under some moderate conditions, the hedge component is proportional to the conditional variance of the discount-rate shock. One can then use Campbell and Shiller's (1988) log-linearization method to show that the log dividend yield is a linear function of conditional stock market variance and the conditional variance of the discount-rate shock. Therefore, the scaled stock price forecasts stock market returns because of its close relation with the hedge component. For brevity, we do not provide these derivations here but they are available on request.

[3] Appendix A shows that this specification is consistent with Campbell and Cochrane's (1999) habit formation model. In their model, the coefficient of the risk-return tradeoff is a complex function of RRA, which increases monotonically with CAY. Therefore, a positive effect of CAY on the risk-return tradeoff indicates a positive relation between RRA and the risk-return tradeoff. Because the two measures are closely related and identical in some models considered here, we use RRA and the coefficient of the risk-return tradeoff interchangeably in the paper. Appendix A also shows that, in Campbell and Cochrane's model, the Sharpe ratio is approximately a linear function of RRA. To address this issue, we also investigate the relation between the conditional excess stock market return and the conditional volatility (instead of the conditional variance) and find essentially the same results. (See Figure A1 in Appendix A.)

For robustness, we conduct two additional tests. First, we use a nonparametric model and find a significantly positive relation between RRA and the conditional stock market variance. However, again, the countercyclical variation in RRA disappears after we control for CAY as a proxy for the hedge component of the conditional excess stock market returns. Second, we find qualitatively the same results by using other commonly used stock return predictors as instrumental variables for time-varying RRA.

We may fail to reject constant RRA in the time-series data because of a lack of power. To address this issue, we investigate whether the conditional CAPM helps explain the cross section of stock returns by using both conditional stock market variance and its interaction with lagged CAY as risk factors. The conditional CAPM performs substantially better in explaining the 25 Fama and French (1993) portfolios sorted on size and the book-to-market (B/M) ratio than does the unconditional CAPM. However, by contrast with habit formation models, the interaction term carries a significantly *negative* risk premium because growth stocks have larger loadings on it than do value stocks. Because the interaction term is closely correlated with CAY, this seemingly puzzling result reflects the fact that CAY is a proxy for the hedge against changes in the investment opportunity set. The interaction term loses its explanatory power after we control for CAY or the Fama and French (1993) B/M factor in the cross-sectional regressions.

Lastly, solid line in Figure 2 shows that we replicate the countercyclical risk-return tradeoff in the conditional CAPM specification by using simulated data from Guo's (2004) model. Because of (exogenously assumed) limited participation, Guo shows that shareholders also require an illiquidity premium, ILL_t, for holding stocks, in addition to the risk premium:

(2) $$r_{M,t+1} = \gamma\sigma_{M,t}^2 + \lambda ILL_t + \varepsilon_{t+1} .$$

Two implications of Guo's model generate the time-varying risk-return tradeoff. First, the illiquidity premium is positively related to CAY. This is because a positive (negative) liquidity shock to shareholders decreases (increases) the illiquidity premium as well as CAY. Second, stock market variance is a U-shaped function of CAY because liquidity shocks, either positive or negative, always drive up volatility.[4] Therefore, the risk-return tradeoff increases monotonically with CAY because the illiquidity premium and the risk premium in equation (2) are negatively (positively) correlated when CAY is low (high). To illustrate this point, the dashed line in Figure 2 shows that, after we control for CAY as a proxy for the illiquidity premium, the countercyclical variation in CAY essentially disappears because RRA is constant in Guo's model.

Our results are consistent with a number of recent studies. Campbell and Vuolteenaho (2004), Brennan et al. (2004), and Petkova (2006) find that changes in the investment opportunity set are important for understanding the cross-section of stock returns. Lettau and Wachter (2006) argue that, to jointly account for both time-series and cross-sectional stock return predictability, there must be a weak relation between the discount-rate shock and the cash-flow shock. Because the two shocks have a perfect negative relation in habit formation models, Lettau and Wachter show that these models cannot explain the B/M effect (e.g., Fama and French (1993)). Li (2005) finds that the consumption surplus in habit formation models does not fully account for the predictive power of CAY for stock market returns. Using household-level data, Brunnermeier and Nagel (2005) show that, by contrast with habit formation models, wealth fluctuations do not generate time-varying risk aversion.

Many studies, e.g., Whitelaw (1994), Lettau and Ludvigson (2003), Brandt and Kang (2004), Bliss and Panigirtzoglou (2004), Bollerslev et al. (2004), Post and Levy (2005), and

[4] Consistent with this prediction, we find that, over the post-World War II period, the relation between stock market volatility and CAY is positive in the first subsample and is negative in the second subsample. By contrast, this result is inconsistent with habit formation models, which predict a positive relation between the two variables.

Lundblad (2006), have documented countercyclical variation in the risk-return tradeoff. These authors often interpret such a finding as evidence of time-varying RRA. The evidence presented here suggests that this interpretation could be misleading because by ignoring the hedge component, the specifications in these studies potentially suffer from an omitted variable problem. Also, these studies do not investigate the effect of the time-varying RRA on the cross-section of asset returns, which we find to pose a serious challenge to habit formation models.

The remainder of the paper is organized as follows. We describe the data in Section 2 and present the estimation results of the linear specification in Section 3. We provide the nonlinear estimation results in Section 4 and the cross-sectional evidence in Section 5. We discuss theoretical implications in Section 6 and offer some concluding remarks in Section 7.

2. Data

Conditional stock market variance is not directly observable in the data. In this paper, we follow Merton (1980) and Anderson et al. (2003) and use realized variance constructed from daily excess returns as a proxy for conditional stock market variance. Compared with the GARCH model (e.g., see Bollerslev et al. (1992)), this specification has several desirable properties for the purpose of this paper. First, the CAY variable—the main focus of our analysis—is reliably available only at the quarterly frequency; however, the GARCH model is only appropriate for the return data of much higher, e.g., daily or weekly, frequencies. Second, a direct measure of conditional variance allows us to easily adopt the semiparametric and nonparametric models. Third, French et al. (1987) argue that full-information maximum likelihood estimators such as GARCH are generally more sensitive to model misspecification than instrumental variable estimators.[5] More importantly, as we show below, our results appear to be sensible, intuitive, and consistent with predictions of economic theory. That said, we acknowledge that realized variance is not necessarily an efficient measure of conditional variance. To address this issue, we also use monthly implied variance constructed from options contracts on the stock market index as a measure of conditional variance and find qualitatively the same results. The implied variance data are the same as those used in Guo and Whitelaw (2006), which span the period November 1983 to May 2001.

We mainly use quarterly data because the CAY variable is reliably available only at the quarterly or lower frequency. Also, Ghysels et al. (2005) argue that realized variance is a function of long distributed lags of past daily returns; therefore, it is likely to be more precisely estimated at the quarterly frequency than the monthly frequency. We obtain the CAY variable from Martin Lettau at New York University. Realized stock market variance (MV) is the sum of squared daily excess stock market returns in a quarter. We use the daily stock market returns constructed by Schwert (1989) before July 1, 1962, and the daily CRSP (the Center for Research in Security Prices) value-weighted stock market returns afterwards. Because the daily risk-free rate data are not directly available, we assume that the risk-free rate is constant within each month and calculate the daily risk-free rate by dividing the monthly CRSP risk-free rate 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.

For robustness, we also use some other commonly used stock return predictors as proxies for time-varying RRA (see, e.g., Campbell (1987) and Fama and French (1989)). The default premium (DEF) is the yield spread between the Baa- and Aaa-rated corporate bonds. The

[5] Bollerslev et al. (1992, p. 14) also point out that the estimation of a parametric GARCH-in-mean model can be severely biased in the presence of the model misspecification, especially when allowing for time-varying parameters. Time-varying parameters also greatly intensify the concern about the unclear theoretical properties of

dividend yield (DY) is the ratio of the dividend paid in the past one year to the end-of-period stock price for the S&P 500 stocks. The term premium (TERM) is the yield spread between 10-year Treasury bonds and 3-month Treasury bills. The stochastically detrended risk-free rate (RREL) is the difference between the risk-free rate and its average in the previous 12 months. TERM is available over the 1953:Q2 to 2004:Q4 period and all the other variables are available over the 1951:Q4 to 2004:Q4 period.

Figure 3 plots MV and the other stock return predictors, with the shaded areas denoting business recessions dated by the National Bureau of Economic Research (NBER). All the variables are quite persistent and exhibit strong cyclical patterns. While RREL tends to decrease during business recessions, the other variables move countercyclically. The visual inspection is confirmed by the summary statistics presented in panel A of Table 1. All the variables are serially correlated, with the autocorrelation coefficients ranging from 40% for MV to 97% for DY. Also, while RREL is negatively correlated with a business cycle indictor, BCI, which is equal to 1 for the recession quarters and 0 otherwise, the correlation is positive for all the other variables. Panels B and C illustrate similar patterns in the two subsamples.

Table 1 reveals an unstable relation between MV and some other financial variables. MV and CAY are negatively correlated in the full sample (panel A) and the second subsample (panel C); however, the relation is positive in the first subsample (panel B). We find a similar pattern for DY and RREL, which are positively correlated with MV in the first subsample (panel B) and the relation becomes negative in the second subsample (panel C). These results are inconsistent with Campbell and Cochrane's (1999) habit formation model, which predicts that MV is positively correlated with DY and CAY. As we discuss in Section 6, these results, which are consistent with the limited stock market participation model by Guo (2004), are important for

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maximum likelihood estimator (or its variants such as quasi-maximum likelihood estimator) in the multivariate GARCH model (see, e.g., Engle and Kroner (1995)).

understanding the countercyclical variation in the risk-return tradeoff in the stock market. Paye (2006) also finds that financial variables have rather weak forecasting power for realized stock market variance at the business cycle frequency. For robustness, in this paper, we assume that conditional stock market variance is a linear function of realized variance only.[6]

3. Linear Specifications

We use Guo and Whitelaw's (2006) linear specification as the benchmark model, in which the excess stock market return ($r_{M,t+1}$) is a linear function of conditional stock market variance ($\sigma^2_{M,t}$) and financial variables (X_t) that are proxies for the hedge component:

$$r_{M,t+1} = \alpha + \gamma\sigma^2_{M,t} + \lambda X_t + \varepsilon_{t+1}, \tag{3}$$

where α is a constant and ε_{t+1} is the error term.

Panel A of Table 2 presents the ordinary least-squared (OLS) estimation results of equation (3) obtained from quarterly data. Row 1 shows that realized stock market variance, MV, is positively related to the one-quarter-ahead excess stock market returns but the relation is only marginally significant. After we also include CAY in the forecasting regression as a proxy for the hedge component, the positive effect of MV on the expected stock return becomes significant at the 5% level (row 4). Guo and Whitelaw (2006) point out that these results reflect an omitted variable problem. MV and CAY are both positively related to future stock market returns, although they are negatively related to each other in the full sample (panel A, Table 1). Thus, the point estimate of MV is downward biased if we do not control for CAY in the forecasting

[6] Guo and Whitelaw (2006) assume that conditional stock market variance is a linear function of MV, CAY, and RREL. However, they find that some of their results are sensitive to such a specification because of instability in the relation between the conditional variance and CAY (p. 1458).

regression.[7] Similarly, the effect of MV becomes significantly positive at the 1% level after we control for DEF, DY, RREL, and TERM in the forecasting equation (row 5). Overall, row 6 shows that, in the linear specification, CAY appears to be a better proxy for the hedge component than the other financial variables.

Panel B of Table 2 reports very similar results for the monthly implied variance data. In particular, the point estimate of the RRA in the full-fledge specification (row 12) is about 3, which is almost identical to that obtained from the quarterly data (row 6). This result provides confidence that realized variance provides a reasonably good measure of conditional stock market variance. To summarize, consistent with Guo and Whitelaw (2006), we find a positive risk-return tradeoff after controlling for the hedge component, for which CAY is a good proxy.

We then investigate whether the coefficient γ in equation (3) changes countercyclically across time. We first estimate a variant of the conditional CAPM, in which we follow Lettau and Ludvigson (2001b) by assuming that risk return tradeoff is a linear function of state variables:

$$(4) \qquad r_{M,t+1} = \alpha + (\gamma_0 + \gamma X_t)\sigma^2_{M,t} + \varepsilon_{t+1}.$$

Appendix A shows that , in Campbell and Cochrane's (1999) habit formation model, the risk-return tradeoff is a complex nonlinear function of time-varying RRA, which is closely related with the state variables, for example, CAY. In particular, when CAY is high, consumption is closer to its habit level, investors are more risk averse, and thus expect a higher risk-return tradeoff. Recall that, as discussed in footnote 1, equation (4) is also consistent with several other economic theories, in which RRA is time varying. In this paper, we focus on whether the risk-return tradeoff is time-varying and do not distinguish these alternative hypotheses. Note that the linear specification might be a bit too restrictive and we relax this assumption in the next section.

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[7] Section 6 shows that omitting CAY from the forecasting regression can also generate an upward bias in the point estimate of MV when CAY and MV are positively correlated, as in the first subsample (panel B, Table 1).

We report the GMM (generalized method of moments) estimation results in Table 3. Because Table 1 shows that the cyclical variables are closely correlated with each other, we include only one of them in a regression. For example, for the column under BCI, we assume that RRA is a linear function of a constant and the business cycle indicator BCI. However, to improve the estimation efficiency, we include all the cyclical variables and a constant in the instrumental variable set. We use Hansen's (1982) J-test to evaluate the goodness of fit for each specification.

Panel A of Table 3 shows that, consistent with Lettau and Ludvigson's (2001b) finding, there appears to be strong support for the hypothesis that RRA moves countercyclically in quarterly data. The relation between RRA and CAY is positive and statistically significant at the 1% level (row 3). The conditional CAPM accounts for about 8% of variation in quarterly excess stock market returns, which is very similar to that of the unrestricted linear specification reported in row 4, Table 2. This result reflects the fact that CAY and its interaction term with MV (as in equation 4) are closely correlated, with a correlation coefficient of 76%. Not surprisingly, the over-identifying restriction test does not reject the model at any conventional significance level, indicating the conditional CAPM provides a good description of the data.

Panel A of Table 3 also shows that the relations between RRA and all the other instrumental variables have expected signs and are statistically significant at the 1% level for TERM, the 5% level for BCI, MV, DY, and the 10% level for RREL. However, because Table 2 shows that CAY is a better predictor of stock market returns, the over-identifying restriction test overwhelmingly rejects the specifications with these variables as the proxies for RRA. Panel B of Table 3 shows that we find similar results by using the monthly implied variance data. The relation between RRA and CAY is positive and significant at the 1% level, and we fail to reject the conditional CAPM at any conventional significance level. However, because the sample of the monthly implied variance data is relatively short, we do not precisely identify the effect of the other variables on RRA.

Noteworthy, we need to interpret the results reported in Table 3 with caution. By ignoring the hedge component, the specification in equation (4) potentially suffers from an omitted variable problem, which could bias the risk-return tradeoff estimate. As mentioned above, in quarterly data, CAY is closely related to its interaction with MV. Therefore, the interaction term in equation (4) is found to be significantly positive possibly because of its close correlation with CAY—a proxy for the hedge component. To address this issue, we add CAY to the conditional CAPM as a control for the hedge component:

(5) $$r_{M,t+1} = \alpha + (\gamma_0 + \gamma X_t)\sigma^2_{M,t} + \lambda CAY_t + \varepsilon_{t+1}.$$

Note that including the other instrumental variables as proxies for the hedge component does not change the results in any qualitative manner because Table 2 shows that they provide little information about future stock returns beyond CAY.

Table 4 presents the estimation results of equation (5). For quarterly data (panel A), the relation between RRA and CAY becomes statistically insignificant at any conventional level, although it is remains positive. Interestingly, the relations between RRA and all the other state variables are also statistically insignificant after we control for CAY as a proxy for the hedge component. Also, panel B shows that we find very similar results by using the monthly implied variance data. Lastly, for robustness, we assume that time-vary RRA is a linear function of all the state variables. These variables are jointly significant in the conditional CAPM specification (equation 4); however, the joint explanatory power becomes statistically insignificant at the conventional level after we control for the hedge component (equation 5). For brevity, we do not report these results here but they are available on request. To summarize, the countercyclical risk-return tradeoff appears to be mainly explained by the hedge against changes in the investment opportunity set but not the countercyclical variation in RRA.

Equation (A9) in Appendix A shows that, in Campbell and Cochrane's (1999) habit formation model, the Sharpe ratio is approximately a linear function of RRA. To address this issue, we use conditional volatility instead of conditional variance in equations (4) and (5) and find essentially the same results. For example, the Sharpe ratio is positively and significantly related to CAY; however, the relation becomes insignificant at any conventional level after we control for CAY a proxy for the hedge component. For brevity, these results are not reported here but are available on request.

4. Nonlinear Specifications

Asset pricing theories do not provide unambiguous guidance for the functional form of the empirical specification, and it is a bit too restrictive to assume that RRA and the hedge component are linear functions of state variables, as in equation (5). In particular, Ghysels (1998) argues that a parametric asset pricing model with a known functional form may yield misleading results if the functional form is misspecified. It is tempting to use fully nonparametric models because they are robust against the functional form misspecification; however, they also have some drawbacks. First, it may not estimate the conditional mean with high accuracy. Second, it often cannot be estimated without running into a serious 'curse of dimensionality' problem, when the data are rather limited, as in our study. This is because the rate of convergence of many nonparametric estimators worsens dramatically as the number of covariates increases. For example, it appears that the number of quarterly data in this paper can meaningfully allow for no more than one covariate in the nonparametric estimation.

To address these issues, we adopt several popular classes of semiparametric nonlinear specifications, which are well suited for capturing the potentially complex nonlinearity without much loss of generality. In general, the semiparametric models have the advantage of allowing for more appreciable flexibility in functional forms than does a parametric linear or nonlinear model. At the same time, they can gain more estimation efficiency than nonparametric models with (correctly) imposed linearity restrictions on some components of the model. Also, these models can avoid much of the 'curse of dimensionality' problem that plagues fully nonparametric models, which often render (meaningful) nonparametric model estimation (and inference) infeasible for the limited amount of economic data. Lastly, these models tend to be easier to interpret and thus could be more informative than fully nonparametric models.

In addition to the general appealing statistical properties, the semiparametric models considered here are particularly suitable for the main purpose of the paper. The multifactor asset pricing models, as in equation (1), are not interested in general interactions between different risk factors, which can be best captured by a fully nonparametric model. Instead, we are interested in whether the prices of risk factors are potentially nonlinear functions of some state variables, e.g., CAY, as suggested by finance theories. As we show below, one can illustrate this dependence in an intuitive manner by using the semiparametric smooth coefficient model (Cai et al., 2000; Li et al., 2002), which allows for a state variable to affect RRA in a nonparametric nonlinear manner. For robustness, we also consider semiparametric partially linear and additive models (and a nonparametric model in the one-factor context), in which the price of market risk does not depend on any state variable. We obtain essentially the same conclusion by using both classes of semiparametric nonlinear models. See Appendix B for more details on estimation of these models and associated model specification tests.

4.1. Semiparametric Smooth Coefficient Model

To address the potential nonlinearity in both the risk and hedge components, we first adopt the following smooth coefficient model:

(6) $r_{M,t+1} = \gamma(X_t)\sigma_{M,t}^2 + \lambda(X_t) + \varepsilon_{t+1}$,

where the coefficients $\gamma(X_t)$ and $\lambda(X_t)$ are unspecified smooth functions of state variables X_t. The model is quite general and nests threshold regression models, smooth transition regression, and many other regime-switching models as special cases. Due to the relatively small number of observations, we can allow for only one state variable in the coefficients $\gamma(X_t)$ and $\lambda(X_t)$. This limitation is innocuous because our main focus is to test whether CAY proxies for time-varying RRA or the hedge component, as suggested by finance theories.

Similar to Li et al. (2002), we estimate the term $\gamma(X_t)$ nonparametrically using a local constant estimator. We use the normal distribution as the kernel function, in which the smoothing parameter or the bandwidth of the window of the kernel estimation is determined by popular leave-one-out least square cross-validation method. We first test the null hypothesis of a constant risk-return tradeoff

(7) $r_{M,t+1} = \alpha + \gamma\sigma_{M,t}^2 + \varepsilon_{t+1}$

against the general smooth coefficient model, as in equation (6). This test, which is equivalent to a semiparametric variant of the omitted variable test as discussed in Fan and Li (1996), addresses whether state variables X_t provide additional information about future stock market returns beyond conditional stock variance that enters the equation linearly as implied by the CAPM. To evaluate the relative performance of the two models, we use the bootstrap version of the goodness-of-fit test statistic advocated by Cai et al. (2000), which can be understood as a type of generalized likelihood ratio tests. Panel A of Table 5 shows that CAY provides important information about future stock market returns beyond the conditional stock market variance, and such a relation is statistically significant at the 1% level.

We then investigate whether the effect of the state variables comes from their roles as the conditioning variables for time-varying RRA, as in habit formation models:

(8) $$r_{M,t+1} = \alpha + \gamma(X_t)\sigma^2_{M,t} + \varepsilon_{t+1}.$$

The benchmark or null model remains to be the conditional CAPM with constant RRA, as in equation (7). Panel B of Table 5 shows that we reject the linear one-factor model and accept the alternative of the model with state-variable-dependent RRA for CAY at the 1% level. Moreover, the solid line in Figure 1 shows that the estimated RRA increases monotonically with CAY and the relation is strikingly close to being a linear one. These results confirm that the specification of RRA as a linear function of CAY (equation 4) provides a good description of the expected stock market returns, as reported in row 3, Table 3. Interestingly, the estimated RRA is negative when CAY is low but becomes positive when CAY is high. Many early studies, e.g., Campbell (1987), Glosten, Jagannathan, and Runkle (1993), Whitelaw (1994), Lettau and Ludvigson (2003), and Brandt and Kang (2004), have also documented a negative risk-return tradeoff. Note that the negative RRA poses a challenge to habit formation models because they predict a positive risk-return tradeoff. Next, we show that the seemingly puzzling finding reflects an omitted variable problem.

Table 4 shows that the time-varying risk-return tradeoff might reflect the countercyclical variation in the hedge component. To address this issue, in panel C of Table 5, we investigate whether the countercyclical variation in RRA remains statistically significant after we control for the hedge component, which is a linear function of the state variable:

(9) $$r_{M,t+1} = \gamma(X_t)\sigma^2_{M,t} + \lambda X_t + \varepsilon_{t+1}.$$

The benchmark model is that the expected excess stock market return is a linear function of conditional stock market variance and the hedge component, as in equation (3).

Consistent with the results reported in Table 4, panel C of Table 5 shows that we fail to reject the null hypothesis of no relation between RRA and CAY at the 40% significance level after controlling for CAY as a proxy for the hedge component. The dashed line in Figure 1 shows that, although the estimated RRA still increases with CAY, the relation is dramatically weaker than the case without the control for the hedge component, as illustrated by the solid line in Figure 1. Interestingly, after we control for CAY as a proxy for the hedge component, the estimated RRA is always positive and falls into a tight range 0.9 to 3.3. The point estimate also falls comfortably within the plausible range 1 to 10, as advocated by Mehra and Prescott (1985). Therefore, allowing for time-varying RRA does not change Guo and Whitelaw's (2006) main finding of a positive risk-return tradeoff in any qualitative manner.

Many finance theories, e.g., Campbell and Cochrane's (1999) habit formation model and Guo's (2004) limited participation model, predict a positive relation between CAY and future excess stock market returns; however, such a relation does not have to be linear. To address this issue, we allow for the possible nonlinear presence of the hedge component, which is modeled as a nonparametric function of a single state variable, $\lambda(X_t)$:

(10) $$r_{M,t+1} = \gamma\sigma^2_{M,t} + \lambda(X_t) + \varepsilon_{t+1}.$$

As a starting point, we assume that RRA is constant in equation (10) but will relax this assumption later. The benchmark model is that the expected excess stock market return is a linear function of conditional variance and the hedge component, as in equation (3). Panel D of Table 5 shows that we fail to reject the null hypothesis of the linear presence of the hedge component for CAY at the 50% significance level. Similarly, the solid line in Figure 4 shows that the effect of CAY on the expected excess stock market return is essentially linear.

We then compare the linear specification of equation (3) with the general smooth coefficient specification in equation (6). Panel G of Table 5 shows that, again, we cannot reject the linear specification at any significance level for the CAY variable. Also, the estimated coefficients $\gamma(X_t)$ and $\lambda(X_t)$ are essentially the same as those plotted in Figure 1 (dashed line) and Figure 4 (solid line), respectively. Lastly, for completeness, we also compare the specifications in equations (10) and (9) with the general smooth coefficient specification in equation (6) and find no evidence of nonlinearity in either the risk (panel E) or the hedge (panel F) component. To summarize, the linear specification of equation (3), as adopted in Guo and Whitelaw (2006), has explanatory power for the expected stock market return almost identical to that of the more elaborate nonparametric smooth coefficient model. This finding suggests that one can use the simple linear specification without much loss of generality.

We find similar results by using the other financial variables as proxies for the time-varying RRA. Panel A of Table 5 shows that DEF, DY, and TERM provide important information about future stock market returns beyond conditional stock market variance. Consistent with the results reported in Table 3, panel B shows that DEF, DY, and TERM have a significant effect on RRA in the one-factor model. Also, the estimated RRA moves countercyclically in all cases. (For brevity, this result is not reported here but available on request) However, by contrast with the results reported in Table 4, panel C shows that their effects in RRA remain statistically significant (DY and TERM) or marginally significant (DEF) after we control for the hedge component, which is a linear function of these state variables. There are two reasons for the difference. First, consistent with the finding in Boudoukh et al. (1997) and Harvey (1988), panels D and F of Table 5 show that there is a significant nonlinear relation between TERM (as a proxy for the hedge component) and the expected stock market return. After we control for the nonlinear effect of the hedge component on the expected return, panel E of Table 5 shows that we fail to reject the null hypothesis of no relation between TERM and RRA at the 17% significance level.

Second, Table 2 shows that DEF and DY alone do not capture all the variation in the hedge component. To address this issue, we augment the proxy for the hedge component with additional state variable(s):

$$r_{M,t+1} = \gamma(X_{1,t})\sigma_{M,t}^2 + \lambda_1 X_{1,t} + \lambda_2 X_{2,t} + \varepsilon_{t+1} \tag{11}$$

or

$$r_{M,t+1} = \gamma(X_{1,t})\sigma_{M,t}^2 + \lambda_1(X_{1,t}) + \lambda_2 X_{2,t} + \varepsilon_{t+1}. \tag{12}$$

We then test the augmented models with time-varying RRA against the augmented benchmark model with constant RRA:

$$r_{M,t+1} = \gamma\sigma_{M,t}^2 + \lambda_1 X_{1,t} + \lambda_2 X_{2,t} + \varepsilon_{t+1}. \tag{13}$$

The models in equations (11) and (12) allow for potential nonlinear dependence of RRA on one state variable (i.e., DEF and DY), which is of central interest. Also, while the first model (equation 11) allows for the linear presence of both itself and one or all of the other state variables as proxy for the hedge component, the second model (equation 12) allows for the nonlinear presence of itself and the linear presence of one or all of the other state variables as proxy for the hedge component. When we use all the state variables as arguably the best empirical proxy for the hedge component, we fail to reject the null hypothesis of no dependence of RRA on DEF or DY at the 10% significance level in both specifications. For brevity, these results are not reported here but are available on request.

Lastly, we investigate the relation between expected excess stock market returns and conditional stock market variance, as implied by Campbell and Cochrane's habit formation (see equation (A9) in Appendix A). The results are essentially the same as those reported above. For example, we find that the Sharpe ratio is positively related to CAY and such a relation is statistically significant at the 1% level. However, it becomes insignificant at the over 40% level after we control for CAY as a proxy for the hedge component. Figure A1 in Appendix A shows that there is a strong positive relation between the Sharpe ratio and CAY (solid line); and it is attenuated dramatically after we control for the hedge component (dashed line). These patterns are essentially the same as those in Figure 1.

4.2 Volatility-Dependent Risk Aversion

The full-fledged semiparametric smooth coefficient two-factor model is quite general because it allows for the effect of both the risk and hedge components on the expected return to vary across business cycles. However, it does not adequately address the possibility of time-varying risk aversion driven by volatility regimes shift, which may or may not be the same as the state-variable-dependent risk aversion. To address this issue, we consider a rather general additive two-factor model,

(14) $$r_{M,t+1} = g(\sigma^2_{M,t}) + \lambda(X_t) + \varepsilon_{t+1},$$

where we still allow the state variable as proxy for the hedge component to have potentially nonlinear effects on the expected stock return, as in the smooth coefficient model.

The difference between the additive model (equation 14) and the smooth coefficient model (equation 6) lies in the specification of volatility. In the additive model, time-varying RRA is modeled as an unspecified functional form in volatility. Such an issue of potential volatility-dependent risk aversion is also considered by Mayfield (2004), Bliss and

Panigirtzoglou (2004), and Lundblad (2006); and their specifications can be nested in the two-factor model in equation (14). Nevertheless, unlike the smooth coefficient model, the additive model does not allow for the potential interaction between the state variable and the volatility. Hence, these two classes of nonparametric models are designed to capture different types of nonlinearity, both of which have been investigated in the existing literature.

Again, we start with testing the general additive two-factor model (equation 14) against the CAPM with constant RRA (equation 7). We also use the bootstrap version of the goodness-of-fit test statistic advocated by Cai et al. (2000) to evaluate the relative performance of the two models.[8] Panel A of Table 6 shows that, in the cases of CAY and TERM, there is again evidence against the adequacy of the linear CAPM model, which could be due to either the nonlinearly priced risk component (as driven by the volatility-dependent risk aversion) or the linearly or nonlinearly priced hedge component.

Next, recognizing the possibility of rejection due to inadequacy of capturing volatility-dependent risk aversion in the linear one-factor model (equation 7), we consider a one-factor CAPM model with potentially volatility-dependent risk aversion as the alternative specification:

(15) $$r_{M,t+1} = g(\sigma^2_{M,t}) + \varepsilon_{t+1}.$$

Several recent studies have investigated specifications that are similar to that in equation (15). Bliss and Panigirtzoglou (2004) consider two equal-sized subsamples corresponding to periods of high and low volatility and examine whether the estimated RRA differs across the two subsamples. Mayfield (2004) uses a more sophisticated model to allow for two regimes of stock market volatility but assumes the same RRA in both states of volatility. Lundblad (2006) not only allows for two regimes of stock market volatility but also allows for the different values of RRA in the two regimes. Our model is more general than these specifications by observing that

$g(\sigma_{s,t}^2)$ can approximate for $\gamma(\sigma_{s,t}^2)\sigma_{s,t}^2$, where S denotes different regimes of volatility (e.g., high versus low) as determined by different threshold levels of volatility. Note that $\gamma(\sigma_{s,t}^2)\sigma_{s,t}^2$ allows for both multiple (rather than two) regimes in volatility and different risk aversion coefficients in each regime.[9]

Panel B of Table 6 shows that we can reject the linear one-factor model and accept the alternative specification of the one-factor CAPM with volatility-dependent risk aversion at the 5% level. Solid line in Figure 5 plots the fitted dependent variable from the nonlinear one-factor model against conditional variance, and the slope of the curve represents the risk aversion coefficient. It is clear that the slope of the nonparametrically fitted curve is generally upward, and not downward, indicating a positive risk-return tradeoff. Interestingly, Our result appears to verify the existence of roughly two regimes of volatility, as assumed in Mayfield (2004). When conditional stock market variance is relatively low, the slope is flat, indicating weak risk aversion. However, when stock market variance is higher, the upward slope becomes steeper and thus suggests stronger risk aversion. This finding is consistent with the results reported in row 2 of Table 3, which shows that the risk-return tradeoff increases with conditional or realized stock market variance. But it differs from that in Bliss and Panigirtzoglou (2004), who find an inverse relation between stock market variance and their option-based measures of RRA. One possible reason is that these authors use a relatively short sample spanning the period 1983 to 2001, as opposed to the 1953 to 2004 period used here.

[8] For partially linear and additive model specification tests in Table 6, we also implement another goodness of fit test due to Dette (1999) and Fan and Huang (2001), and find that the results are qualitatively the same.

[9] Mayfield (2004) uses a two-factor model, and our point here would better apply to our additive two-factor model with such nonparametric function in volatility.

To address the concern about the potential omitted-variable problem, we allow for a linear presence of the hedge component (proxied by one state variable) in the model of volatility-dependent risk aversion:

(16) $$r_{M,t+1} = g(\sigma_{M,t}^2) + (\alpha + \lambda X_t) + \varepsilon_{t+1} .$$

The benchmark is the linear two-factor model, as in equation (3). Panel C of Table 2 shows that we fail to reject the null hypothesis of no volatility-dependent risk aversion at any conventional significance levels across all the five state variables considered after allowing for the linear presence of the hedge component. In particular, the dashed line in Figure 5 shows that the positive relation between $g(\sigma_{M,t}^2)$ and $\sigma_{M,t}^2$ becomes very close to being a linear one after we control for CAY as a proxy for the hedge component.

Lastly, we estimate the additive model, which allows for nonlinear presence of both risk and hedge components, as specified in equation (14). The benchmark model is again the linear two-factor model, as in equation (3). The result (Panel D, Table 6) confirms no rejection of the linear two-factor model except for TERM. Note that the rejection of the linear model for TERM reflects its nonlinear effects on the expected stock return as a proxy for the hedge component. Overall, consistent with the smooth coefficient model, the result suggests that the Guo and Whitelaw's (2006) specification of the expected excess stock market return as a linear function of conditional variance and CAY provides a reasonably good description of the data.

The disappearance of volatility-dependent risk aversion in the two-factor model could again be a manifestation of the omitted variable bias in the one-factor model and can be well explained by the model of Mayfield (2004). Specifically, Mayfield (2004) theoretically demonstrates that changes in investment opportunities can be roughly proxied by unpredictable, state-dependent changes in the level of stock market volatility. Nevertheless, as his model is only a special case of Merton's ICAPM, the explanatory power of the state-dependent volatility regimes may well be subsumed by the state variables, which could be better proxies for investment opportunities.

4.3 Monthly Data

We have repeated the above analysis using monthly implied variance data. In general, the results are qualitatively the same as those found in quarterly data. For example, in the additive model, we find a significant nonlinear risk-return tradeoff in the stock market, which tends to comove positively with stock market variance. Also, the countercyclical variation in RRA disappears after we control for CAY as a proxy for the hedge component. In the smooth coefficient model, we find that CAY provides important information about future stock market returns beyond conditional stock market variance. However, because of the relatively short span, countercyclical variation in RRA is never significant in the smooth coefficient model, even without the control for the hedge component. For brevity, we do not report these results here but they are available on request.

5. Cross-Sectional Evidence

We have shown that the risk-return tradeoff in the stock market moves countercyclically in the conditional CAPM specification, and such a relation becomes statistically insignificant after we control for CAY as a proxy for the hedge component. This result appears to be robust because we reach the same conclusion by using three different specifications.

We argue that these results are consistent with the hypothesis of time-varying investment opportunities, as in Merton's ICAPM. However, it is important to note that we cannot completely rule out the hypothesis of time-varying RRA, as in habit formation models. In particular, because of the close relation between CAY and its interaction with MV (CAY*MV), the time-series data do not allow us to draw a clear-cut distinction between the two hypotheses. To illustrate this point, we run a regression of stock market returns on a constant, MV, CAY (as a proxy for the hedge component), and the interaction term between MV and CAY (as a proxy for time-varying RRA). We find that, because of the multicollinearity problem, the interaction term is statistically insignificant and CAY is significant only at the 10% level. Thus, there is only marginal support for time-varying investment opportunities. To further differentiate the two hypotheses, in this section, we follow Lettau and Wachter's (2006) suggestion and investigate their implications for the cross-section of stock returns.

We investigate whether a variant of the conditional CAPM helps explain the cross-section of stock returns on the 25 Fama and French (1993) portfolios sorted on size and the book-to-market ratio over the 1952:Q1 to 2004:Q4 period. For each of the 25 portfolios, we first run the time-series regression:

(17) $$r_{P,t+1} = \alpha_p + \gamma_{p0} MV_t + \gamma_p MV_t * CAY_t + \varepsilon_{t+1},$$

where $r_{P,t+1}$ is the excess return on the portfolio *p*. If loadings on the market risk are constant across time, as assumed in Lettau and Ludvigson (2001b), the coefficients γ_{p0} and γ_p are proportional to loadings on the market risk. Under the null hypothesis of habit formation models, the interaction term CAY*MV in equation (17) should carry a positive risk premium.

We can also motivate equation (17) using the equilibrium model by Zhang (2005). Zhang shows that, in the presence of adjustment costs for investment, stocks with high B/M (value stocks) have higher expected returns than stocks with low B/M (growth stocks) because the former tend to be more risky when the risk-return tradeoff or RRA is high. Therefore, under the null hypothesis of habit formation models, we expect that value stocks have higher loadings on the interaction term MV*CAY in equation (17) than do value stocks.

Figures 6 and 7 plot loadings of the 25 Fama and French portfolios on conditional stock market variance MV and the interaction term MV*CAY, respectively.[10] Each portfolio is identified with a two-digit number. The first digit refers to size, with 1 denoting the smallest stocks and 5 the largest stocks. The second digit refers to B/M, with 1 denoting the lowest B/M ration and 5 the highest B/M ratio. Figure 6 shows that, consistent with early studies, e.g., Lettau and Wachter (2006), growth stocks tend to have higher loadings on the market risk than do value stocks within each size quintile. However, by contrast with habit formation models, Figure 7 shows that growth stocks have substantially *higher* loadings on the interaction term than do value stocks within each size quintile.

We then investigate whether loadings on MV and MV*CAY help explain the cross-section of stock returns by using the Fama and MacBeth (1973) cross-sectional regression approach. Row 1 of Table 7 shows that the conditional CAPM accounts for over 40% of variation in the cross-section of stock returns. This result clearly indicates that the conditional CAPM is a substantial improvement over the unconditional CAPM, which has negligible explanatory power for the 25 Fama and French portfolios (see, e.g., Lettau and Ludvigson (2001b)). More importantly, the interaction term MV*CAY is significantly priced at the 5% level, according to Shanken's (1992) corrected standard errors (as reported in squared brackets). However, there is a problem with the conditional CAPM interpretation.[11] The interaction term carries a negative risk premium, as opposed to the positive premium predicted by habit formation models. The negative premium reflects the fact that growth stocks have higher loadings on the interaction term than do value stocks (Figure 7). Therefore, consistent with the theoretical work by Lettau and Wachter (2006), our empirical results indicate that habit formation models cannot explain the B/M effect. To summarize, the cross-sectional evidence casts doubt on the hypothesis

[10] In the time-series regressions, the two factors are statistically significant at the 5% level for most portfolios. For brevity, we do not report the results here but they are available on request.

[11] Several recent studies, e.g., Petkova and Zhang (2005), Lewellen and Nagel (2005), and Fama and French (2005), have also cast doubt on explanatory power of the conditional CAPM for the cross-section of stock returns.

that CAY forecasts stock returns because it is a proxy for time-varying RRA.

One possible explanation is that the interaction term MV*CAY is significantly priced because of its close relation to CAY, which is a proxy for the hedge against changes in the investment opportunity set. To address this issue, we also include CAY as an additional risk factor in the cross-sectional regression:

(18) $$r_{P,t+1} = \alpha_p + \gamma_{p0} MV_t + \gamma_p MV_t * CAY_t + \lambda_p CAY_t + \varepsilon_{t+1}.$$

As conjectured, row 2 of Table 7 shows that the interaction term MV*CAY becomes insignificant at the 5% level, while loadings on CAY carry a significantly negative premium.[12]

Recent studies, e.g., Campbell and Vuolteenaho (2004) and Guo et al. (2005), show that the value premium is a priced risk factor because it moves closely with changes in the discount rate, which is the measure of investment opportunities in Campbell's (1993) ICAPM. To illustrate this point, we run regressions of the excess portfolio returns on realized stock market variance (MV) and realized value premium variance (V_HML):

(19) $$r_{P,t+1} = \alpha_p + \gamma_{p0} MV_t + \phi_p V\_HML_t + \varepsilon_{t+1}.$$

We calculate the realized value premium variance using daily data obtained from Ken French at Dartmouth College, which span the July 1963 to December 2004 period. Figure 8 shows that loadings on V_HML are negative and decrease with B/M within each size quintile. Guo et al. (2005) show that, because the value premium is a proxy for the discount-rate shock, the negative loadings on V_HML reflect a correction for overpricing of the discount-rate shock in the CAPM, as first pointed out by Campbell and Vuolteenaho (2004). Row 3 of Table 7 shows that,

[12] Campbell (1996) suggests that we should use innovations in the state variables as the risk factors. However, Chen (2003) and Chen and Zhao (2005) find that, because stock return predictors are usually persistent, the estimation results could be sensitive to the identification scheme of these innovations. By contrast, we avoid such a problem in our estimation of the ICAPM (e.g., equation 18).

consistent with Fama and French (1993, 1996), for example, loadings on V_HML are positively and significantly priced at the 5% level.[13]

As mentioned in footnote 2, the scaled stock price such as CAY forecasts stock market returns because of its close relation with the hedge factor, e.g., V_HML, which is omitted from the CAPM. Consistent with this hypothesis, Guo et al. (2005) show that CAY forecasts stock market returns because of its close (negative) relation to V_HML. Their results suggest that loadings on CAY are negatively priced in the cross-section of stock returns because of their inverse relation with loadings on realized value premium variance, V_HML. Row 4 of Table 7 confirms this conjecture by showing that CAY provides no additional information beyond V_HML at the 5% level. Similarly, row 5 of Table 7 shows that the explanatory power of the interaction term MV*CAY becomes insignificant at any conventional level after we also include V_HML in the cross-sectional regression.

To summarize, our cross-sectional evidence clearly indicates that CAY is not a proxy for time-varying RRA, but it might be a proxy for the hedge against changes in the investment opportunity set.[14]

6. Discussion

We find that, in the time-series data, the risk-return tradeoff in the stock market increases monotonically with CAY. The cross-sectional results also clearly suggest that the countercyclical risk-return tradeoff mainly reflects time-varying investment opportunities (as in Merton's or

[13] We obtain a substantially higher R-squared (about 80%) if we use the Fama and French 3-factor model in the cross-sectional regression. The difference reflects the fact that loadings are much less precisely estimated in the first-pass regression for our forecasting model than the Fama and French (1993) factor model. To improve the efficiency, we can impose the restriction that the constant term is equal to zero in the first-pass regression; and we find that the coefficient of value premium volatility is statistically significant at the 5% level and the R-squared is about 80%. Also see Guo and Savickas (2005) for discussion on this issue.

[14] We find that the interaction terms of MV with the other financial variables are not priced in the cross-section of stock returns. For brevity, we do not report these results here but they are available on request.

Campbell's ICAPM) but not time-varying RRA (as in habit formation models). However, Merton (1973) and Campbell (1993) do not explicitly explain why investment opportunities change across time. In this section, we provide a tentative explanation by showing that our main findings are consistent with Guo's (2004) limited stock market participation model.[15]

In Guo's (2004) model, there are two (types of) agents: shareholders and nonshareholders. While both shareholders and nonshareholders can trade with each other in a one-period bond market, only shareholders own stocks. In the presence of idiosyncratic income (or liquidity) shock and borrowing constraints, (exogenously assumed) limited participation generates an illiquidity premium, ILL_t, for holding stocks, in addition to the risk premium as in the CAPM (see equation (2)). Guo (2004) shows that under some reasonable parameter configuration, the limited participation model provides a good explanation for the equity premium puzzle, the excess volatility puzzle, and stock return predictability. The model also has a new prediction that stock market volatility is a U-shaped function of the dividend yield, by contrast with the positive relation between the two variables, as implied by the conventional wisdom of the leverage effect (see, e.g., Campbell and Cochrane (1999) and Chan and Kogan (2002)). Below, we show that Guo's model also helps explain the positive relation between the risk-return tradeoff and CAY, as documented in this paper.

Two implications of Guo's (2004) model help explain our main findings. First, the state variable CAY is positively correlated with conditional stock market returns because of its close relation with the illiquidity premium. This result is quite intuitive. A positive income or liquidity shock lowers the illiquidity premium because it makes shareholders less vulnerable to binding borrowing constraints. The reduced illiquidity premium raises the stock prices and thus lowers

[15] Our results might be potentially consistent with some other equilibrium asset pricing models, e.g., Whitelaw (2000), Bansal and Yaron (2004), and Santos and Veronesi (2006). For brevity, we omit the discussion of these models.

the CAY variable. Similarly, the negative shock raises the illiquidity premium and CAY. Second, stock market volatility is a U-shaped function of CAY because shocks, either positive or negative, always raise volatility. That is, volatility and CAY are positively correlated when CAY is high and negatively correlated when CAY is low. Note that the second implication helps explain the unstable relation between CAY and MV, as documented in Table 1. By contrast, Campbell and Cochrane's (1999) habit formation model cannot explain the unstable relation because it predicts a positive relation between MV and CAY.

These two implications explain why the risk-return tradeoff is positively related to CAY even though RRA is constant in Guo's (2004) model. When CAY is relatively low, the illiquidity premium (ILL_t) and the risk premium ($\sigma^2_{M,t}$) in equation (2) are negatively correlated. Therefore, omitting CAY as a proxy for the hedge component generates a downward bias in the estimated risk-return tradeoff. When CAY is relatively high, the illiquidity premium and the risk premium in equation (2) are positively correlated; therefore, omitting CAY as a proxy for the hedge component generates an upward bias in the estimated risk-return tradeoff. Overall, Guo's (2004) model predicts a positive relation between the risk-return tradeoff and CAY.

To illustrate this point, we estimate the semiparametric smooth coefficient models of equations (8) and (9) using simulated data generated from Guo's (2004) benchmark model. For comparison with the actual data, we also use CAY as the conditioning variable in the estimation. We use 20,000 simulated observations; however, we find a very similar pattern by using a sample with the number of simulated observations similar to that of the post-World War II quarterly data. Figure 2 shows that, consistent with the finding obtained from the actual data (as shown in Figure 1), the risk-return tradeoff increases monotonically with CAY (solid line) in the conditional CAPM specification. But the relation essentially disappears after we control for CAY as a proxy for the illiquidity premium (dashed line). More importantly, as conjectured (and also confirmed by actual data in Figure 1), the dashed line is above the solid line when CAY is low and the dashed line is below the solid line when CAY is high.

For robustness, we also estimate the additive models of equations (15) and (16). By omitting the hedge component, the solid line in Figure 9 clearly shows that stock market variance has a nonlinear effect on the expected stock market returns in the conditional CAPM specification. In particular, consistent with the data (Figure 5), the effect appears to depend positively on variance. Again, after we control for CAY as a proxy for the hedge component, the dashed line in Figure 9 shows that the nonlinear effect of variance on the expected stock market essentially disappears. Although Figure 9 suggests that Guo's (2004) model appears to explain the data well, it is important to note that modeling the stock return process as solely depending on the volatility regimes could generate misleading results because of the unstable relation between conditional variance and CAY. Instead, Guo's (2004) model suggests that it is advisable to use CAY as the state variable.

Lastly, Table 8 presents further empirical evidence on the effect of the unstable relation between CAY and MV on the risk-return tradeoff. In particular, it shows that, consistent with Guo's (2004) model (as illustrated in Figure 2), the bias of the estimated risk-return tradeoff in the conditional CAPM specification could be either positive or negative, depending on the level of CAY. For example, Table 1 shows that MV and CAY are positively correlated in the first subsample spanning the period 1952:Q1 to 1979:Q4. Consistent with the prediction of Guo's (2004) model, we find that controlling for CAY as a proxy for investment opportunities lowers the point estimate of MV. By contrast, in the second subsample spanning the period 1980:Q1 to 2004:Q4, controlling for CAY increases the point estimate of MV because CAY and MV are negatively correlated.

7. Conclusion

In this paper, we find that the risk-return tradeoff in the stock market increases monotonically with CAY across time. This result cannot be explained by the countercyclical variation in RRA, as well-accepted habit formation models imply. Instead, we argue that it mainly reflects the countercyclical variation in investment opportunities. In particular, we show that it is consistent with Guo’s (2004) limited stock market participation model, in which the risk-return tradeoff comoves with shareholders’ liquidity conditions even though RRA is constant.

Our results have important implications for future empirical studies. First, the specification of the excess expected stock market return as a linear function of conditional variance and the consumption-wealth ratio appears to provide a reasonably good description of the data. Second, because of the unstable relation between conditional variance and the consumption-wealth ratio across time, caution must be taken when modeling conditional stock market variance as a linear function of some state variables.

Our results also have important implications for future theoretical explorations. We show that, in Guo’s (2004) model, the time-varying risk-return tradeoff (as observed in the data) is mainly driven by the illiquidity premium. This result is in contrast with many early studies, e.g., Constantinides (1986), Heaton and Lucas (1996), and Huang (2003), who suggest that the effect of illiquidity premium is negligible. However, it appears to be consistent with a large number of empirical findings, which document important effects of the illiquidity premium on asset prices in many financial markets (e.g., see Amihud et al. (2005) for a recent survey). Moreover, Guo and Savickas (2006) find that many standard liquidity measures have predictive power for excess stock market returns very similar to that of CAY. These results highlight the important link between the general equilibrium theory and the microstructure, as stressed by O’Hara (2003).

Lastly, the prediction of Guo’s (2004) model differs from that in the early studies because of the (exogenously assumed) limited participation in the stock market. While it is unclear why many households stay away from the equity market even though the equity premium is large in the historical data, a few empirical studies, e.g., Mankiw and Zeldes (1991), Vissing-Jorgensen (2002), Ait-Sahalia et al. (2004), Malloy et al. (2005), and Lettau and Ludvigson (2006), have illustrated its promising role in explaining the dynamic of stock prices. In future research, it will be interesting to develop equilibrium models with endogenous limited participation.

Appendix A

The Relation between Risk-Return Tradeoff and Relative Risk Aversion in Campbell and Cochrane's (1999) Habit Formation Model

In Campbell and Cochrane's (1999) habit formation model, the utility function is

(A1) $$U(C_t - X_t) = \begin{cases} \ln(C_t - X_t) & if \quad \alpha = 1 \\ \dfrac{(C_t - X_t)^{1-\alpha} - 1}{1-\alpha} & if \quad \alpha > 0 \; but \; \alpha \neq 1 \end{cases}.$$

In equation (A1), C_t is the consumption, X_t is the habit level of consumption, and α measures the curvature of the representative agent's utility function with respect to it argument $C_t - X_t$.

Brandt and Wang (2003) show that RRA, which measures the curvature of the utility function with respect to consumption, is time-varying:

(A2) $$RRA_t = \alpha \frac{1}{S_t},$$

where $S_t = \frac{C_t - X_t}{C_t}$ is the consumption surplus ratio. Campbell and Cochrane (1999) assume that the log consumption surplus ratio $s_t = \ln(S_t)$ follows an exogenous process. Note that the risk aversion measure in equation (A2) is very closely related to the risk aversion measure in Campbell and Cochrane (1998), which is defined as the curvature of the value function with respective to the wealth. For example, both measures decrease monotonically with S_t. For the ease of illustration, we use the definition in equation (A2) here.

Brandt and Wang (2003, p. 1466) show that the conditional equity premium is

(A3) $$E_t r_{M,t+1} = \alpha(\lambda(s_t) + 1) Cov_t(\varepsilon^g_{t+1}, r_{M,t+1}),$$

where $\lambda(s_t)$ is the sensitivity function defined in Campbell and Cochrane (1999) and ε^g_{t+1} is the consumption growth. In Campbell and Cochrane's (1999) model, the volatility of the consumption growth, σ_g, is constant, and ε_{t+1}^{g} and $r_{M,t+1}$ are perfectly correlated. Also, their Figure 5 shows that conditional stock market volatility decreases monotonically with the consumption surplus ratio. For illustration, we assume that

(A4) $\sigma_{M,t} = V(s_t)\sigma_g$,

where $V(s_t)$ is a nonlinear function of s_t. We then can write equation (A3) as

(A5) $E_t r_{M,t+1} = [\alpha(\lambda(s_t)+1)/V(s_t)]\sigma_{M,t}^2$.

Equation (A2) implies

(A6) $s_t = \ln(\alpha) - \ln(RRA_t)$.

Therefore, in Campbell and Cochrane's (1999) habit formation model, the risk-return tradeoff is a complex nonlinear function of relative risk aversion:

(A7) $E_t r_{M,t+1} = [\alpha(\lambda(\ln(\alpha)-\ln(RRA_t))+1)/V(\ln(\alpha)-\ln(RRA_t))]\sigma_{M,t}^2$.

Figure 1 in Campbell and Cochrane (1999) shows that $\lambda(s_t)$ decreases monotonically with s_t and the relation is essentially linear. Therefore, we can rewrite equation (A7) approximately as

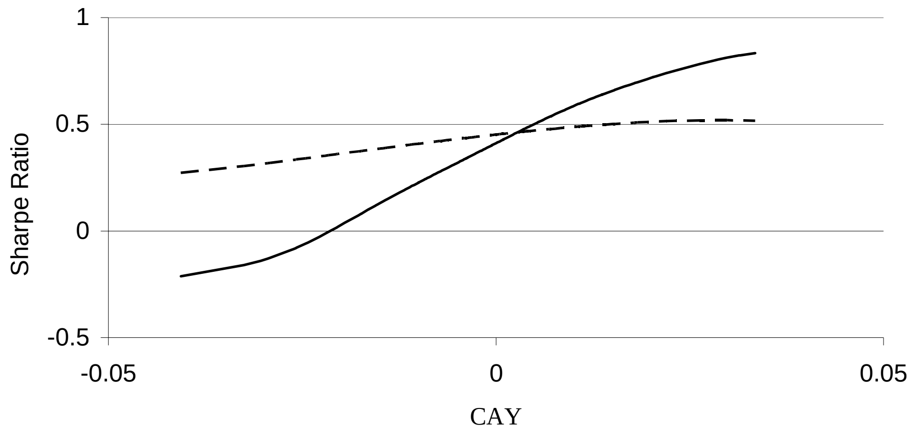
(A8) $E_t r_{M,t+1} \approx [\alpha(\ln(RRA_t)-\ln(\alpha)+1)/V(\ln(\alpha)-\ln(RRA_t))]\sigma_{M,t}^2$.

Therefore, the risk-return tradeoff increases with RRA if $V(\ln(\alpha)-\ln(RRA_t))$ is not very sensitive to changes on RRA. Moreover, Equation (A4) and (A8) imply positive relation between the Sharpe ratio and RRA:

(A9) $E_t r_{M,t+1} \approx \alpha(\ln(RRA_t)-\ln(\alpha)+1)\sigma_g\sigma_{M,t}$.

Figure A1 plots the smooth-coefficient estimates of the Sharpe ratio as a nonlinear function of CAY, with and without control for CAY as the proxy for the hedge component.

Figure A1 Smooth-Coefficient Estimates of the Sharpe Ratio as a Nonlinear Function of CAY



Note: The solid line plots the estimate of the coefficient $\gamma(X_t)$ in the one-factor CAPM, $r_{M,t+1} = \alpha + \gamma(X_t)\sigma_{M,t} + \varepsilon_{t+1}$; and the dashed line is for the two-factor ICAPM, $r_{M,t+1} = \alpha + \gamma(X_t)\sigma_{M,t} + \lambda X_t + \varepsilon_{t+1}$. The data span the period 1951:Q4 to 2004:Q4.

Appendix B

Nonparametric and Semiparametric Model Estimation and Specification Tests

This appendix provides a brief summary of estimation procedures and model specification tests of various nonparametric and semiparametric models considered in the paper. We start with a general linear model for data (X_t, Y_t):

(B1) $Y_t = \beta_0 + X_t^{'}\beta + \varepsilon_t,\ t = 1, 2, ..., T$

where X_t is a ($d \times 1$) vector of regressors and β is the corresponding vector of parameters. The data can be independent or weakly dependent (i.e., stationary) with $E(\varepsilon_t \mid X_t) = 0$. In all the following models, we also allow for a conditionally heteroscedastic error process of unknown form: $E(\varepsilon_t \mid X_t) = \sigma^2(X_t)$.

1. The estimation of nonparametric and semiparametric models

In general, a nonparametric regression model corresponding to equation (B1) can be generally expressed as:

(B2) $Y_t = g(X_t) + \varepsilon_t$,

where $g(\cdot)$ is an unknown smooth function. Although as general as it may be, equation (B2) cannot be estimated without running into a serious 'curse of dimensionality' problem, when d is relatively large while the data are limited. To address the problem, we consider several popular semiparametric models.

The first model under consideration is a partially linear model, which is originally considered by Robinson (1988). Let $X_t = (W_t^{'}, Z_t^{'})^{'}$ and W_t and Z_t are respectively ($p \times 1$) and ($q \times 1$) vectors ($p + q = d$). The partially linear model is given as follows:

(B3) $Y_t = Z_t^{'}\delta + f(W_t) + \varepsilon_t,\ t = 1, 2, ..., T.$

Note that the partially linear model of equation (B3) consists of a linear component $Z_t^{'}\delta$ and nonparametric components $f(W_t)$, where the functional form of $f(\cdot)$ is left unspecified.

The second type of semiparametric models is an additive model, which is similar to the one discussed in Linton and Nielsen (1995). The model can be generally expressed as follows:

(B4) $$Y_t = \beta_0 + g_1(X_{1t}) + g_2(X_{2t}) + ... + g_d(X_{dt}) + \varepsilon_t.$$

Compared to the partially linear models above, the additive model (B4) jointly allows for the potential nonlinearity in each independent variable X_{it}. On the other hand, it still has the advantage of mitigating much curse of dimensionality, as the partial linear model. Such advantage is obtained through the imposition of an additive structure on the unspecified function $g(\cdot)$, compared to a fully nonparametric model (B2).

The third semiparametric model we consider is the following smooth (varying) coefficient model:

(B5) $$Y_t = Z_t^{'}\theta(W_t) + \psi(W_t) + \varepsilon_t$$

where both model coefficients $\theta(W_t)$ and $\psi(W_t)$ are unspecified smooth functions of vector W_t. The model, as considered in Cai et al. (2000) and Li et al. (2002), is a relatively new nonlinear time series model with state-dependent coefficients. The smooth coefficient model generally allows more flexibility than a partially linear model, and at the same time it still avoids much of the 'curse of dimensionality' problem as the nonparametric function is restricted only to a subset of the vector X_t (i.e., W_t). Note that by allowing for $\psi(W_t) = \psi_0 + W_t^{'}\psi_1$, we also have the following partially linear smooth coefficient model:

(B6) $$Y_t = Z_t^{'}\theta(W_t) + \psi_0 + W_t^{'}\psi_1 + \varepsilon_t$$

We estimate model (B3) using the standard Robinson's (1988) procedure, and model (B4) using the marginal integration method as proposed by Linton and Nielson (1995), among others. Since there has been much discussion about models (B2)-(B4) in the literature, their estimation details are omitted here. We only discuss in a bit more detail on the estimation of model (B5) due to its relative newness. Denote $\beta(W_t) = (\theta(W_t)^{'}, \psi(W_t)^{'})'$ and $V_t = (Z_t^{'}, 1)'$, the smooth coefficient model (B5) can be estimated as follows (Li et al., 2002; Cai et. al., 2000):

$$\text{(B7)} \qquad \hat{\beta}(w) = \left[\sum_{t=1}^{T} V_t V_t^{'} K_h \left(\frac{W_t - w}{h} \right) \right]^{-1} \sum_{t=1}^{T} V_t Y_t K_h \left(\frac{W_t - w}{h} \right),$$

where $K_h(.)$ is a kernel estimator, and h is the vector of bandwidths associated with W_t. Under some regularity conditions, it can be shown that $\hat{\beta}(w)$ follows a normal distribution at the rate of $\sqrt{nh_1 h_2 \cdots h_q}$. The partially linear smooth coefficient model (B6) can be estimated by combining the estimation procedures for models (B3) and (B5).

Throughout the paper we use the local constant estimator due to its popularity and well-developed theoretical properties, while the basic results are doubled checked with the local linear estimator. We use the standard Normal kernel, and it is well known in the literature that the choice of the kernel function would have little effect on nonparametric estimation. The selection of the smoothing parameter (bandwidth) h is based on the data-driven leave-one-out least squares cross-validation method.

2. The model specification test

To test a nonparametric or semiparametric model against another semiparametric or a linear specification, we consider a bootstrap version of goodness of fit test due to Cai et al. (2000). This is based on the difference of the sums of squared residuals between the two competing models:

(B8) $$LR = \left(\sum_{t=1}^{T} \hat{e}_t^2 - \sum_{t=1}^{T} \tilde{e}_t^2 \right) / \sum_{t=1}^{T} \tilde{e}_t^2 ,$$

where $\hat{e}_t$ is the estimated residual from the null model, and $\tilde{e}_t$ is the residual from the alternative model. The empirical distribution of the *LR* test is obtained via the bootstrap approach with the number of simulations equal to 500. In particular, we bootstrap the centralized residuals from the alternative mode instead of the null model, because for all semi- and nonparametric models considered here residuals from the alternative model are consistent under both null and alternative hypotheses (Cai et al. (2000)).

To control for possible serial correlation in the innovations (ε_t), we adopt a block bootstrap method in generating the pseudo samples. We use overlapping rather than nonoverlapping blocks here. The steps involved in generating random samples are as follows:

(i) Denote the block length as *l*. For *k* = 1, 2, …, (*T/l*), randomly draw with replacement *k*th block of consecutive residuals e_k^* of length *l* from $\hat{e}_t$: $e_k^* = \{\tilde{e}_{k-1+1}, \tilde{e}_{k-1+2}, ..., \tilde{e}_{k-1+l}\}$. A vector of random residuals of length *T* is formed as $e^* = \{e_1^*{}', e_2^*{}', ..., e_{(T/l)}^*{}'\}'$.

(ii) Obtain $Y_t^* = m(X_t, \hat{\delta}) + e_t^*$, where $m(X_t, \hat{\delta})$ is, in our application, the conditional mean under the null hypothesis. The resulting sample $(X_t, Y_t^*)_{t=1}^T$ is called the bootstrap sample. Then estimate the bootstrap sample under both null and alternative hypotheses to obtain bootstrap residuals $\hat{e}_t^*$ and $\tilde{e}_t^*$.

(iii) Use the bootstrap residuals to compute the test statistic $LR^* = \left(\sum_{t=1}^{T} \hat{e}_t^{*2} - \sum_{t=1}^{T} \tilde{e}_t^{*2} \right) / \sum_{t=1}^{T} \tilde{e}_t^{*2}$.

(iv) Repeat steps (i) through (iii) a large number of times, say *nb*, and then construct the empirical distribution of the bootstrap statistics, $\{LR_j^*\}_{j=1}^{nb}$. This bootstrap empirical distribution is used to approximate the null distribution of the test statistic *LR* in equation (B8). One then rejects the null model for a relatively large value of *LR*.

For simplicity, we set the nonrandom block length to 4 (quarters). Nevertheless, we also examined various block lengths ranging from 1 to 12 (quarters, with the maximum length equivalent to three years). We find that the results are not sensitive to the choice of the block length. Also note that when the block length is 1, the block bootstrap reduces to the basic bootstrap assuming no dependence in the innovations. In this case, to improve the finite sample performance of the test, we also compute the wild bootstrap statistics as advocated by Li and Wang (1998). The reported results in the paper still remain qualitatively unchanged.

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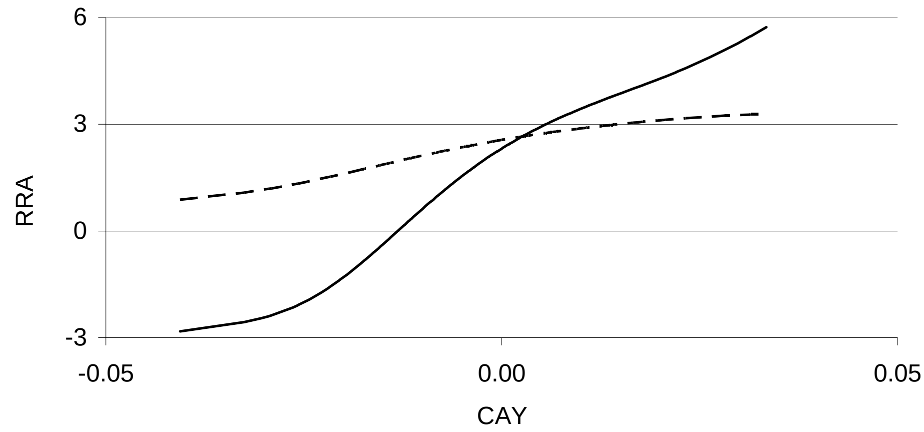
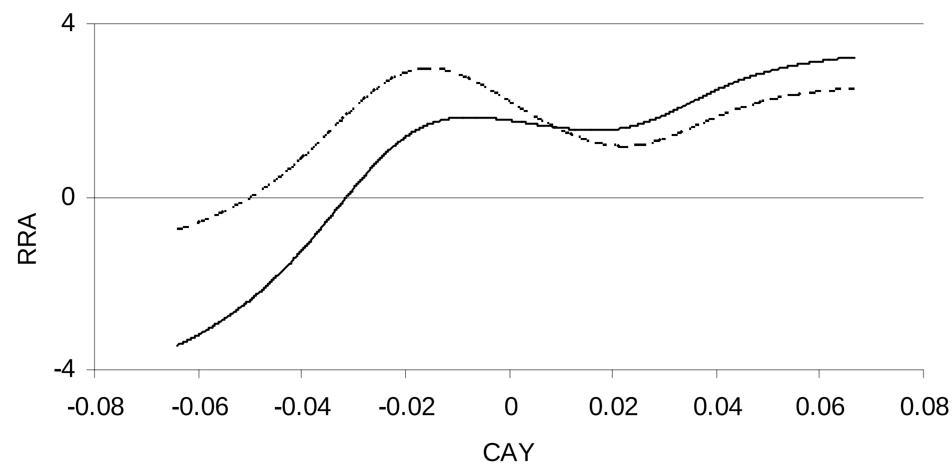
Figure 1 Smooth-Coefficient Estimates of RRA as a Nonlinear Function of CAY



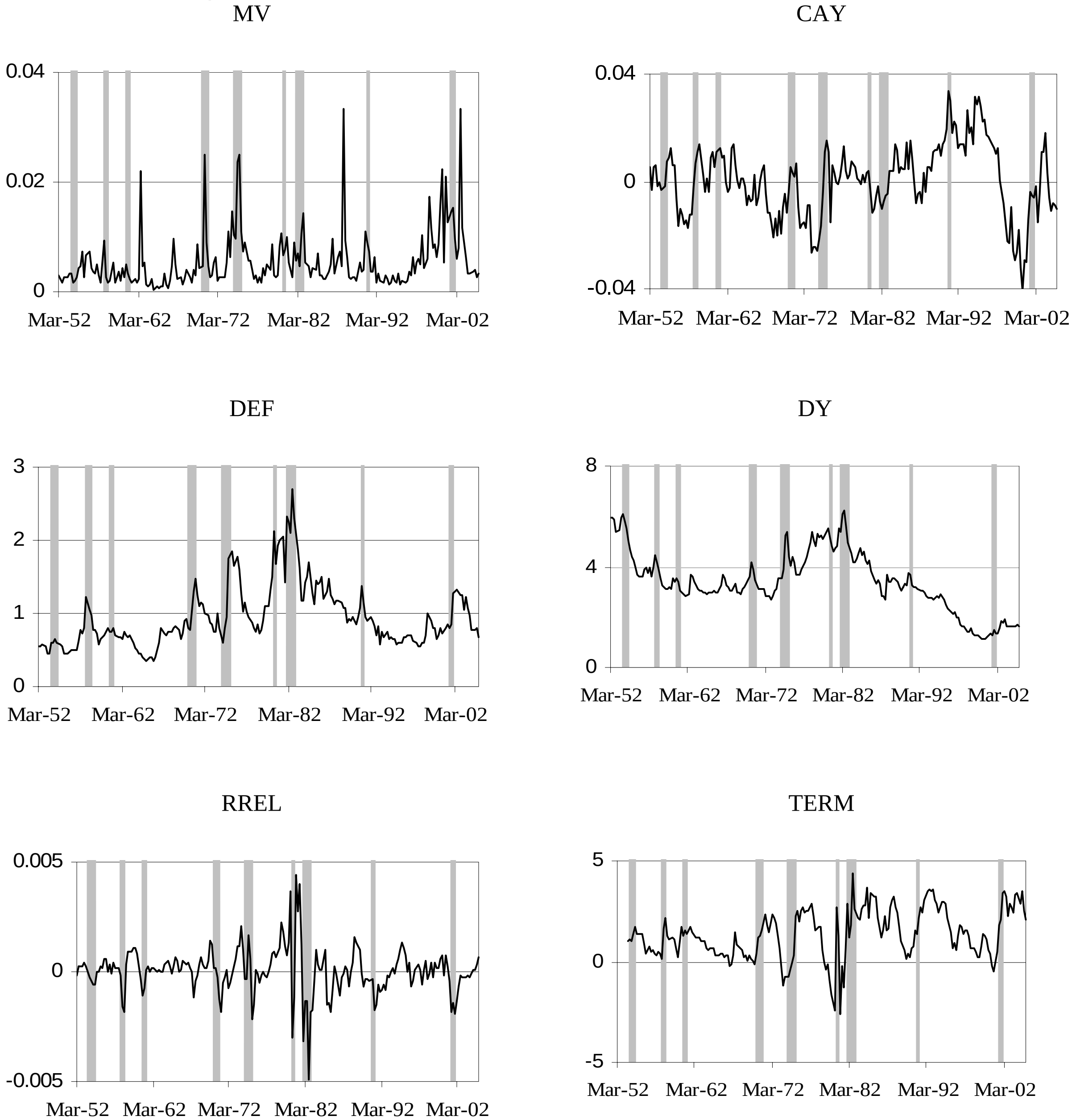
Note: The solid line plots the estimate of the coefficient $\gamma(X_t)$ in the one-factor CAPM, $r_{M,t+1} = \alpha + \gamma(X_t)\sigma_{M,t}^2 + \varepsilon_{t+1}$; and the dashed line is for the two-factor ICAPM, $r_{M,t+1} = \alpha + \gamma(X_t)\sigma_{M,t}^2 + \lambda X_t + \varepsilon_{t+1}$. The data span the period 1951:Q4 to 2004:Q4.

Figure 2 Smooth-Coefficient Estimates of RRA as a Nonlinear Function of CAY
Using Guo's (2004) Simulated Data



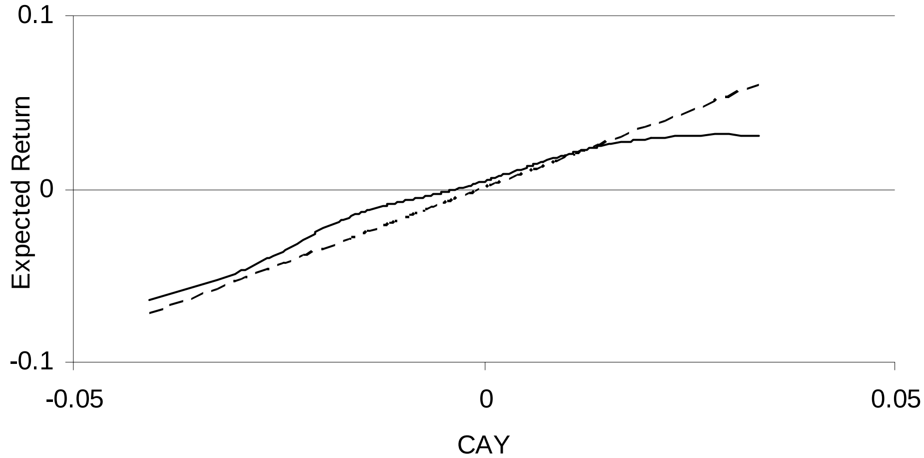
Note: The solid line plots the estimate of the coefficient $\gamma(X_t)$ in the one-factor CAPM, $r_{M,t+1} = \alpha + \gamma(X_t)\sigma_{M,t}^2 + \varepsilon_{t+1}$; and the dashed line is for the two-factor ICAPM, $r_{M,t+1} = \alpha + \gamma(X_t)\sigma_{M,t}^2 + \lambda X_t + \varepsilon_{t+1}$. We use 20,000 simulated observations generated from Guo's (2004) benchmark model.

Figure 3 Realized Stock Market Variance and State Variables



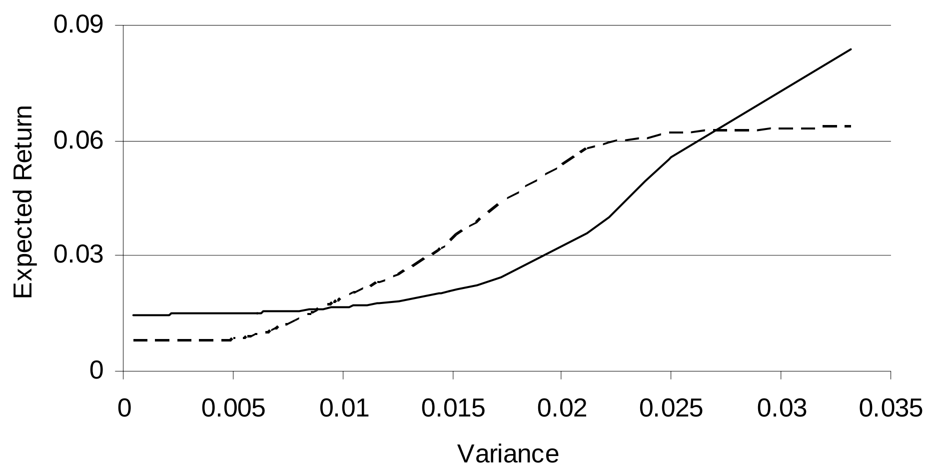
Note: MV is realized stock market variance; CAY is the consumption-wealth ratio; DEF is the yield spread between Baa- and Aaa-rated corporate bonds; DY is the ratio of the dividend in the past year to the end-of-period stock price for S&P 500 stocks; RREL is the difference between the short-term interest rate and its average in the previous 12 months; and TERM is the yield spread between 10-year Treasury bonds and 3-month Treasury bills. TERM is available over the period 1953:Q2 to 2004:Q4 and the other variables are available over the period 1951:Q4 to 2004:Q4. Shared areas indicate business recessions, as dated by NBER.

Figure 4 Smooth-Coefficient Estimate of the Hedge Component as a Nonlinear Function of CAY



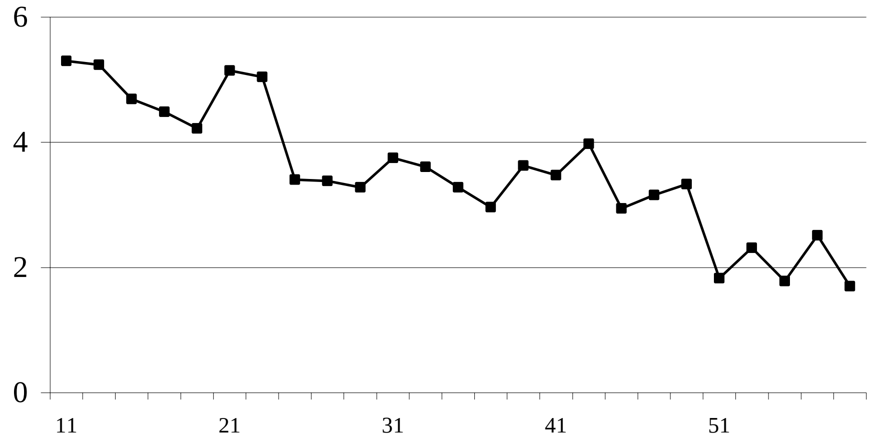
Note: The solid line plots the coefficient $\lambda(X_t)$ in the semiparametric model, $r_{M,t+1} = \gamma\sigma^2_{M,t} + \lambda(X_t) + \varepsilon_{t+1}$; and the dashed line plot the coefficient λ in the linear model $r_{M,t+1} = \alpha + \gamma\sigma^2_{M,t} + \lambda X_t + \varepsilon_{t+1}$. The data span the period 1951:Q4 to 2004:Q4.

Figure 5 Volatility-Dependent Risk Aversion Estimates



Note: The solid line plots the term $g(\sigma^2_t)$ in the one-factor CAPM, $r_{M,t+1} = g(\sigma^2_{M,t}) + \varepsilon_{t+1}$; and the dashed line is for the two-factor ICAPM, $r_{M,t+1} = g(\sigma^2_{M,t}) + (\alpha + \lambda X_t) + \varepsilon_{t+1}$. We use CAY as proxy for the hedge component in the ICAPM. The data span the period 1951:Q4 to 2004:Q4.

Figure 6 Loadings on Realized Stock Market Variance

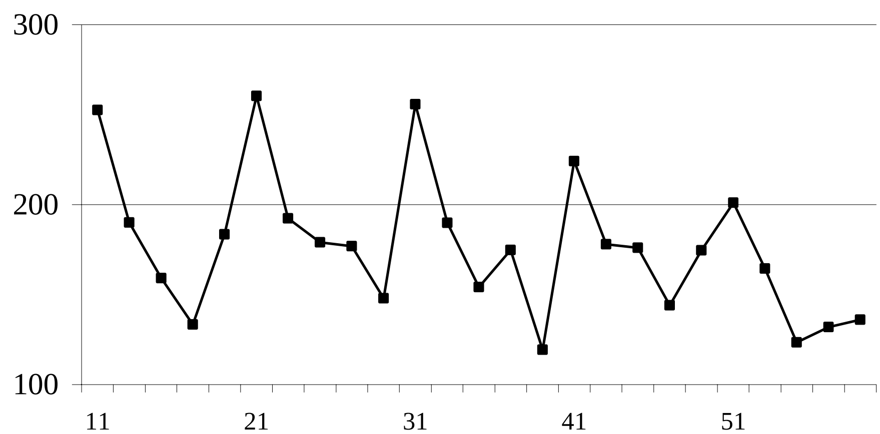


Note: The line plots the coefficient estimate γ_{p0} obtained from the forecasting regression:

$$r_{P,t+1} = \alpha_p + \gamma_{p0} MV_t + \gamma_p MV_t * CAY_t + \varepsilon_{t+1}.$$

Each portfolio is identified with a two-digit number on the horizontal axis. The first digit refers to size, with 1 denoting the smallest stocks and 5 the largest stocks. The second digit refers to B/M, with 1 denoting the lowest B/M and 5 the highest B/M.

Figure 7 Loadings on Realized Stock Market Variance Scaled by CAY

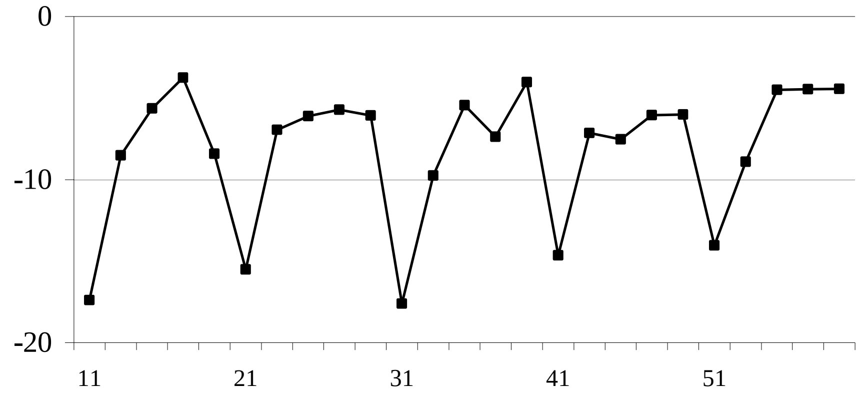


Note: The line plots the coefficient estimate γ_p obtained from the forecasting regression:

$$r_{P,t+1} = \alpha_p + \gamma_{p0} MV_t + \gamma_p MV_t * CAY_t + \varepsilon_{t+1}.$$

Each portfolio is identified with a two-digit number on the horizontal axis. The first digit refers to size, with 1 denoting the smallest stocks and 5 the largest stocks. The second digit refers to B/M, with 1 denoting the lowest B/M and 5 the highest B/M.

Figure 8 Loadings on Realized Value Premium Variance

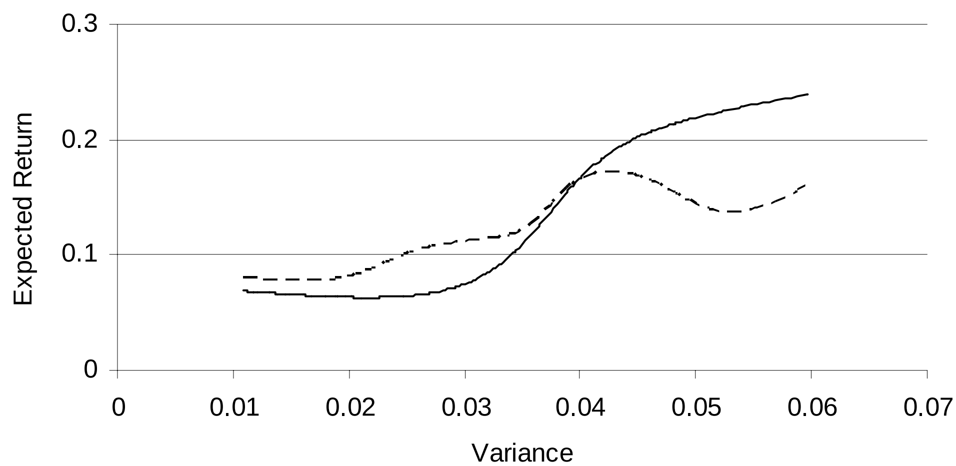


Note: The line plots the coefficient estimate ϕ_p obtained from the forecasting regression:

$r_{P,t+1} = \alpha_p + \gamma_{p0} MV_t + \phi_p V\_HML_t + \varepsilon_{t+1}$.

Each portfolio is identified with a two-digit number on the horizontal axis. The first digit refers to size, with 1 denoting the smallest stocks and 5 the largest stocks. The second digit refers to B/M, with 1 denoting the lowest B/M and 5 the highest B/M.

Figure 9 Volatility-Dependent Risk Aversion Estimates: Guo's (2004) Simulated Data



Note: The solid line plots the term $g(\sigma^2_{M,t})$ in the one-factor CAPM, $r_{M,t+1} = g(\sigma^2_{M,t}) + \varepsilon_{t+1}$; and the dashed line is for the two-factor ICAPM, $r_{M,t+1} = g(\sigma^2_{M,t}) + (\alpha + \lambda X_t) + \varepsilon_{t+1}$. We use CAY as proxy for the hedge component in the ICAPM. We use 2,000 simulated observations generated from Guo's (2004) benchmark model.

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Table 1 Summary Statistics

	MV	CAY	DEF	DY	RREL	TERM
Panel A Full Sample 1953:Q2 to 2004:Q4						
Autocorrelation						
	0.424	0.856	0.909	0.971	0.511	0.790
Correlation with BCI						
	0.245	0.108	0.311	0.338	-0.433	0.046
Cross-Correlation						
MV	1.000					
CAY	-0.107	1.000				
DEF	0.238	0.037	1.000			
DY	-0.060	0.237	0.427	1.000		
RREL	-0.034	-0.075	-0.282	0.029	1.000	
TERM	-0.091	0.335	0.262	-0.106	-0.610	1.000
Panel B Subsample 1953:Q2 to 1979:Q4						
Autocorrelation						
	0.460	0.764	0.898	0.931	0.619	0.857
Correlation with BCI						
	0.350	0.386	0.210	0.374	-0.385	0.039
Cross-Correlation						
MV	1.000					
CAY	0.152	1.000				
DEF	0.326	0.146	1.000			
DY	0.308	0.431	0.255	1.000		
RREL	0.159	-0.154	-0.289	0.106	1.000	
TERM	-0.192	0.284	0.348	-0.016	-0.605	1.000
Panel C Subsample 1980:Q1 to 2004:Q4						
Autocorrelation						
	0.367	0.890	0.897	0.983	0.457	0.711
Correlation with BCI						
	0.183	-0.076	0.516	0.328	-0.546	0.128
Cross-Correlation						
MV	1.000					
CAY	-0.322	1.000				
DEF	0.117	-0.124	1.000			
DY	-0.169	0.291	0.767	1.000		
RREL	-0.098	-0.002	-0.236	-0.069	1.000	
TERM	-0.158	0.282	0.055	0.045	-0.611	1.000

Note: The table reports the summary statistics of the instrumental variables used in the paper. MV is realized stock market variance; CAY is the consumption-wealth ratio; DEF is the yield spread between Baa- and Aaa-rated corporate bonds; DY is the ratio of the dividend in the past year to the end-of-period stock price for S&P 500 stocks; RREL is the difference between the short-term interest rate and its average in the previous 12 months; TERM is the yield spread between 10-year Treasury bonds and 3-month Treasury bills; and BCI is a business cycle indicator, which is equal to 1 for the recession quarters and 0 otherwise.

Table 2 Forecast One-Period-Ahead Excess Stock Market Returns

	MV	CAY	DEF	DY	RREL	TERM	$\bar{R}^2$ (%)
				Panel A Quarterly Data			
1	2.030*						1.1
	(1.737)						
2		1.671***					6.6
		(4.436)					
3			-0.010	0.013**	-3.585	0.011	3.0
			(-0.625)	(2.275)	(-0.462)	(1.599)	
4	2.540**	1.783***					8.7
	(2.389)	(4.834)					
5	3.023***		-0.025	0.017***	-2.413	0.014**	5.6
	(2.685)		(-1.500)	(2.902)	(-0.321)	(2.181)	
6	2.951***	1.412***	-0.016	0.011*	-6.016	0.005	9.1
	(2.725)	(3.213)	(-0.962)	(1.894)	(-0.784)	(0.697)	
				Panel B Monthly Data			
7	1.314						0.3
	(1.431)						
8		0.483**					2.3
		(2.246)					
9			-1.266	0.425	-4.877	-0.047	-1.0
			(-0.914)	(0.823)	(-1.186)	(-0.152)	
10	2.806***	0.717***					4.9
	(3.400)	(3.189)					
11	3.104***		-2.726*	1.121*	-5.381	0.020	1.5
	(3.727)		(-1.777)	(1.934)	(-1.330)	(0.066)	
12	3.036***	0.783**	0.728	-0.102	-5.041	0.047	4.2
	(3.806)	(2.540)	(0.354)	(-0.139)	(-1.292)	(0.163)	

Note: The table reports the OLS estimation results of forecasting one-period-ahead excess stock market returns. We report heteroskedasticity-corrected t-statistics in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. MV is realized stock market variance; CAY is the consumption-wealth ratio; DEF is the yield spread between Baa- and Aaa-rated corporate bonds; DY is the ratio of the dividend in the past year to the end-of-period stock price for S&P 500 stocks; RREL is the difference between the short-term interest rate and its average in the previous 12 months; and TERM is the yield spread between 10-year Treasury bonds and 3-month Treasury bills. The quarterly data span the period 1953:Q3 to 2004:Q4 for TERM and the period 1952:Q1 to 2004:Q4 for all the other variables. The monthly data span the period January 1984 to May 2001.

Table 3 RRA as a Linear Function of State Variables in the Conditional CAPM

	Const.	BCI	MV	CAY	DEF	DY	RREL	TERM	OIR	$\bar{R}^2$ (%)
					Panel A Quarterly Data					
1	0.669	5.803**							17.791	2.1
	(0.516)	(2.230)							(0.003)	
2	-19.236**		8.329**a						11.385	-0.3
	(-2.350)		(2.389)						(0.044)	
3	2.065*			2.756***a					2.492	7.8
	(1.854)			(4.648)					(0.778)	
4	-1.324				3.291				19.688	2.4
	(-0.442)				(1.402)				(0.001)	
5	-3.230					1.694**			17.069	4.2
	(-1.299)					(2.535)			(0.004)	
6	2.298*						-1.474*b		18.566	0.5
	(1.951)						(-1.713)		(0.002)	
7	-1.711							2.416***	12.787	1.0
	(-0.976)							(2.957)	(0.025)	
					Panel B Monthly Data					
8	-6.379		6.407a						6.351	-0.6
	(-0.795)		(0.841)						(0.174)	
9	-1.161***a			2.679***a					1.214	2.7
	(-2.649)			(2.652)					(0.876)	
10	0.966				-0.672a				7.285	0.1
	(0.210)				(-0.150)				(0.122)	
11	-1.365					0.677a			7.132	-0.7
	(-0.433)					(0.536)			(0.129)	
12	-0.415						-1.850b		6.264	1.3
	(-0.330)						(-1.183)		(0.180)	
13	-0.944							66.995	6.870	-0.7
	(-0.445)							(0.635)	(0.143)	

Note: The table reports the GMM estimation results of the conditional CAPM,

$$r_{M,t+1} = \alpha + (\gamma_0 + \gamma X_t)\sigma_{M,t}^2 + \varepsilon_{t+1},$$

in which RRA is a linear function of a state variable. We include all the state variables in the instrumental variable set. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. Letters a and b denote being scaled by 100 and 1000, respectively. Column OIR presents Hansen's (1982) J-test statistics, with the p-value in parentheses. MV is realized stock market variance; CAY is the consumption-wealth ratio; DEF is the yield spread between Baa- and Aaa-rated corporate bonds; DY is the ratio of the dividend in the past year to the end-of-period stock price for S&P 500 stocks; RREL is the difference between the short-term interest rate and its average in the previous 12 months; TERM is the yield spread between 10-year Treasury bonds and 3-month Treasury bills; and BCI is a business cycle indicator, which is equal to 1 for the recession quarters and 0 otherwise. The quarterly data span the period 1953:Q3 to 2004:Q4 for TERM and the period 1952:Q1 to 2004:Q4 for all the other variables. The monthly data span the period January 1984 to May 2001.

Table 4 RRA as a Linear Function of State Variables with Control for the Hedge Component

	Const.	BCI	MV	CAY	DEF	DY	RREL	TERM	OIR	$\bar{R}^2$ (%)
					Panel A Quarterly Data					
1	1.910	2.727							3.687	8.7
	(1.545)	(1.054)							(0.450)	
2	-3.136		2.257a						3.841	6.4
	(-0.385)		(0.716)						(0.428)	
3	1.402			5.215a					1.835	4.4
	(0.831)			(1.513)					(0.766)	
4	1.464				1.096				4.348	8.7
	(0.498)				(0.468)				(0.361)	
5	-0.377					0.914			2.941	9.6
	(-0.151)					(1.340)			(0.568)	
6	2.818**						-8.760a		3.749	7.8
	(2.642)						(-1.054)		(0.441)	
7	1.309							0.955	3.482	7.9
	(0.779)							(1.101)	(0.481)	
					Panel B Monthly Data					
8	8.903		-6.906a						1.672	0.4
	(0.911)		(-0.753)						(0.643)	
9	-1.309a			3.015a					1.189	2.1
	(-1.112)			(1.124)					(0.756)	
10	-0.066				1.532a				2.167	1.7
	(-0.014)				(0.339)				(0.539)	
11	1.198					9.435			2.249	1.8
	(0.370)					(0.074)			(0.522)	
12	0.825						-1.747b		1.075	3.4
	(0.622)						(-1.139)		(0.783)	
13	1.026							23.501	2.204	1.8
	(0.470)							(0.225)	(0.531)	

Note: The table reports the GMM estimation results of the conditional ICAPM,

$$r_{M,t+1} = \alpha + (\gamma_0 + \gamma X_t)\sigma^2_{M,t} + \lambda CAY_t + \varepsilon_{t+1}.$$

in which RRA is a linear function of a state variable and the hedge component is a linear function of CAY. We include all the state variables in the instrumental variable set. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. Letters a and b denote being scaled by 100 and 1000, respectively. Column OIR presents Hansen's (1982) J-test statistics, with the p-value in parentheses. MV is realized stock market variance; CAY is the consumption-wealth ratio; DEF is the yield spread between Baa- and Aaa-rated corporate bonds; DY is the ratio of the dividend in the past year to the end-of-period stock price for S&P 500 stocks; RREL is the difference between the short-term interest rate and its average in the previous 12 months; TERM is the yield spread between 10-year Treasury bonds and 3-month Treasury bills; and BCI is a business cycle indicator, which is equal to 1 for the recession quarters and 0 otherwise. The quarterly data span the period 1953:Q3 to 2004:Q4 for TERM and the period 1952:Q1 to 2004:Q4 for all the other variables. The monthly data span the period January 1984 to May 2001.

Table 5 Semiparametric Smooth Coefficient Models

State Variables	Statistics	P-Value	Bootstrap Empirical Distributions (Upper Percentiles)				R^2 (%)
			99%	95%	90%	80%	
Panel A $H_0: r_{M,t+1} = \alpha + \gamma\sigma^2_{M,t} + \varepsilon_{t+1}$ *vs* $H_A: r_{M,t+1} = \gamma(X_t)\sigma^2_{M,t} + \lambda(X_t) + \varepsilon_{t+1}$							
CAY	0.087	0.01	0.084	0.051	0.042	0.032	1.6 / 9.5
DEF	0.024	0.05	0.035	0.024	0.019	0.014	1.6 / 3.9
DY	0.027	0.02	0.034	0.020	0.016	0.012	1.6 / 4.2
RREL	0.052	0.14	0.128	0.082	0.060	0.045	1.6 / 6.4
TERM	0.196	0.01	0.165	0.121	0.100	0.081	1.6 / 17.8
Panel B $H_0: r_{M,t+1} = \alpha + \gamma\sigma^2_{M,t} + \varepsilon_{t+1}$ *vs* $H_A: r_{M,t+1} = \alpha + \gamma(X_t)\sigma^2_{M,t} + \varepsilon_{t+1}$							
CAY	0.071	0.01	0.061	0.035	0.025	0.017	1.6 / 8.1
DEF	0.013	0.05	0.024	0.013	0.010	0.006	1.6 / 2.9
DY	0.089	0.02	0.093	0.061	0.053	0.042	1.6 / 9.7
RREL	0.013	0.24	0.073	0.032	0.023	0.015	1.6 / 2.9
TERM	0.146	0.01	0.140	0.099	0.078	0.062	1.6 / 14.1
Panel C $H_0: r_{M,t+1} = \alpha + \gamma\sigma^2_{M,t} + \lambda X_t + \varepsilon_{t+1}$ *vs* $H_A: r_{M,t+1} = \alpha + \gamma(X_t)\sigma^2_{M,t} + \lambda X_t + \varepsilon_{t+1}$							
CAY	0.005	0.44	0.033	0.019	0.013	0.008	9.5/10.0
DEF	0.048	0.06	0.097	0.050	0.037	0.028	1.8/6.3
DY	0.076	0.04	0.104	0.067	0.057	0.046	3.6/10.4
RREL	0.012	0.25	0.064	0.030	0.021	0.014	2.9/4.0
TERM	0.089	0.02	0.104	0.063	0.049	0.037	4.1/11.9
Panel D $H_0: r_{M,t+1} = \alpha + \gamma\sigma^2_{M,t} + \lambda X_t + \varepsilon_{t+1}$ *vs* $H_A: r_{M,t+1} = \gamma\sigma^2_{M,t} + \lambda(X_t) + \varepsilon_{t+1}$							
CAY	0.002	0.58	0.052	0.029	0.019	0.012	9.5/9.8
DEF	-0.002	0.75	0.012	0.008	0.005	0.003	1.8/1.6
DY	-0.007	0.54	0.005	0.001	0.000	-0.002	3.6/2.9
RREL	0.003	0.31	0.044	0.022	0.012	0.005	2.9/3.1
TERM	0.133	0.00	0.102	0.074	0.061	0.045	4.1/15.3
Panel E $H_0: r_{M,t+1} = \gamma\sigma^2_{M,t} + \lambda(X_t) + \varepsilon_{t+1}$ *vs* $H_A: r_{M,t+1} = \gamma(X_t)\sigma^2_{M,t} + \lambda(X_t) + \varepsilon_{t+1}$							
CAY	-0.003	0.50	0.036	0.018	0.013	0.006	9.8/9.5
DEF	0.023	0.01	0.019	0.013	0.010	0.007	1.6/3.9
DY	0.013	0.07	0.024	0.016	0.012	0.008	2.9/4.2
RREL	0.035	0.19	0.098	0.054	0.042	0.034	3.1/6.4
TERM	0.030	0.17	0.109	0.058	0.042	0.027	15.3/17.8
Panel F $H_0: r_{M,t+1} = \alpha + \gamma(X_t)\sigma^2_{M,t} + \lambda X_t + \varepsilon_{t+1}$ *vs* $H_A: r_{M,t+1} = \gamma(X_t)\sigma^2_{M,t} + \lambda(X_t) + \varepsilon_{t+1}$							
CAY	-0.005	0.65	0.034	0.021	0.013	0.007	10.0/9.5
DEF	-0.025	0.54	-0.005	-0.008	-0.011	-0.015	6.3/3.9
DY	-0.065	0.74	-0.021	-0.025	-0.029	-0.037	10.4/4.2
RREL	0.026	0.17	0.083	0.044	0.031	0.024	4.0/6.4
TERM	0.071	0.03	0.098	0.062	0.051	0.040	11.9/17.8
Panel G $H_0: r_{M,t+1} = \alpha + \gamma\sigma^2_{M,t} + \lambda X_t + \varepsilon_{t+1}$ *vs* $H_A: r_{M,t+1} = \gamma(X_t)\sigma^2_{M,t} + \lambda(X_t) + \varepsilon_{t+1}$							
CAY	0.000	0.52	0.063	0.034	0.021	0.012	9.5/9.5
DEF	0.021	0.02	0.027	0.015	0.012	0.008	1.8/3.9
DY	0.006	0.09	0.017	0.009	0.006	0.003	3.6/4.2
RREL	0.038	0.21	0.119	0.075	0.051	0.038	2.9/6.4
TERM	0.166	0.01	0.159	0.112	0.093	0.074	4.1/17.8

Note: The table reports the model specification test results for various smooth coefficient models (and partially linear models in Panel D). The bootstrap version goodness-of-fit test statistics are based on Cai et al. (2000). MV is realized stock market variance; CAY is the consumption-wealth ratio; DEF is the yield spread between Baa- and Aaa-rated corporate bonds; DY is the ratio of the dividend in the past year to the end-of-period stock price for S&P 500 stocks; RREL is the difference between the short-term interest rate and its average in the previous 12 months; and TERM is the yield spread between 10-year Treasury bonds and 3-month Treasury bills. The quarterly data span the period 1953:Q3 to 2004:Q4 for TERM and the period 1952:Q1 to 2004:Q4 for all the other variables.

Table 6 Partially Linear and Additive Models

State Variables	Statistics	P-Value	Bootstrap Empirical Distributions (Upper Percentiles)				R^2 (%)
			99%	95%	90%	80%	
Panel A $H_0: r_{M,t+1} = \alpha + \gamma\sigma^2_{M,t} + \varepsilon_{t+1}$ *vs* $H_A: r_{M,t+1} = g(\sigma^2_{M,t}) + \lambda(X_t) + \varepsilon_{t+1}$							
CAY	0.272	0.03	0.302	0.260	0.236	0.205	1.6/22.7
DEF	0.133	0.26	0.255	0.197	0.168	0.142	1.6/13.1
DY	0.171	0.16	0.249	0.212	0.187	0.162	1.6/16.0
RREL	0.090	0.74	0.282	0.222	0.191	0.159	1.6/9.8
TERM	0.286	0.01	0.262	0.208	0.191	0.167	1.6/23.5
Panel B $H_0: r_{M,t+1} = \alpha + \gamma\sigma^2_{M,t} + \varepsilon_{t+1}$ *vs* $H_A: r_{M,t+1} = g(\sigma^2_{M,t}) + \varepsilon_{t+1}$							
	0.936	0.04	1.299	0.897	0.580	0.221	1.6/1.9
Panel C $H_0: r_{M,t+1} = \alpha + \gamma\sigma^2_{M,t} + \lambda X_t + \varepsilon_{t+1}$ *vs* $H_A: r_{M,t+1} = \alpha + g(\sigma^2_{M,t}) + \lambda X_t + \varepsilon_{t+1}$							
CAY	-0.005	0.59	0.025	0.013	0.008	0.003	9.5/9.0
DEF	0.001	0.38	0.026	0.013	0.009	0.005	1.8/1.9
DY	-0.002	0.44	0.025	0.014	0.009	0.004	3.6/3.4
RREL	0.004	0.23	0.027	0.014	0.010	0.004	2.9/3.2
TERM	0.001	0.34	0.025	0.015	0.010	0.005	4.1/4.2
Panel D $H_0: r_{M,t+1} = \alpha + \gamma\sigma^2_{M,t} + \lambda X_t + \varepsilon_{t+1}$ *vs* $H_A: r_{M,t+1} = g(\sigma^2_{M,t}) + \lambda(X_t) + \varepsilon_{t+1}$							
CAY	0.170	0.37	0.290	0.248	0.223	0.194	9.5/22.7
DEF	0.130	0.24	0.247	0.193	0.164	0.137	1.8/13.1
DY	0.148	0.26	0.242	0.207	0.181	0.155	3.6/16.0
RREL	0.076	0.82	0.276	0.212	0.185	0.154	2.9/9.8
TERM	0.254	0.01	0.255	0.203	0.186	0.163	4.1/23.5

Note: The table reports the model specification test results for the nonparametric model and its partially linear and additive variants. The bootstrap version goodness-of-fit test statistics are based on Cai et al. (2000). MV is realized stock market variance; CAY is the consumption-wealth ratio; DEF is the yield spread between Baa- and Aaa-rated corporate bonds; DY is the ratio of the dividend in the past year to the end-of-period stock price for S&P 500 stocks; RREL is the difference between the short-term interest rate and its average in the previous 12 months; and TERM is the yield spread between 10-year Treasury bonds and 3-month Treasury bills. The quarterly data span the period 1953:Q3 to 2004:Q4 for TERM and the period 1952:Q1 to 2004:Q4 for all the other variables.

Table 7 Cross-Sectional Regressions Using 25 Fama and French (1993) Portfolios

	Constant	MV	MV*CAY	CAY	V_HML	R^2
1	0.049	0.003	-0.012[a]**			41.0
	(6.813)	(1.670)	(-3.266)			
	[4.264]	[1.059]	[-2.070]			
2	0.061	0.002	-0.014[a]*	-0.019**		46.6
	(6.856)	(1.503)	(-3.389)	(-2.553)		
	[3.789]	[0.848]	[-1.905]	[-1.992]		
3	0.024	0.002			0.002**	45.3
	(3.642)	(1.331)			(3.253)	
	[2.546]	[0.940]			[2.311]	
4	0.038	0.003		-0.016*	0.002**	42.0
	(4.322)	(1.399)		(-2.739)	(3.169)	
	[2.649]	[0.868]		[-1.697]	[1.990]	
5	0.021	0.002	-0.003		0.002**	39.0
	(3.239)	(1.255)	(-0.945)		(3.277)	
	[2.239]	[0.878]	[-0.670]		[2.305]	

Note: The table reports the Fama and MacBeth (1973) cross-sectional regression results. In parentheses, we report t-statistics obtained using the original Fama and MacBeth standard error. In squared bracket, we report t-statistics obtained using the Shanken (1992) corrected standard error. ***, **, * denote significant at the 1%, 5%, and 10% levels, according to the Shanken corrected t-statistics. The letter a denotes being scaled by 100. MV is realized stock market variance; CAY is the consumption-wealth ratio; and V_HML is realized value premium variance. MV and CAY are available over the period 1951:Q4 to 2004:Q4 and V_HML is available over the period 1963:Q3 to 2004:Q4.

Table 8 Forecasting One-Quarter-Ahead Excess Stock Market Returns: Subsamples

	MV	CAY	$\bar{R}^2$ (%)
	Subsample 1952:Q1 to 1979:Q4		
1	3.836**		3.9
	(2.131)		
2		3.032***	14.0
		(4.678)	
3	2.979*	2.845***	16.1
	(1.807)	(4.516)	
	Subsample 1980:Q1 to 2004:Q4		
4	0.752		-0.8
	(0.535)		
5		1.085**	2.8
		(2.189)	
6	1.954	1.324**	3.2
	(1.431)	(2.566)	

Note: The table reports the OLS estimation results of forecasting one-quarter-ahead excess stock market returns. We report heteroskedasticity-corrected t-statistics in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. MV is realized stock market variance and CAY is the consumption-wealth ratio.