Time-Varying Risk-Return Tradeoff in the Stock Market

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Abstract

We document a strong comovement of the stock market risk-return tradeoff with the consumption-wealth ratio (CAY). The finding appears to imply countercyclical aggregate relative risk aversion; however, we show in three ways that it may also reflect time-varying investment opportunities. First, the *partial* risk-return tradeoff is positive and time-invariant when we control for CAY as a proxy for investment opportunities. Second, conditional market variance scaled by CAY is *negatively* priced in the cross-section of stock returns, and its explanatory power is similar to that of Fama and French's (1996) HML factor. Last, our findings are consistent with a limited stock market participation model, in which shareholders require an illiquidity premium that increases with CAY, in addition to the risk premium that is proportional to conditional market variance. As the model predicts, the observed countercyclical risk-return tradeoff reflects a U-shaped relation between conditional market variance and CAY.

Keywords: 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

Several recent asset pricing models, e.g., Campbell and Cochrane (1999), Chan and Kogan (2002), and Guo (2004), have emphasized countercyclical variation in the stock market risk-return tradeoff. We can illustrate potential sources of this variation using Merton's (1973) intertemporal capital asset pricing model (ICAPM), in which the conditional excess market return, $E_t r_{M,t+1}$, is determined by its conditional variance, $\sigma^2_{M,t}$ (the risk component), and its conditional covariance, $\sigma_{MF,t}$ (the hedge component), with the state variable(s), *F*:

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

where γ_t and λ_t are the prices of risk. Following Scruggs (1998), the (simple) risk-return tradeoff is $\gamma_t + \frac{\partial \lambda_t \sigma_{MF,t}}{\partial \sigma^2_{M,t}}$ and the partial risk-return tradeoff is γ_t. Equation (1) encompasses two main hypotheses of the time-varying risk-return tradeoff—either the aggregate relative risk aversion (RRA), γ_t, or the correlation of the hedge component with conditional market variance, $\frac{\partial \lambda_t \sigma_{MF,t}}{\partial \sigma^2_{M,t}}$, changes across time. While many authors have tested whether the risk-return tradeoff is positive, few have investigated whether and why it changes across time. We try to fill the gap in this paper.

For two reasons, we use mainly the consumption-wealth ratio (CAY) proposed by Lettau and Ludvigson (2001a)—a measure of scaled market price—as the conditioning variable. First, the scaled market price is an endogenous state variable in intertemporal asset pricing models because, as Campbell and Shiller (1988) illustrate, it has a mechanical relation to expected future market returns. For example, in Campbell and Cochrane's (1999) habit-formation model, RRA increases monotonically with the scaled market price. In a similar vein, Appendix A shows that, if γ_t and λ_t

are constant in equation (1), the scaled market price can serve as an instrumental variable for the hedge component.[1] In their empirical studies, Lettau and Ludvigson (2001b) and Guo and Whitelaw (2006) have used CAY as a proxy for RRA and for the hedge component, respectively. Second, CAY has substantially stronger predictive power for market returns than alternative measures of the scaled market price, e.g., the dividend yield. The weak predictive power of the dividend yield may reflect structural changes in the payout policy (e.g., Boudoukh, Michaely, Richardson, and Roberts (2007) and Lettau and Van Nieuwerburgh (2008)).[2] Nevertheless, as a robustness check, we also consider other commonly used market return predictors as the conditioning variables and find qualitatively similar results.

We estimate equation (1) assuming that γ_t is a linear function of conditioning variables and document two important findings.[3] First, if we ignore the hedge component, γ_t is a measure of the stock market risk-return tradeoff. Under this specification, we find that the tradeoff correlates positively and significantly with CAY at the 1% level. The estimated γ_t, however, is *negative* over a wide range of values for CAY. Because RRA is arguably positive, this result indicates that time-varying RRA is unlikely the only driver of countercyclical variation in the stock market risk-return tradeoff. Second, the negative risk-return tradeoff might reflect an omitted variable problem: The

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[1] Consistent with this interpretation, Guo, Savickas, Wang, and Yang (2009) find that the predictive ability of CAY for market returns is similar to that of the conditional covariance of market returns with the value premium—arguably a proxy for shocks to investment opportunities (e.g., Fama and French (1996)). In this paper, we show that CAY and conditional variance of the value premium have similar explanatory power for the cross-section of stock returns.

[2] Brennan and Xia (2005) argue that the predictive power of CAY comes mainly from a look-ahead bias because Lettau and Ludvigson (2001a) estimate the cointegration vector using the full sample. In this paper, we address a quite different issue, i.e., the time-varying stock market risk-return tradeoff, and see no apparent reason why the use of the full sample cointegration vector should spuriously affect the estimation of this relation. The reason for choosing the full sample estimate is that it greatly reduces the estimation error (e.g., Lettau and Ludvigson (2005)). As a robustness check, we address the potential look-ahead bias in two ways. First, we show that the cross-sectional explanatory power of CAY is similar to that of the value premium. Second, to illustrate that CAY is a theoretically motivated variable, we replicate our main empirical findings using simulated data from Guo's (2004) limited stock market participation model.

[3] In an earlier draft, we show that our main findings are qualitatively similar using the semiparametric smooth (or varying) coefficient model considered in Cai, Fan, and Yao (2000) and Li, Huang, Li, and Fu (2002).

γ_t estimate becomes positive when we include CAY as a proxy for the hedge component in equation (1). While the relation between γ_t and CAY remains positive, it attenuates substantially and becomes statistically insignificant at conventional levels. These results suggest that variation in the stock market risk-return tradeoff reflects at least partly time-varying investment opportunities.

We fail to reject the null hypothesis of constant RRA possibly because of a multicollinearity problem; for example, conditional market variance increases with CAY in Campbell and Cochrane's (1999) habit-formation model. We address the issue in two ways. First, the relation between CAY and conditional market variance is positive in the first half sample but is negative in the second half sample; overall, it is *negative* albeit weak over the full sample 1953:Q2 to 2004:Q4 period. Second, we investigate whether the conditional CAPM helps explain the cross-section of stock returns using both conditional market variance and its interaction term with CAY as the risk factors. If CAY forecasts market returns because it is a proxy for time-varying RRA, loadings on the interaction term should carry a positive risk premium. Growth stocks have larger loadings on the interaction term than do value stocks, and the risk premium is found to be significantly *negative*, however. Because the interaction term correlates closely with CAY, the seemingly puzzling result may reflect the fact that CAY is a proxy for investment opportunities. Consistent with this conjecture, we show that the interaction term loses its explanatory power when controlling for CAY or the variance of Fama and French's (1996) HML factor in cross-sectional regressions.

Because time-varying risk-return tradeoff can arise in many different settings, our empirical findings are potentially sensitive to the conditioning variables that we used in the paper. With this caveat in mind, we replicate the positive relation between the stock market risk-return tradeoff and CAY using simulated data from Guo's (2004) limited stock market participation model. The model has three refutable implications that help explain this pattern. First, in addition to the risk premium, shareholders also require an illiquidity premium, ILL_t for holding stocks

(2) $$Er_{M,t+1} = \gamma\sigma^2_{M,t} + ILL_t \,,$$

where γ is RRA and is constant. Second, the scaled market price is a proxy for the illiquidity premium, e.g., $ILL_t \approx \lambda CAY_t$ and λ is a positive coefficient. Last, conditional market variance is a U-shaped function of the scaled market price, e.g., $\frac{\partial CAY_t}{\partial \sigma^2_{M,t}} > 0$ when CAY is high and $\frac{\partial CAY_t}{\partial \sigma^2_{M,t}} < 0$ when CAY is low.[4] Thus, investors require a larger risk-return tradeoff, $\gamma + \lambda \frac{\partial CAY_t}{\partial \sigma^2_{M,t}}$, when CAY is high than when CAY is low. Nevertheless, by construction, the model stipulates that RRA is constant when we control for the illiquidity premium.

Many studies, e.g., Whitelaw (1994), Lettau and Ludvigson (2010), Brandt and Kang (2004), Kim, Morley, and Nelson (2004), Bliss and Panigirtzoglou (2004), Bollerslev, Gibson, and Zhou (2004), Post and Levy (2005), Lundblad (2007), Brandt and Wang (2007), Krishnan and Petkova (2009), and Yu and Yuan (2011), have documented countercyclical variation in the stock market risk-return tradeoff. These authors interpret the finding as evidence of time-varying RRA. By contrast, using household-level asset portfolio data, Brunnermeier and Nagel (2008) find little support for the hypothesis that individual investors have time-varying RRA. Similarly, Harrison and Zhang (1999) show that the hedge component has a confounding effect on the stock market risk-return relation. Campbell and Vuolteenaho (2004), Brennan, Wang, and Xia (2004), Guo

[4] As mentioned above, consistent with this implication, over the post-World War II period, the relation between conditional market variance and CAY is positive in the first half sample but is negative in the second half sample. Similarly, Schwert (1989) finds an instable relation between conditional market variance and the dividend yield, and David and Veronesi (2009) document a V-shaped relation between conditional market variance and the dividend yield.

(2006), Petkova (2006), and Hahn and Lee (2006) find that changes in the investment opportunity set are important for understanding the cross-section of stock returns.

The remainder of the paper is organized as follows. We describe the data in Section 2 and present the time-series estimation results in Section 3. We provide the cross-sectional evidence in Section 4 and discuss some tentative theoretical explanations in Section 5. We offer some concluding remarks in Section 6.

2. Data

Conditional stock market variance is not directly observable in data. In this paper, we follow Merton (1980) and Andersen, Bollerslev, Diebold, and Labys (2003) and use realized variance constructed from daily excess market returns as a proxy for conditional stock market variance. Compared with GARCH models (e.g., Bollerslev, Chou, and Kroner (1992)), the specification has several desirable properties for the purpose of this paper. First, CAY—a key variable in our empirical analysis—is reliably available only at the quarterly frequency; however, the GARCH model is appropriate only for the return data of much higher, e.g., daily or weekly, frequencies. Second, a direct measure of conditional variance allows us to adopt easily the elaborate semiparametric and nonparametric models. Third, French, Schwert, and Stambaugh (1987) argue that full-information maximum likelihood estimators such as GARCH are more sensitive to model misspecifications than are instrumental variable estimators.[5] Last, we replicate our main empirical findings using simulated data from Guo's (2004) limited stock market participation model. That said, we acknowledge that realized variance is not necessarily the most

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

efficient measure of conditional variance. We address this issue in two ways. First, as in Guo and Whitelaw (2006), we use monthly implied variance constructed from options contracts on the stock market index as a measure of conditional variance over the January 1984 to May 2001 period. Second, we use MIDAS variance advocated by Ghysels, Santa-Clara, and Valkanov (2005). We find qualitatively similar results using both measures of conditional variance (untabulated).

We obtain the quarterly CAY variable from Martin Lettau at New York University. Realized stock market variance (MV) is the sum of squared daily excess market returns in a quarter. We use the daily stock market returns constructed by Schwert (1989) before July 1, 1962 and use the daily CRSP (the Center for Research in Security Prices) value-weighted stock market returns afterward. 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 market return and the daily risk-free rate.

As a robustness check, we also consider some other commonly used stock return predictors as conditioning variables (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 dividend yield (DY) is the ratio of the dividend paid in the previous twelve months 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 twelve months.[6] 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.

[6] Following an anonymous referee's suggestion, we also considered the earnings price ratio, Amihud's (2002) measure of aggregate illiquidity, and Campbell and Vuolteenaho's (2004) value spread as conditioning variables. The results are qualitatively similar; for brevity, we do not report them here but they are available on request.

Figure 1 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. Panel A of Table 1 shows that all the variables are serially correlated, with the autocorrelation coefficients ranging from 40% for MV, 86% for CAY, to 97% for DY.[7] RREL correlates negatively with a business cycle indictor, BCI, which equals one for recession quarters and zero otherwise, while the correlation is positive for the other variables. Panels B and C illustrate similar patterns in the two subsamples.

Table 1 reveals an instable relation between MV and some conditioning variables. In particular, MV correlates negatively with CAY in the full sample (panel A) and in the second subsample (panel C); however, the correlation is positive in the first subsample (panel B). As we explain in Section 5, this pattern, which is consistent with Guo's (2004) limited stock market participation model, is crucial for understanding our main empirical finding of the countercyclical risk-return tradeoff. We find a similar pattern for DY and RREL. Both variables correlate positively with MV in the first subsample (panel B), while the correlation becomes negative in the second subsample (panel C). Paye (2010) also finds that macrovariables have weak forecasting power for realized 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.[8]

3. Time-Series Evidence

Assuming that the hedge component is negligible, Merton (1980) and numerous subsequent

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[7] While the small sample bias stressed by, e.g., Stambaugh (1999), should be a serious concern for the dividend yield, its effects on MV and CAY—the key variables used in this paper—is negligible because the two variables are substantially less persistent than the dividend yield.

[8] Guo and Whitelaw (2006) assume that conditional stock market variance is a linear function of MV, CAY, and RREL. These authors, however, note that some of their results are sensitive to this specification because of the instable relation between conditional variance and CAY.

authors have investigated empirically whether there is a positive relation between the expected excess market return and conditional market variance: $r_{M,t+1} = \alpha + \gamma\sigma^2_{M,t} + \varepsilon_{t+1}$. Many authors have interpreted that the estimated risk-return tradeoff coefficient as a measure of aggregate RRA. This interpretation is not entirely correct if the hedge component is an important determinant of conditional equity premium and correlates with conditional market variance. To address this issue, following Scruggs (1998) and Guo and Whitelaw (2006), we consider a benchmark model with constant RRA, in which the excess market return, $r_{M,t+1}$, is a linear function of conditional market variance, $\sigma^2_{M,t}$, and the conditioning variables, X_t, that serve as proxies for the hedge component:

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

where α is a constant and ε_{t+1} is the error term. In this empirical specification, we can interpret the coefficient γ as a measure of RRA if and only if we have a precise measure of conditional market variance and X_t correlates perfectly with the hedge component. That is, our empirical findings are potentially sensitive to the conditioning variables used in equation (3). We try to alleviate this problem in two ways. First, we use theoretically motivated conditioning variables. Specifically, as we explain in Section 5, the scaled stock market price, e.g., CAY, is a measure of investment opportunities in Guo's (2004) limited stock market participation model. Second, as a robustness check, we find qualitatively similar results using other commonly used conditioning variables. With this caveat in mind, we present our main empirical findings below.

Table 2 presents the ordinary least-squared (OLS) estimation of equation (3). Row 1 shows that realized market variance, MV, correlates positively with the one-quarter-ahead excess market return but the relation is only marginally significant. When we add CAY to the forecasting regression as a proxy for the hedge component, the positive effect of MV on the expected excess market return becomes significant at the 5% level (row 4). These results reflect an omitted variable problem. Both MV and CAY correlate positively with future stock market returns, although they correlate negatively with each other in the full sample (panel A, Table 1). Thus, the point estimate of the coefficient on MV is downward biased if we exclude CAY from the forecasting regression.[9] Similarly, the effect of MV on the expected excess market return becomes significantly positive at the 1% level when we control for DEF, DY, RREL, and TERM in the forecasting equation, and DY and TERM are also statistically significant at the 1% and 5% levels, respectively (row 5). The result suggests that the evidence of a positive RRA does not depend crucially on the use of CAY as the conditioning variable. Nevertheless, in row 6, we find that CAY appears to be a better proxy for the hedge component than do the other conditioning variables.

In habit-formation models, e.g., Constantinides (1990), Campbell and Cochrane (1999), Brandt and Wang (2003), Menzly, Santos, and Veronesi (2004), and Santos and Veronesi (2006), investors' RRA changes countercyclically across time. Alternatively, in Chan and Kogan's (2002) heterogeneous-agent model, aggregate RRA changes countercyclically with the wealth distribution, although individual investors have constant RRA.[10] These models imply that stock market return predictability reflects countercyclical variation in both aggregate RRA and conditional market variance. To investigate this hypothesis, we allow the coefficient γ to be a linear function of the conditioning variables:

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

[9] In Section 5, we show that omitting CAY from predictive regression can also generate an upward bias in the estimate of the coefficient on MV when CAY and MV are positively correlated, as in the first subsample (panel B, Table 1).

[10] Time-varying RRA is consistent with some other economic theories. For example, Ang, Bekaert, and Liu (2005) and Post and Levy (2005) argue that investors are 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. Note that, while these theories provide economic rationales for time-varying RRA, they are not special cases of Merton's ICAPM.

Again, we note that the empirical evidence is potentially sensitive to the choice of the conditioning variables in equation (4). We address this problem in two ways. First, we use theoretically motivated conditioning variables. Specifically, in both Campbell and Cochrane's (1999) habit-formation model and Chan and Kogan's (2002) heterogeneous-agent model, aggregate RRA increases monotonically with the scaled stock market price, e.g., CAY. Second, as a robustness check, we find qualitatively similar results using other commonly used conditioning variables.

We report the GMM (generalized method of moments) estimation results in Table 3. Because Table 1 shows that the conditioning variables correlate closely 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 BCI. To improve the estimation efficiency, we include all the conditioning 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.

Table 3 shows that the relation between RRA and CAY is positive and statistically significant at the 1% level (row 3). The model accounts for 7.9% of variation in quarterly excess market returns, which is quite similar to that of the unrestricted linear specification reported in row 4, Table 2. The over-identifying restriction test does not reject the model at the conventional significance level. These results reflect the fact that CAY and its interaction term with MV (as in equation 4) correlate closely with each other, with a correlation coefficient of 76%. Similarly, the relations between RRA and the other conditioning variables have expected signs and are statistically significant at the 1% level for TERM, at the 5% level for BCI, MV, DY, and at the 10% level for RREL. Because Table 2 shows that CAY is a stronger predictor of stock market returns than are other conditioning variables, the over-identifying restriction test overwhelmingly rejects the specifications with these variables as proxies for RRA. To illustrate further this point, we assume that time-varying RRA is a linear function of all the conditioning variables. Row 8 shows that only CAY is statistically significant at the conventional level, while the Wald test indicates that all the conditioning variables are jointly significant at the 1% level. To summarize, our results indicate that the stock market risk-return tradeoff changes countercyclically across time.

It is tempting to suggest that findings in Table 3 are consistent with the hypothesis of time-varying RRA, as in Campbell and Cochrane's (1999) habit-formation model or in Chan and Kogan's (2002) heterogeneous-agent model. This interpretation, however, is inconsistent with some other aspects of the data. First, both models imply a monotonically *positive* relation between conditional market variance and CAY. By contrast, we document an instable relation between MV and CAY, and their correlation is *negative* over the full sample (Table 1). Second, both models suggest that adding CAY to the forecast regression weakens the predictive power of MV for excess market returns due to the multicollinearity problem. However, we find that the predictive power of MV increases substantially when in conjunction with CAY (Table 2) due to the omitted variable problem. Last, the solid line in Figure 2 shows the risk-return tradeoff estimated using CAY as the conditioning variable (row 3 of Table 3) is often *negative*. We document a similar pattern using the specification reported in row 8 of Table 3 as well (untabulated).

Alternatively, we document the time-varying risk-return tradeoff possibly because we omit the hedge component. As mentioned above, the interaction term of MV with CAY is found to have a significantly positive effect on expected market returns because of its close correlation with CAY—possibly a proxy for the hedge component. To address formally this issue, we add CAY to the excess return equation 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 conditioning variables as proxies for the hedge component does not change our results in any qualitative manner because Table 2 shows that they provide little information about future stock market returns beyond CAY. For brevity, we do not report these results but they are available on request.

The empirical specification in equation (5) encompasses the specifications in equations (3) and (4). While equation (3) is consistent with Guo (2004) and equation (4) is consistent with Campbell and Cochrane (1999) or Chan and Kogan (2002), to the best of our knowledge, equation (5) is not a reduced form of a specific equilibrium model other than Merton's (1973) ICAPM. Because ICAPM provides little economic intuition on why RRA or investment opportunities change across time, the specification in equation (5) is admittedly ad hoc, and we do not literally suggest that both RRA and investment opportunities should comove with CAY. Rather, we use the specification to evaluate empirically the relative importance of these two important alternative hypotheses. Under the hypothesis that CAY is a proxy for time-varying RRA, γ is significantly positive but λ is statistically insignificant. Alternatively, if CAY is a proxy for time-varying investment opportunities, λ is statistically significant but γ is not. Obviously, the time-varying RRA and investment opportunities can arise in some other settings that we are not aware of. In this case, it will be interesting to revisit the time-varying risk-return tradeoff using the conditioning variables stipulated in these alternative models.

Table 4 presents the estimation results. Interestingly, the relation between RRA and CAY becomes statistically insignificant at the conventional level; by contrast, the effect of the hedge component on the expected excess market return remains significantly positive at the 5% level (row 3). Similarly, the relations between RRA and all the other conditioning variables become statistically insignificant after we control for CAY as a proxy for the hedge component. Moreover, if we assume that RRA is a linear function of all conditioning variables, row 8 shows that none of them is statistically significant and the Wald test indicates that they are jointly insignificant as well. Lastly, after controlling for the hedge component, the dashed line in Figure 2 shows that the estimated RRA is always positive except for three quarters in 2000.[11]

To summarize, we document a countercyclical risk-return tradeoff, which appears to reflect mainly changes in investment opportunities. To alleviate partially the concern that our findings are potentially sensitive to the conditioning variables that we used in the empirical analysis, we provide some cross-sectional evidence in Section 4 and some theoretical explanations in Section 5.

4. Cross-Sectional Evidence

We find that the stock market risk-return tradeoff changes countercyclically across time partly because of time-varying investment opportunities. As a robustness check, in this section, we investigate the issue using the cross-section of stock returns.[12]

Specifically, we investigate whether a variant of the conditional CAPM helps explain the cross-section of stock returns on the twenty-five Fama and French (1993) portfolios sorted on size and the book-to-market equity ratio over the 1952:Q1 to 2004:Q4 period. While Lettau and Ludvigson (2001b) show that a variant of the conditional CAPM motivated by Campbell and Cochrane's (1999) habit-formation model explains the value premium, others, e.g., Campbell and Vuolteenaho (2004) argue that the value premium is a proxy for shocks to investment opportunities. Therefore, the Fama and French portfolios allow us to test formally these two hypotheses. For each of the twenty-five portfolios, we first run the time-series regression:

[11] The negative RRA estimate for the three quarters in 2000 reflects the fact that the linear specification in equation (5) is somewhat too restrictive. In an earlier draft, we allow RRA to depend on state variables in a nonlinear manner using the semiparametric smooth coefficient model (e.g., Cai, Fan, and Yao (2000), and Li, Huang, Li, and Fu (2002)) and find that the estimated RRA is always positive. Nevertheless, we fail to reject the linear specification at the conventional significance level, and our main findings do not change in any qualitative manner for the semiparametric estimation. These results are omitted for brevity but are available on request.

[12] Bali (2008) also investigates the intertemporal risk-return tradeoff using the cross-section of portfolio returns.

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

where $r_{P,t+1}$ is the excess return on the portfolio *p*. As we show in Appendix B, if loadings on the market risk are constant across time—as assumed in Lettau and Ludvigson (2001b), for example—the coefficients γ_{p0} and γ_p are proportional to loadings on the market risk. This specification is consistent with Campbell and Cochrane's (1999) habit-formation model. Specifically, if CAY is a proxy for time-varying RRA, loadings on the interaction term CAY*MV in equation (6) should have a positive risk premium. This is the main refutable hypothesis.

Figures 3 and 4 plot loadings of the twenty-five Fama and French portfolios on conditional market variance (MV) and on the interaction term (MV*CAY), respectively.[13] Each portfolio is identified with a two-digit number. The first digit refers to size, with 1 denoting the smallest stocks and 5 the biggest stocks. The second digit refers to the book-to-market equity ratio, with 1 denoting the lowest and 5 the highest ratio. Figure 3 shows that, consistent with early studies, e.g., Lettau and Wachter (2007), growth stocks tend to have higher loadings on the market risk than do value stocks within each size quintile. Interestingly, Figure 4 shows that growth stocks have substantially *higher* loadings on the interaction term than do value stocks.

We then investigate whether loadings on MV and MV*CAY help explain the cross-section of stock returns using the Fama and MacBeth (1973) cross-sectional regression approach. Row 1 of Table 5 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 twenty-five Fama and French portfolios (untabulated). Moreover, the interaction term MV*CAY is significantly priced at the 5% level, according to Shanken's (1992) corrected standard errors (squared brackets).

[13] 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.

There is a problem with the conditional CAPM interpretation, however. Specifically, loadings on the interaction term carry a negative risk premium because they are higher for growth stocks than for value stocks (Figure 4).[14] Therefore, the cross-sectional evidence casts doubt on the hypothesis that CAY forecasts stock returns mainly 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 investment opportunities. To address formally the issue, we include CAY as an additional risk factor in the cross-sectional regression:

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

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

Recent studies, e.g., Campbell and Vuolteenaho (2004), show that the value premium is a priced risk factor because of its comovement with unexpected changes in the expected discount rate—a measure of investment opportunities in Campbell's (1993) ICAPM. To illustrate this point, we follow Guo and Savickas (2008) and run regressions of the excess portfolio returns on realized stock market variance (MV) and realized value premium variance (V_HML)[15]:

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

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 5 shows that loadings on V_HML are negative and decrease with the book-to-market equity ratio within each size quintile. 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

[14] Several recent studies, e.g., Petkova and Zhang (2005), Lewellen and Nagel (2006), and Fama and French (2006), have cast some doubt on explanatory power of the conditional CAPM for the cross-section of stock returns.
[15] We do not include the size premium in the Fama and French (1993) three-factor model in equation (8) because it has become negligible since early 1980s, and including it does not change our results in any qualitative manner.

(Campbell and Vuolteenaho (2004)). Row 3 of Table 5 shows that, consistent with Fama and French (1993), for example, the estimated risk premium for loadings on V_HML is significantly positive at the 5% level.[16]

Appendix A shows that the scaled stock price such as CAY forecasts stock market returns because of its close correlation with the hedge factor, e.g., V_HML, which is omitted from the CAPM. Consistent with this conjecture, Guo, Savickas, Wang, and Yang (2009) 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 (see Appendix C). Row 4 of Table 5 confirms this conjecture by showing that CAY provides no additional information beyond V_HML at the 5% significance level. Similarly, row 5 of Table 5 shows that the explanatory power of the interaction term MV*CAY becomes statistically insignificant at the 10% level when we also include V_HML in the cross-sectional regression.

To summarize, the cross-sectional evidence shows that loadings on CAY help explain the cross-section of stock returns possibly because CAY is a proxy for investment opportunities.[17]

5. Discussion

Both the time-series and cross-sectional results show that the countercyclical stock market risk-return tradeoff reflects changes in investment opportunities. In this section, we provide a tentative explanation for our main empirical findings using Guo's (2004) limited stock market

[16] 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 for the Fama and French (1993) factor model.

[17] 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.

participation model, while further theoretical studies are surely warranted in future research.[18] The model was built on several important assumptions, First, there are two (types of) agents—shareholder and non-shareholder. Second, as in Allen and Gale (1994), both agents receive stochastic labor income and can diversify labor income risk through trading with each other in a one-period bond market. Last, both agents are subject to borrowing constraints.

Although Guo (2004) assumes a constant RRA, its three refutable implications account for a time-varying stock market risk-return tradeoff. First, the conditional equity premium has two components, as in equation (2). The first component (risk premium) is conditional market variance, as in standard asset pricing models. The second component (illiquidity premium) reflects the fact that stocks are not as liquid as bonds due to the limited stock market participation.[19] Second, the scaled stock market price, e.g., the dividend yield or CAY, is a proxy for the illiquidity premium. This is because, when borrowing constraints are binding, the shareholder finds it less desirable to hold stocks and thus require a higher illiquidity premium, which in turn lowers stock prices. Third, conditional market variance is a U-shaped function of the dividend yield or CAY. This is because extreme values of the dividend yield reflect extreme labor income or liquidity shocks, which lead to a high level of conditional market variance. Jointly, these implications predict a positive relation between the risk-return tradeoff and CAY: When CAY is low (high), the illiquidity premium and the risk premium are negatively (positively) correlated, and omitting CAY as a proxy for the illiquidity premium generates a downward (upward) bias in the estimated RRA. To illustrate this

[18] Several empirical studies, e.g., Mankiw and Zeldes (1991), Vissing-Jorgensen (2002), Ait-Sahalia, Parker, and Yogo (2004), Malloy, Moskowitz, and Vissing-Jorgensen (2009), and Lettau and Ludvigson (2009), have illustrated the promising role of limited stock market participation in explaining the dynamics of stock prices.

[19] The nonnegative illiquidity premium helps explain Mehra and Prescott's (1985) equity premium puzzle. Specifically, by contrast with Basak and Cuoco (1998) and Constantinides, Donaldson, and Mehra (2002), because of the illiquidity premium, shareholders' consumption does not need to be extremely volatile to account for the observed large equity premium. The illiquidity premium component in equation (2) thus sheds light on the empirical finding by Vissing-Jorgensen (2002) that shareholders' consumption data do not fully resolve the equity premium puzzle.

point, in an earlier draft, we replicate the main empirical findings in Section 3 using simulated data from Guo (2004).

The interpretation of CAY as a proxy for the illiquidity premium is novel and warrants some further discussion as below. For the first refutable implication, we have shown that MV and CAY jointly have significant predictive power for market returns. The third refutable implication is confirmed by David and Veronesi (2009), who document a V-shaped relation between conditional market volatility and the dividend yield. Similarly, Table 1 documents an instable relation between market variance and CAY. We present additional empirical results in Table 6. MV and CAY are positively correlated in the first half sample spanning the 1952:Q1 to 1979:Q4 period. Consistent with model's prediction, we find that controlling for CAY as a proxy for the illiquidity premium lowers the point estimate of the coefficient on MV. By contrast, in the second subsample spanning the period 1980:Q1 to 2004:Q4, controlling for CAY as a proxy for the illiquidity premium increases the point estimate of the coefficient on MV because CAY and MV are negatively correlated in this period. In a subsequent study, Yu and Yuan (2011) document a positive (negative) risk-return tradeoff during periods of low (high) investor sentiment. Because stock market prices correlate closely with investor sentiment (e.g., Baker and Wurgler (2006)), Yu and Yuan's (2011) findings are potentially consistent with the limited stock market participation model.

In Guo (2004), CAY is a proxy for illiquidity premium because shareholder' borrowing constraints are occasionally binding following negative labor income or liquidity shocks. Specifically, expected stock market returns are high when the shareholder has binding borrowing constraints and anticipates high consumption growth. The model thus predicts that CAY or the dividend yield correlates positively with shareholder's expected consumption growth. This conjecture seems overly unrealistic because many would argue that shareholders can substantially better smooth their consumption than nonshareholders or a representative household. In Table 7, we provide prelimilary empirical evidence on this issue using consumption data constructed by Malloy, Moskowitz, and Vissing-Jorgensen (2009).[20] We consider three groups of households—nonshareholders, shareholders, and top third shareholders with largest stock holdings. Panel A shows that CAY correlates positively with expected consumption growth of both shareholders and of top third shareholders, and the relation is statistically significant at the 1% level for the top third shareholders (panel A). By contrast, the relation between CAY and expected consumption growth of nonshareholders is negative albeit statistically insignificant. Moreover, Lettau and Ludvigson (2001a) find that CAY has negligible predictive power for aggregate consumption growth. Panel B shows that the results are qualitatively similar albeit weaker when we use the dividend yield as the forecasting variable for consumption growth. Therefore, even the largest shareholders do not perfectly smooth their consumption. To the best of our knowledge, this finding is novel and warrants further empirical and theoretical studies.

In the limited stock market participation 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 studies that document important effects of the illiquidity premium on asset prices in many financial markets (see Amihud, Mendelson, and Pedersen (2005) for a recent survey). These results highlight the importance of establishing a link between the general equilibrium theory and the microstructure model, as stressed by O'Hara (2003).

[20] We thank an anonymous referee for suggesting this test.

6. Conclusions

In this paper, we find that the risk-return tradeoff changes countercyclically across time. Because the estimated risk-return tradeoff is sometimes negative, our findings cannot be fully attributed to time-varying relative risk aversion. Instead, we show empirically and theoretically that the countercyclical risk-return tradeoff may also partially reflect changes in investment opportunities.

Our empirical analyses have some potential limitations. We motivate time-varying RRA and time-varying investment opportunities using some specific existing models. Nevertheless, because time-varying RRA or investment opportunities might arise in some different settings, our empirical models and conditioning variables may fail to distinguish adequately the two hypotheses in these alternative models. That said, our evidence of time-varying risk-return tradeoff appears to be quite robust and thus provides some useful guidance for future theoretical research.

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Appendix A: The Dividend Yield and Conditional Variances of Risk Factors

We provide conditions under which the dividend yield is a linear function of conditional variances of priced risk factors. For the ease of illustration, we consider a special case of one hedging risk factor, as in Campbell's (1993) ICAPM. It is straightforward to show that our main results hold in general Merton's (1973) ICAPM, in which there may be more hedging risk factors.

In Campbell's (1993) ICAPM, the conditional simple excess market return, $E_t(R_{M,t+1})$, is a linear function of its conditional variance, $\sigma^2_{M,t}$, and its conditional covariance with the shock to discount rates (a measure of investment opportunities in Campbell's (1993) ICAPM), $\sigma_{M,DR,t}$:

(A1) $$E_t(R_{M,t+1}) = \gamma\sigma^2_{M,t} + (\gamma - 1)\sigma_{M,DR,t},$$

where γ is a measure of relative risk aversion. By definition, we can write the covariance term as

(A2) $$\sigma_{M,DR,t} = \beta_{M,DR,t}\sigma^2_{DR,t},$$

where $\beta_{M,DR,t}$ is the loading of stock market returns on the discount-rate shock and $\sigma^2_{DR,t}$ is the conditional variance of the discount-rate shock. Substituting equation (A2) into (A1), we obtain

(A3) $$E_t(R_{M,t+1}) = \gamma\sigma^2_{M,t} + (\gamma - 1)\beta_{M,DR}\sigma^2_{DR,t},$$

For simplicity, in equation (A3), we assume that $\beta_{M,DR,t}$ is constant across time, as in Campbell and Vuolteenaho (2004), among others.

Following Campbell and Shiller (1988), we write the log dividend yield, $d_t - p_t$, as

(A4) $$d_t - p_t = -\frac{\kappa}{1-\rho} + E_t\sum_{j=0}^{\infty}\rho^j(r_{M,t+j+1} + r_{f,t+j+1} - \Delta d_{t+j+1}),$$

where $-\frac{\kappa}{1-\rho}$ is a constant, $r_{M,t+j+1}$ is the log excess stock market return, $r_{f,t+j+1}$ is the log real risk-free rate, and Δd_{t+j+1} is the dividend growth rate. Using the relation $E_t(R_{M,t+1}) = E_t(r_{M,t+1}) + \frac{1}{2}\sigma^2_{M,t}$, we can rewrite equation (A3) as

(A5) $$E_t(r_{M,t+1}) = (\gamma - \frac{1}{2})\sigma^2_{M,t} + (\gamma - 1)\beta_{M,DR}\sigma^2_{DR,t}.$$

For simplicity, we assume that the conditional variances $\sigma^2_{M,t}$ and $\sigma^2_{DR,t}$ follow a joint VAR(1) process:

(A6) $$\begin{bmatrix} \sigma^2_{M,t+1} \\ \sigma^2_{DR,t+1} \end{bmatrix} = A_0 + A\begin{bmatrix} \sigma^2_{M,t} \\ \sigma^2_{DR,t} \end{bmatrix} + \begin{bmatrix} \varepsilon_{1,t+1} \\ \varepsilon_{2,t+1} \end{bmatrix}.$$

Assuming constant expected dividend growth and real risk-free rate, we show that

(A7) $$d_t - p_t = C + \begin{bmatrix} \gamma - \frac{1}{2} & (\gamma - 1)\beta_{M,DR} \end{bmatrix}(I - \rho A)^{-1}\begin{bmatrix} \sigma^2_{M,t} \\ \sigma^2_{DR,t} \end{bmatrix},$$

where C is a collection of the constant terms. Similarly, it is straightforward to show that if changes in consumption and labor income are unpredictable, as found by Lettau and Ludvigson (2001a), the consumption-wealth ratio is also a linear function of the conditional variances $\sigma^2_{M,t}$ and $\sigma^2_{DR,t}$. For brevity, we do not provide the deviation here but it is available on request.

Appendix B: Conditional CAPM

As Lettau and Ludvigson (2001b) illustrate, Campbell and Cochrane's (1999) habit formation model implies the conditional CAPM:

(B1) $r_{i,t} = \beta_i r_{M,t} + \varepsilon_{i,t}$.

We can take the conditional expectation on both sides of equation (B1) and obtain

(B2) $E_{t-1} r_{i,t} = \beta_i E_{t-1} r_{M,t} = \beta_i (\gamma_0 + \gamma X_t) \sigma_{M,t}^2 = \gamma_0 \beta_i \sigma_{M,t}^2 + \gamma \beta_i X_t \sigma_{M,t}^2$.

Note that we use equation (4) get the second equality in equation (B2). If we take the unconditional expectation on both sides of equation (B2), we obtain

(B3) $Er_{i,t} = \gamma_0 \beta_i E\left[\sigma_{M,t}^2\right] + \gamma \beta_i E\left[X_t \sigma_{M,t}^2\right]$.

Equation (B3) shows that that cross-sectional excess stock returns depend on their sensitivities to market variance and to market variance scaled by the state variable. As in Lettau and Ludvigson (2001b), we can also derive this specification using the pricing kernel of Campbell and Cochrane's (1999) habit formation model. Specifically, the pricing kernel is approximately a linear function of market returns and market returns scaled by the surplus consumption ratio (see, e.g., Campbell and Cochrane (2000)). If loadings on these two factors are constant, as assumed in Lettau and Ludvigson (2001b), we obtain equation (B3).

Appendix C: Estimating Factor Loadings Using Forecasting Regressions

This Appendix shows that we can estimate factor loadings by regressing asset returns on conditional variances of risk factors. For simplicity, we assume a two-factor ICAPM, as in Appendix A. In the two-factor ICAPM, the conditional excess return on an asset depends on its covariances with the excess market return, $R_{M,t+1}$, and the hedging factor, $R_{F,t+1}$:

(C1) $$E_t R_{i,t+1} = \gamma Cov_t(R_{i,t+1}, R_{M,t+1}) + \lambda Cov_t(R_{i,t+1}, R_{F,t+1}),$$

where γ and λ are prices of risk. We can think of $R_{F,t+1}$ as the return on a mimicking portfolio for shocks to investment opportunities, e.g., the value premium. We can rewrite equation (C1) as:

(C2) $$E_t R_{i,t+1} = \gamma \beta_{i,M,t} Var_t(R_{M,t+1}) + \lambda \beta_{i,F,t} Var_t(R_{F,t+1}),$$

where $\beta_{i,M,t} = \dfrac{Cov_t(R_{i,t+1}, R_{M,t+1})}{Var_t(R_{M,t+1})}$ and $\beta_{i,F,t} = \dfrac{Cov_t(R_{i,t+1}, R_{F,t+1})}{Var_t(R_{F,t+1})}$.

In empirical tests of asset pricing models (e.g., Fama and MacBeth (1973)), it is a common practice to estimate factor loadings, e.g., $\beta_{i,M,t}$ and $\beta_{i,F,t}$ using the full sample. Specifically, if $\beta_{i,M,t}$ and $\beta_{i,H,t}$ are relatively stable across time, then the expected excess return is *approximately* a linear function of conditional variances of the two risk factors:

(C3) $$E_t R_{i,t+1} \approx \gamma \beta_{i,M} Var_t(R_{M,t+1}) + \lambda \beta_{i,F} Var_t(R_{F,t+1}).$$

Under the hypothesis that CAY is a proxy of investment opportunities, as shown in Appendix A, it forecasts stock returns because of its correlation with $Var_t(R_{F,t+1})$. Specifically, like the dividend yield, CAY is a linear function of $Var_t(R_{M,t+1})$ and $Var_t(R_{F,t+1})$

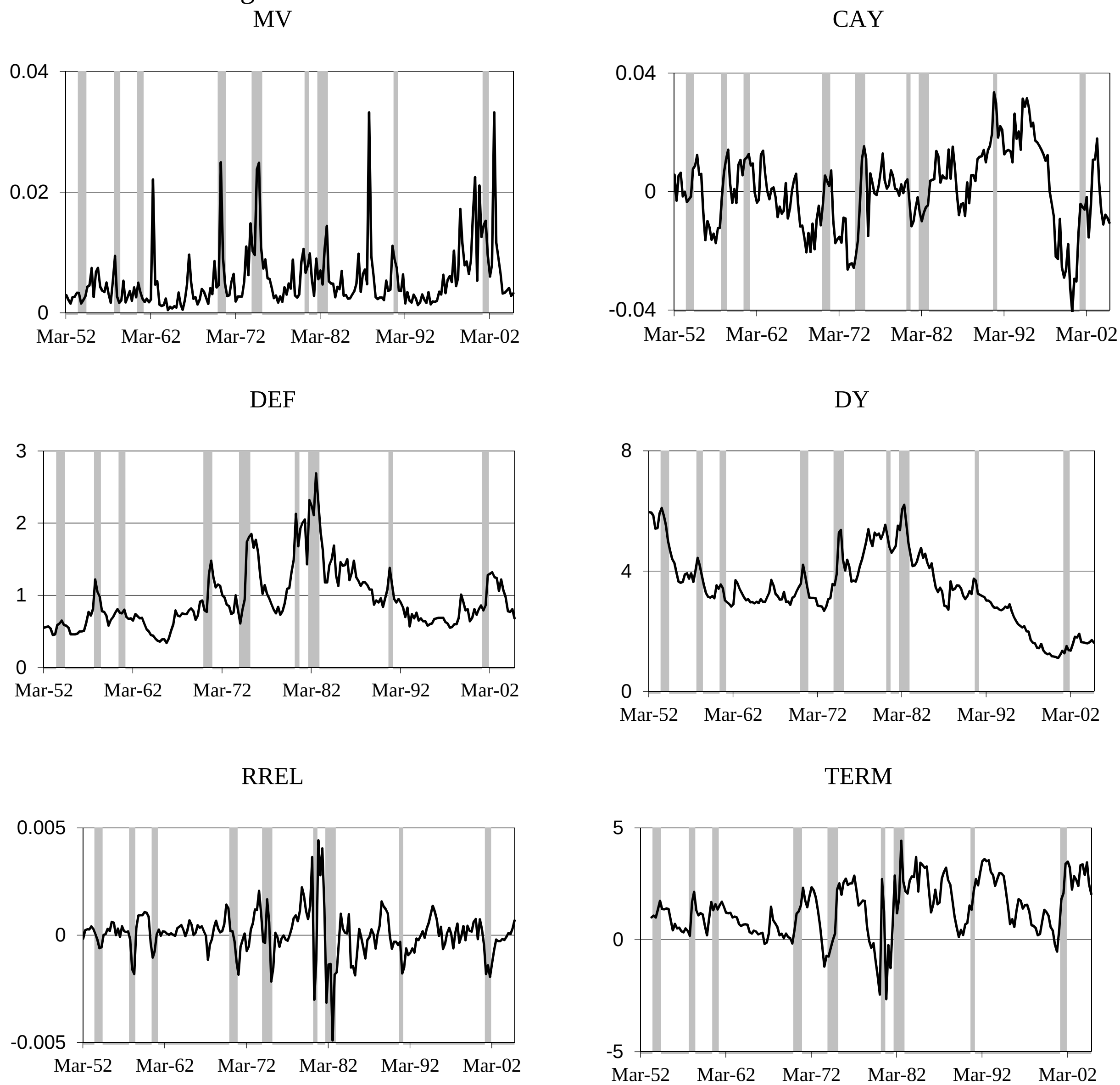
(C4) $$CAY_t = b_1 Var_t(R_{M,t+1}) + b_2 Var_t(R_{F,t+1}).$$

Substitute equation (C4) into equation (C3), we obtain

(C5) $$E_t R_{i,t+1} \approx (\gamma\beta_{i,M} - \frac{\lambda\beta_{i,F} b_1}{b_2}) Var_t(R_{M,t+1}) + \frac{\lambda\beta_{i,F}}{b_2} CAY_t \, .$$

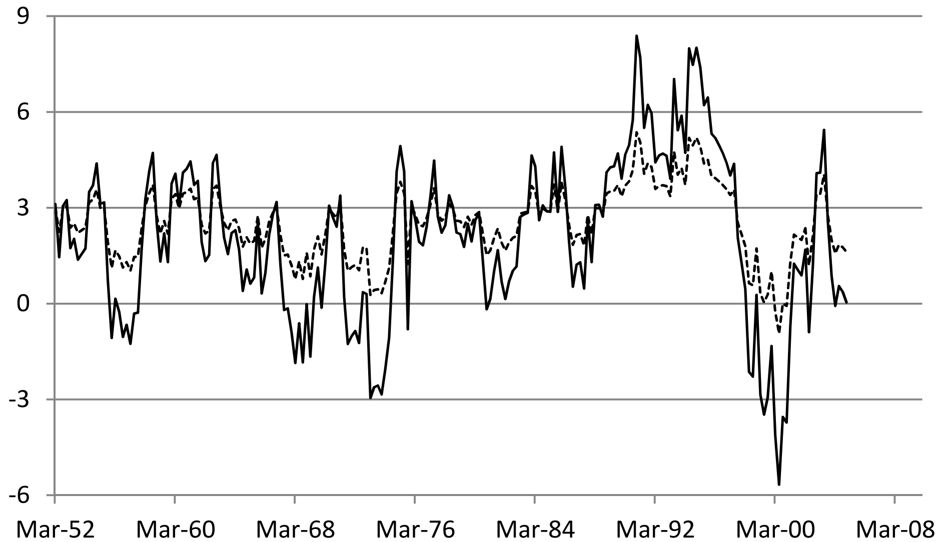
Therefore, if we run a regression of stock returns on conditional market variance and CAY, the coefficients on CAY is proportional to loadings the hedging risk factor. Therefore, CAY should have explanatory power for the cross-section of stock returns similar to that of $Var_t(R_{F,t+1})$.

Figure 1 Realized Stock Market Variance and State Variables



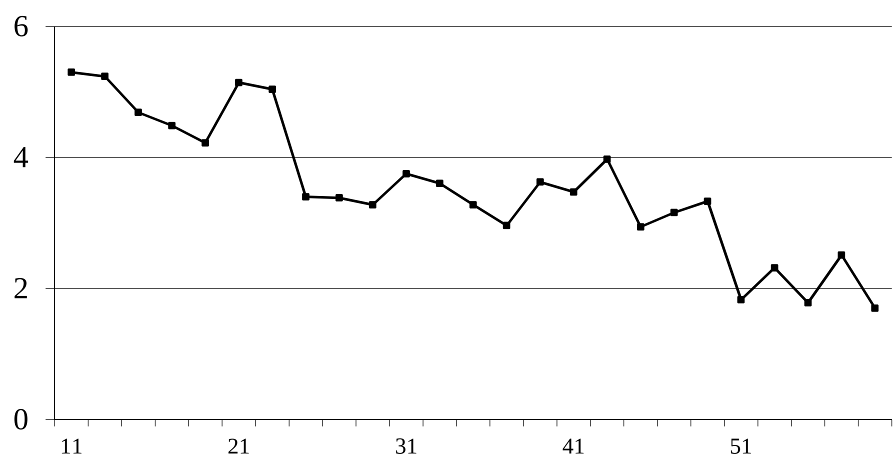
Note: MV is realized stock market variance; CAY is the consumption-wealth ratio; DEF is the yield spread between Baa- and Aaa-rated corporate bonds; DY is the ratio of the dividend in the previous twelve months to the end-of-period stock price for S&P 500 stocks; RREL is the difference between the short-term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

Figure 2 Estimates of RRA as a Linear Function of CAY



Note: The solid line plots the estimate of the coefficient $\gamma(X_t)$ in the one-factor CAPM, $r_{M,t+1} = \alpha + (\gamma_0 + \gamma X_t)\sigma^2_{M,t} + \varepsilon_{t+1}$, and the dashed line is for the two-factor ICAPM, $r_{M,t+1} = \alpha + (\gamma_0 + \gamma X_t)\sigma^2_{M,t} + \lambda X_t + \varepsilon_{t+1}$. The data span the 1951:Q4 to 2004:Q4 period.

Figure 3 Loadings on Realized Stock Market Variance

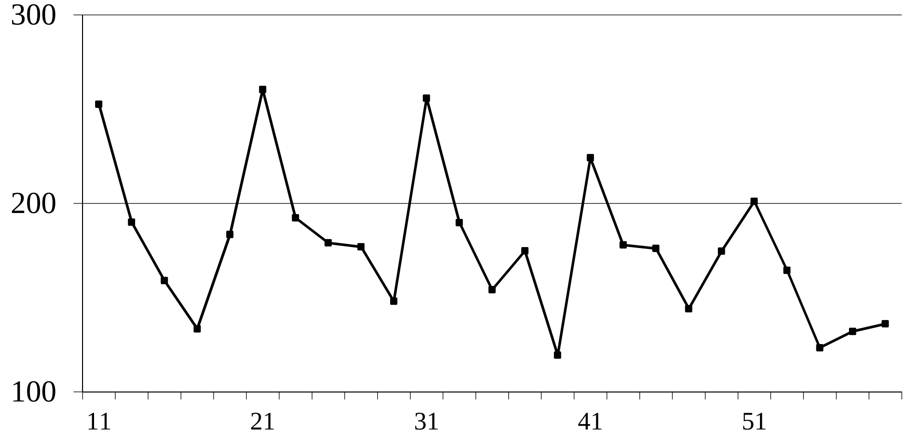


Note: The line plots the coefficient estimate γ_{p0} obtained from the forecasting regression:

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

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 the book-to-market equity ratio, with 1 denoting the lowest and 5 the highest book-to-market equity ratio.

Figure 4 Loadings on Realized Stock Market Variance Scaled by CAY

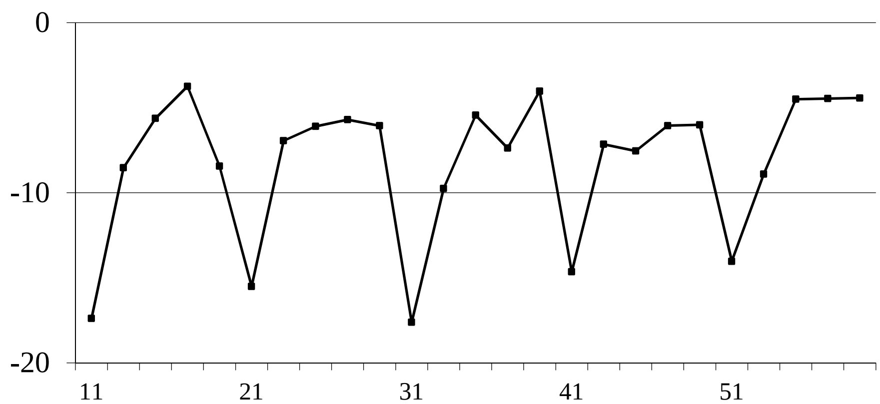


Note: The line plots the coefficient estimate γ_p obtained from the forecasting regression:

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

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 the book-to-market equity ratio, with 1 denoting the lowest and 5 the highest book-to-market equity ratio.

Figure 5 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 the book-to-market equity ratio, with 1 denoting the lowest and 5 the highest book-to-market equity ratio.

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 previous twelve months 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	$\bar{R}^2$ (%)
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)	

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; 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 previous twelve months 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 1953:Q3 to 2004:Q4 period for TERM and the 1952:Q1 to 2004:Q4 period for all the other variables.

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

	γ_0	γ							OIR	$\bar{R}^2$ (%)
		BCI	MV	CAY	DEF	DY	RREL	TERM		
1	0.634	5.959**							17.801	2.1
	(0.487)	(2.349)							(0.007)	
2	-14.378**		6.458**a						13.512	-0.2
	(-2.049)		(2.186)						(0.036)	
3	2.041**			1.897***a					8.109	7.9
	(2.013)			(4.388)					(0.230)	
4	-1.504				3.486				19.755	2.4
	(-0.503)				(1.513)				(0.003)	
5	-3.083					1.648***			17.093	4.2
	(-1.340)					(2.761)			(0.009)	
6	2.288*						-1.466*b		18.579	0.5
	(1.952)						(-1.708)		(0.005)	
7	-1.379							2.283***	13.232	1.2
	(-0.866)							(2.903)	(0.039)	
8	0.982	2.415	-93.220	1.355***a	0.528	0.216	7.182a	0.973	9.776	5.7
	(0.208)	(1.128)	(-0.926)	(2.670)	(0.275)	(0.288)	(0.561)	(0.882)	(0.134)	

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

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

in which RRA is a linear function of a conditioning variable. For example, in the column under the name "BCI" we report the estimation results for the specification that RRA is a linear function of BCI. We include all the conditioning variables in the instrumental variable set. The heteroskedasticity-consistent t-statistics are reported in parentheses. ***, **, 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 previous twelve months 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 1953:Q3 to 2004:Q4 period for TERM and the 1952:Q1 to 2004:Q4 period for all the other variables.

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

	γ_0	γ							λ	OIR	$\bar{R}^2$ (%)
		BCI	MV	CAY	DEF	DY	RREL	TERM			
1	1.858	3.385							1.584***	4.403	8.4
	(1.507)	(1.365)							(4.226)	(0.493)	
2	-4.490		2.782a						1.492***	3.813	5.7
	(-0.713)		(1.121)						(3.673)	(0.577)	
3	2.515**			0.852a					1.168**	3.812	8.8
	(2.490)			(1.438)					(2.263)	(0.577)	
4	0.769				1.781				1.647***	5.177	8.9
	(0.269)				(0.804)				(4.458)	(0.395)	
5	-0.846					1.070*			1.557***	3.196	9.6
	(-0.363)					(1.766)			(4.200)	(0.670)	
6	2.813***						-9.573a		1.621***	4.453	7.6
	(2.621)						(-1.161)		(4.395)	(0.486)	
7	0.959							1.134	1.432***	3.739	7.5
	(0.613)							(1.410)	(3.528)	(0.588)	
8	-1.216	1.657	-23.068	19.526	1.105	0.490	4.634a	0.686	1.237**	4.795	7.4
	(-0.254)	(0.771)	(-0.224)	(0.321)	(0.580)	(0.647)	(0.368)	(0.598)	(2.505)	(0.441)	

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 conditioning variable and the hedge component is a linear function of CAY. For example, in the column under the name "BCI" we report the estimation results for the specification that RRA is a linear function of BCI. We include all the conditioning 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 previous twelve months 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 1953:Q3 to 2004:Q4 period for TERM and the 1952:Q1 to 2004:Q4 period for all the other variables.

Table 5 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 significance 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 1951:Q4 to 2004:Q4 period and V_HML is available over the 1963:Q3 to 2004:Q4 period.

Table 6 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.

Table 7: Forecasting One-Year-ahead Consumption Growth

	NONSHAREHOLDER	SHAREHOLDER	TOP-SHAREHOLDER	Adjusted R^2
		Panel A Consumption-Wealth Ratio (CAY)		
1	-0.302			-0.026
	(0.351)			
2		0.437		-0.028
		(0.538)		
3			3.163***	0.089
			(1.122)	
		Panel B Dividend Yield (DY)		
4	-0.018			0.022
	(0.012)			
5		0.017		-0.018
		(0.019)		
6			0.072	0.020
			(0.055)	

Note: The table reports the OLS estimation results of forecasting consumption growth over the 1983 to 2003 period. NONSHAREHOLDER is the consumption growth of nonshareholders; SHAREHOLDER is the consumption growth of all shareholders; and TOP-SHAREHOLDER is the consumption growth of top third shareholders with largest stock holdings. We obtain the consumption data from Malloy, Moskowitz, and Vissing-Jorgensen (2009). We use the consumption-wealth ratio as the predictive variable in panel A and use the dividend yield in panel B. Heteroskedasticity-consistent standard errors are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.