Cho, Sungjun

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Sungjun Cho

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Manchester Business School

Manchester Business School
The University of Manchester
Booth Street West
Manchester M15 6PB

+44(0)161 306 1320
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Author(s) and affiliation

Dr. Sungjun Cho
Manchester Business School
Booth Street West
Manchester M15 6PB
Fax: +44 161-275-4023
E-Mail: Sungjun.Cho@mbs.ac.uk

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What Drives Stochastic Risk Aversion *

Sungjun Cho†

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JEL Classification: G12

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†**Correspondence Information:** Sungjun Cho is with Manchester Business School, Crawford House, University of Manchester, Oxford Road, Manchester M13 9PL, UK. Tel.:+44(0)161 306 3483;fax:+44(0)161 275 4023;*Email address*: sungjun.cho@mbs.ac.uk

1. Introduction

Investors demand compensation for holding assets with uncertain payoffs. The degree of risk aversion determines the amount of this compensation(risk premium). Since time-varying risk premiums in financial markets are a stylized fact, time-varying risk aversion is equally emphasized in asset pricing literature. Notably, the external habit formation model of Campbell and Cochrane (1999) uses the surplus consumption ratio to proxy for time-varying risk aversion, and their model successfully matches the historical equity premium. Furthermore, Wachter (2006) and Verdelhan (2006) extend the Campbell and Cochrane (1999) model to the bond market and the foreign exchange market, respectively, to explain the expectation hypotheses puzzle. The relationship between the stock and the bond markets has also been modeled with a latent time-varying risk aversion process in Bekaert, Engstrom, and Grenadier (2006).

While time-varying risk aversion is proxied by the surplus consumption ratio in consumption asset pricing literature, most of the empirical asset pricing studies in finance use financial market variables as instruments for time-varying risk aversion. Although these studies often motivate their specifications of time-varying risk aversion using the external habit specification of Campbell and Cochrane (1999), it seems rather arbitrary to choose proxies of risk aversion in an attempt to improve pricing performances of their models without specification tests;the surplus consumption ratio(Duffee (2005)), the consumption wealth ratio(Lettau and Ludvigson (2001b)),the dividend price ratio(Duffee (2005) and(Ferson and Harvey (1999)), the yield spread(Brennan, Wang, and Xia (2004) and(Ferson and Harvey (1999)),the default spread(Jagannathan and Wang (1996) and(Ferson and Harvey (1999)), the inflation rate(Brandt and Wang (2003)), the real GDP growth(Hodrick and Zhang (2001)), the stochastically detrended short term interest rate(Ferson and Harvey (1999))

The first goal of this paper is to develop time series specification tests of time-varying risk aversion under the generalized versions of conditional asset pricing framework, which allow several nonlinear features, heteroskedasticity, and misspecification. By applying nonlinear state-space models with heteroskedasticity, I examine whether empirically proposed variables in previous studies are indeed significant determinants of time-varying risk aversion and compare them with the surplus consumption ratio. To check this hypothesis empirically, I construct the surplus consumption ratio data following Duffee (2005) and Wachter (2006). Since many empirical asset pricing models seem to motivate time-varying risk aversion with the surplus consumption ratio, it would be illuminating to investigate how previously proposed financial variables sustain their explanatory powers on risk aversion once I include the surplus consumption ratio along with those variables.

Recently, in a closely related paper to the present study, Guo, Wang, and Yang (2006) use semi-parametric techniques to investigate time-varying risk aversion hypothesis. They find that risk aversion is constant once they include CAY of Lettau and Ludvigson (2001a) as a proxy for hedging components in the ICAPM. In fact, the same variables used in the conditional CAPMs with time-varying risk aversion are often selected as proxy variables for hedging components in the ICAPMs. Campbell (1996), Brennan, Wang, and Xia (2004), and Petkova (2006) build the models based on Merton (1973), in which only the factors that forecast future investment opportunities or stock returns are admitted. These studies propose the same proxy variables for time-varying risk aversion as the ICAPM factors. Without appropriate treatment of this ICAPM intuition,i.e., the hedging components, time-varying risk aversion might be a spurious fact indicated as in Guo, Wang, and Yang (2006). To check this possibility, I use conditional ICAPMs based on Campbell (1996).

In summary, I present testing grounds to investigate determinants of relative risk aversion. Specifically, I develop econometric models which allow both the positivity of risk aversion and the conditional heteroskedasticity. I also estimate several volatility models and risk aversion specifications using both full sample and sub sample periods to check the robustness of my results. Finally, I examine how selected conditional models can explain the cross-section of the Fama-French 25 size and B/M sorted portfolios alone or with 30 industry portfolios.[1]

My empirical findings from both time series and cross-sectional investigations unequivocally suggest that time-varying relative risk aversion is important for explaining the risk-return relation in the stock market. I find, among other things, that only consumption related variables are significant determinants for relative risk aversion while other return forecasting variables frequently suggested in finance literature lose their statistical significance once I include those variables along with the surplus consumption ratio. Even though the consumption CAPM

[1]Lewellen, Nagel, and Shanken (2006) criticizes most of the cross-sectional asset pricing studies for the choice of the Fama-French 25 portfolios.(Possible Data Snooping problem) Especially, they show that many empirical asset pricing models could price only the Fama-French 25 portfolios(R^2 is above 75 %) but not the 55 portfolios including 30 industry portfolios.(R^2 is typically below 10%) Therefore I check the robustness of the proposed CAPMs and ICAPMs for the value premium and for the capability to explain the industry portfolios.

might not be useful to understand stock return behavior, I argue that we must include these consumption variables in conditioning information sets. These results are quite robust across six different time-series model specifications and the two cross-sectional tests.

I summarize the main findings as follows. First, I uncover that the surplus consumption ratio has the most explanatory power,along with correct negative sign, for time-varying relative risk aversion. Typically low surplus consumption ratio is interpreted as the indicator of recession. Negative estimates imply that during the bad times, investors' sensitivity to risk increases since those are the time when investors' marginal utility is the highest and they are eager to increase their consumption and avoid the risky investment.

Secondly, I construct the consumption wealth ratio without a look-ahead bias(CAYA) to re-evaluate its significance on time-varying relative risk aversion and hedging components. While Lettau and Ludvigson (2001b) suggest that consumption wealth ratio(CAY) is a crucial variable for time-varying risk aversion, several papers have questioned the usefulness of CAY because they use the full sample data to construct CAY and that information is not available when investors try to use it. In spite of the criticisms on CAY, I find that the consumption wealth ratio without a look-ahead bias still captures part of time-varying relative risk aversion. My results support empirical specifications of Lettau and Ludvigson (2001b) while they do not support the interpretation of Guo and Whitelaw (2006) that CAY mostly explains the hedging component.

Thirdly, the stochastically detrended short term interest rate(RREL) has some explanatory power on hedging components. This result confirms the suggestion of Merton (1973) that the interest rate should be the main determinant of hedging components. However, other possible candidates such as the dividend price ratio, the default spread, the inflation and the real GDP growth do not have any incremental impact on either components while some of the variables are critical to explaining the volatility of stock returns. Even though some of the variables are capable of explaining one of the components alone, they lose statistical significance in the presence of the surplus consumption ratio, CAYA, or RREL.

Finally, I compare the proposed CAPMs and ICAPMs from the time series tests with the Fama-French three factor model on the ability to explain the cross-section of the average returns. I find that the selected conditional ICAPMs with both time-varying relative risk aversion and hedging components are not only comparable to Fama-French three factor model in explaining the value premium but also satisfy the robustness criteria of Lewellen, Nagel, and Shanken (2006) since they have a higher explanatory power for the 55 portfolios.

The rest of the paper is organized as follows. Section 2 presents the ICAPM framework of this study and outlines the empirical methods used to identify time-varying risk aversion and hedging components. Section 3 first presents the data and examines the time series specification test results of the conditional CAPM and ICAPM and then discusses the cross-sectional implications of selected empirical models for 25 size and B/M portfolios alone or with 30 industry portfolios. Section 4 summarizes the main findings and concludes.

2. Models

2.1 The general ICAPM framework

The analysis in this paper assumes that asset returns are governed by a variant of pricing kernels motivated by Merton (1973). I use two different risk aversion specifications to show robustness of my results. The first risk aversion specification (2) is consistent with typical empirical approaches in conditional CAPM literature. And the second specification (3) is more consistent with Campbell and Cochrane (1999), which will be presented in the next section. Notably, this second specification guarantees positive risk aversion.

$$r_{m,t+1} = \alpha_0 + \gamma_{t+1} v_t(r_{m,t+1}) + \alpha_1' z_t + \varepsilon_{t+1} \tag{1}$$

$$\gamma_{t+1} = \phi_0 + \phi_1 \gamma_t + \phi_2' x_t + \nu_{t+1} \tag{2}$$

$$\log \gamma_{t+1} = \phi_0 + \phi_1 \log \gamma_t + \phi_2' x_t + \nu_{t+1} \tag{3}$$

where $\varepsilon_{t+1|t} \sim N(0, v_t(r_{m,t+1}))$, $\nu_{\mathrm{t+1}} \sim N(0, \sigma_v^2)$, $r_{m,t+1}$ is the market excess return($R_{m,t+1} - R_{f,t+1}$) and $v_t(r_{m,t+1})$ is the conditional variance of the market excess return given information up to time t, for which I will use either GARCH or realized volatility as a proxy. γ_{t+1} stands for relative risk aversion and z_t and x_t are state variables for hedging components and risk aversion respectively.[2]

[2] There is no theoretical reason to have a lagged term in risk aversion specification. However, if the candidate model does not capture persistent risk aversion appropriately, ϕ_1 in (3) would not be zero. Empirical results in this paper show that ϕ_1 becomes statistically insignificant for the selected models from time series specification tests.

2.1.1 A discrete-time ICAPM

A discrete-time version of Merton ICAPM can be derived as follows.[3]

$$E_t\left[R_{i,t+1}\right] - R^f_{t+1} = \gamma_t \mathrm{cov}_t\left(R_{i,t+1}, \Delta W_{t+1}/W_t\right) + \lambda_{z,t}\mathrm{cov}_t\left(R_{i,t+1}, \Delta z_{t+1}\right) \tag{4}$$

The growth in wealth($\Delta W_{t+1}/W_t$) is approximated by the stock market portfolio return($R_{m,t}$) as usual, and by the same reasoning, the changes in the hedging factors can be approximated by the returns on the corresponding factor-mimicking portfolios. Since equation (4) must hold for any asset, the conditional excess market return($E_t\left[R_{m,t+1}\right] - R^f_{t+1}$) can be written as a function of its conditional variance ($\mathrm{var}_t\left(R_{m,t+1}\right)$) and its covariance with changes in state variables.

$$E_t\left[R_{m,t+1}\right] - R^f_{t+1} = \gamma_t \mathrm{var}_t\left(R_{m,t+1}\right) + \lambda_{z,t}\mathrm{cov}_t\left(R_{m,t+1}, \Delta z_{t+1}\right) \tag{5}$$

Under certain conditions, Merton (1980) argues that hedging component is negligible and the conditional excess market return is proportional to its conditional variance. This form is interpreted as the conditional CAPM because every result of the CAPM is preserved.

$$E_t\left[R_{m,t+1}\right] - R^f_{t+1} = \gamma_t \mathrm{var}_t\left(R_{m,t+1}\right) \tag{6}$$

In its most general form, all of the terms in (5) of the ICAPM could be time-varying. In this paper, however, I only assume that the coefficient of relative risk aversion is time-varying but hedging coefficients($\lambda_{z,t}$) are constant since the present study mainly focuses on the source of time-varying relative risk aversion and the current literature mainly use this fact to explain various empirical puzzles in finance. To my knowledge, none of the papers have estimated the full version of the conditional ICAPM and CAPM with time-varying risk aversion except for Guo, Wang, and Yang (2006). Recent empirical asset pricing studies such as Scruggs (1998) and Scruggs and Glabadanidis (2003) use a version of (5) and elaborate only hedging components with multivariate GARCH-M model with constant risk aversion. However, they find that extension to that direction could be problematic for explaining the risk-return trade off in asset markets.

To model hedging components, I follow the approach taken by Guo and Whitelaw (2006).

[3] A sketch of the derivation is given in the chapter 9 of Cochrane (2001). More detailed derivation is available upon request.

Their ICAPM is convenient since they specify hedging components as linear function of exogenous variables using Campbell (1996)'s ICAPM. This simplification can avoid the complex joint estimation of multivariate GARCH models and nonlinear state-space models.[4] Therefore, hedging components in my empirical models are specified as follows.

$$\mathrm{cov}_t(R_{m,t+1}, \Delta z_{t+1}) = \alpha_0 + \alpha_1' z_t \tag{7}$$

2.1.2 The source of time-varying relative risk aversion(RRA)

In various asset pricing papers, the external habit model proposed by Campbell and Cochrane (1999) is often credited to the rational interpretation of the source of time-varying relative risk aversion. For example, Lettau and Ludvigson (2001b) motivate their conditional CAPM with this specification and suggest to use the consumption wealth ratio(CAY) as a proxy to capture the changing information set. In their model, investors' preferences exhibit an external habit formation and this habit feature generates the time-varying RRA. The implied pricing kernel is denoted as

$$M_{t+1} = \beta(\frac{C_{t+1}}{C_t}\frac{S_{t+1}}{S_t})^{-\gamma} \tag{8}$$

where β is the subjective discount factor;the surplus consumption ratio(S_t) is defined as $S_t = \frac{C_t - H_t}{C_t}$; C_t stands for the aggregate consumption; H_t represents the habit level of the representative investor. And the relative risk aversion(γ_t) is expressed as the following.

$$\gamma_t = \frac{\gamma}{S_t}\frac{\partial \ln(C_t))}{\partial \ln(W_t)} \tag{9}$$

In log forms,

$$\log \gamma_t = \log \gamma - \log S_t + \log \theta_t \tag{10}$$

where θ_t denotes the elasticity of consumption to wealth. In this paper, I assumes θ_t as a constant since it is a constant in Merton's model and I suspect that it would be not too variable at the quarterly frequency. Based on these observations, I use (3) as a relative risk aversion specification.

[4]Brief summary is available upon request about how Campbell's ICAPM motivate this alternative specification with hedging components as a linear function of a vector of state variables z_t.

Usually, an ad-hoc approach is used to identify time-varying relative risk aversion by projecting it into various instruments. But this approach is valid only if the econometrician knows the full set of state variables available to investors. While conditional models are attractive to capture time-varying risk premiums, they can be misspecified with the wrong conditioning variables. Ghysels (1998) finds that conditional models are fragile and may have bigger pricing errors than unconditional models. To accommodate this possibility, I allow possible misspecification of risk aversion with an error term as specified in (2) and (3) and examine whether empirically proposed variables in previous studies are indeed significant determinants of time-varying RRA, in comparison with the surplus consumption ratio.

As an empirical proxy of risk aversion, I first construct the direct measure of the surplus consumption ratio following Duffee (2005) and Wachter (2006). Usually, empirical studies(for example, Ferson and Harvey (1999)) incorporate return forecasting variables as proxies for modeling time-varying risk aversion. Since this specification is purely empirical, it would be interesting to check which variables would be the primary source of time-varying RRA under one common empirical framework. I also use several other candidates (x_t) for time-varying risk aversion; the consumption wealth ratio(Lettau and Ludvigson (2001b)),the dividend price ratio(Duffee (2005) and(Ferson and Harvey (1999)), the yield spread(Brennan, Wang, and Xia (2004) and(Ferson and Harvey (1999)),the default spread(Jagannathan and Wang (1996) and(Ferson and Harvey (1999)), the inflation rate(Brandt and Wang (2003)), the real GDP growth(Hodrick and Zhang (2001)), the stochastically detrended short term interest rate(Ferson and Harvey (1999)).

Finally, the correct specification of hedging component is crucial for estimating relative risk aversion correctly. Guo, Wang, and Yang (2006) argue that after including CAY into hedging components, they can not reject constant relative risk aversion hypothesis. To check this possibility, I include all the instruments for relative risk aversion as candidates of the proxies for hedging components. I follow the ICAPM specification of Hodrick and Zhang (2001),Guo and Whitelaw (2006) and Guo, Wang, and Yang (2006) and use contemporaneous values of the predictive variables rather than their innovations. In particular, Merton (1973) suggests that "one should interpret the effects of a changing interest rate.. in the way economists have generally done in the past: namely, as a single variable representation of shifts in the investment opportunity set." Therefore, interest rate variables such as short-term interest rate or yield spread would be natural instruments for hedging components.

2.1.3 *Proxies for the conditional variance*

We need also a proxy for $v_t(r_{m,t+1})$ to implement these empirical models. Usually, simple versions of the models are estimated by univariate or multivariate GARCH-in-mean models at weekly or monthly horizon.(see Scruggs and Glabadanidis (2003) and references therein) GARCH models at quarterly horizon are not rare either.(Duffee (2005)) However,at quarterly horizon, it is known that GARCH models might not capture conditional heteroskedasticity precisely since GARCH effects typically vanishes at that horizon.[5] In this case, it would be difficult to get correct estimates of relative risk aversion and hedging components. In fact, several GARCH-in-mean studies using monthly return series even find negative relative risk aversion. Harvey (2001) argues that incorrect specification of volatility could be one of the main causes behind this phenomenon. Recently Andersen and Bollerslev (1998) show that the use of high frequency data should give us a better and less noisy measure of volatility. This "realized volatility" approach has since become very popular for modeling volatility. While it is not clear how microstructure noises in high frequency asset market data affect the estimates of realized volatility, quarterly frequency used in this paper could provide a reasonable balance between efficiency and robustness of constructed realized volatility to microstructure noise.[6]

Given the insights from the aforementioned studies, I propose both GARCH and "realized volatility" approach as a proxy for $v_t(r_{m,t+1})$. Specifically, I use the log volatility model since the logarithms of realized volatility series confirms to normality assumption better than the level of realized volatility does.

$$v_t(r_{m,t+1}) = \exp(E_t(\ln \hat{\sigma}_{m,t+1}) + \frac{1}{2}\sigma_\eta^2), \ln \hat{\sigma}_{m,t+1} = \delta_0 + \delta_1 \ln \hat{\sigma}_{m,t} + \delta_2' u_t + \eta_{t+1} \qquad (11)$$

where $\eta_{\mathrm{t+1}} \sim N(0, \sigma_\eta^2)$ and $\hat{\sigma}_{m,t}$ is the measure of realized volatility defined in the appendix. Guo and Whitelaw (2006) argue that certain return forecasting variables might just explain time-varying heteroskedasticity(realized volatility) but not hedging components. By including possible variables for hedging components in realized volatility equation, they argue that they can obtain the better hedging components.[7] Similar criticism can be applied to the models

[5] This fact is confirmed in Table 3. In most of the case, persistence parameter is below 0.6 and estimated parameters are marginally significant.

[6] See Andersen, Bollerslev, Diebold, and Wu (2005) and Guo and Whitelaw (2006) and references therein for other recent applications of quarterly realized volatility in the asset pricing literature.

[7] In actual implementation, they just include RREL and CAY without specification tests on either realized volatility or hedging components.

of time-varying risk aversion. Therefore I project realized volatility on several variables(u_t) and extract all the (linear)information about future realized volatility contained by them. The residual predictive power that these variables have for expected returns should be due either to risk aversion or to hedge components.

2.2 Baseline empirical models

The first empirical model uses the realized volatility and I denote it as case 1 or case 2.

$$r_{m,t+1} = \gamma_{t+1} \exp(E_t(\ln \hat{\sigma}_{m,t+1}) + \frac{1}{2}\sigma_\eta^2) + \varepsilon_{t+1} \tag{12}$$

$$\ln \hat{\sigma}_{m,t+1} = \delta_0 + \delta_1 \ln \hat{\sigma}_{m,t} + \delta_2' u_t + \eta_{t+1} \tag{13}$$

$$f(\gamma_{t+1}) = \phi_0 + \phi_1 f(\gamma_t) + \phi_2' x_t + \nu_{t+1} \tag{14}$$

where $\varepsilon_{t+1|t} \sim N(0, E_t(\hat{\sigma}_{m,t+1}))$, $v_{t+1} \sim N(0, \sigma_v^2)$,$\eta_{t+1} \sim N(0, \sigma_\eta^2)$, $f(\gamma_{t+1}) = \gamma_{t+1}$(case 1) or $\log(\gamma_{t+1})$(case 2).

While the realized volatility approach would be preferable, I also estimate models based on GARCH to check the robustness of the results. Case 3 and 4 use a hybrid of realized volatility-in-mean and GARCH in error terms. Although both terms should be same in theory, this model will clarify in which dimension GARCH might be problematic to explain the data. I replace the variance in (12) with GARCH; $\varepsilon_{t+1|t} \sim N(0, h_{t+1})$,$h_{t+1} = \omega + \beta_1 h_t + \beta_2 \varepsilon_t^2$,$f(\gamma_{t+1}) = \gamma_{t+1}$(case 3) or $\log \gamma_{t+1}$(case 4).

Finally, I estimate the standard GARCH-in-mean type models.

$$r_{m,t+1} = \gamma_{t+1} h_{t+1} + \varepsilon_{t+1} \tag{15}$$

where $\varepsilon_{t+1|t} \sim N(0, h_{t+1})$, $h_{t+1} = \omega + \beta_1 h_t + \beta_2 \varepsilon_t^2$, $f(\gamma_{t+1}) = \gamma_{t+1}$(case 5) or $\log \gamma_{t+1}$(case 6).

In summary, my empirical models are characterized as the state-space formulation. I just present an estimation method for the most complex model(case 4).

$$\text{Measurement equation: } r_{m,t+1} = \alpha_0 + exp(\log \gamma_{t+1}) \exp(E_t(\ln \hat{\sigma}_{m,t+1}) + \frac{1}{2}\sigma_\eta^2) + \alpha_1' z_t + \varepsilon_{t+1},$$

$$\text{Transition equation: } \log \gamma_{t+1} = \phi_0 + \phi_1 \log \gamma_t + \phi_2' x_t + \nu_{t+1}$$

where $r_{m,t+1}$ is the market excess return($R_{m,t+1} - R_{f,t+1}$) and $E_t(\ln \hat{\sigma}_{m,t+1})$ is expectation of realized variance of the market excess return given information up to time t.($VAR_t[R_{m,t+1}]$), $\varepsilon_{t+1} \sim N(0, h_{t+1})$, h_{t+1} stands for the GARCH. x_t and z_t are lagged exogenous variables.

The estimation of this model is cumbersome since I have both nonlinear measurement equation and GARCH type heteroskedasticity. Furthermore, I need to address the generated regressors problem if I jointly maximize this state-space model and the realized volatility equation (11). Following Kim and Nelson (2005), I combine the approximation method of Harvey, Ruiz, and Sentana (1992) with extended Kalman filtering technique to develop a filtering method and to construct the likelihood function. For the easier exposition, I first explain the estimation methods in case where the generated regressor problem does not exist. So, I assume $\exp(E_t(\ln \hat{\sigma}_{m,t+1}) + \frac{1}{2}\sigma_\eta^2)$ is given and denote it as $\sigma_{m,t+1}$. Finally, I describe the joint maximum likelihood estimation techniques developed to solve generated regressor problem based on Pagan (1984). Specifically, I first explain how to approximate nonlinear measurement equation with extended Kalman filtering technique, which is a Taylor expansion of latent variables($\log \gamma_{t+1}$) around previous state variable estimates$\big(\log \gamma_{t+1|t}\big)$. And I apply the state-space model with ARCH disturbances proposed by Harvey, Ruiz, and Sentana (1992) to my nonlinear model.

First, I use extended Kalman filtering technique to linearize measurement equation. I take a Taylor series expansion of the nonlinear function($\exp(\log \gamma_{t+1})\sigma_{m,t+1}$) around $\log \gamma_{t+1} = \log \gamma_{t+1|t}$. In this expression, $\log \gamma_{t+1|t}$ indicates $E[\log \gamma_{t+1}|\Psi_t]$ where Ψ_t denotes the information set available up to time t. After linearization and by redefining some of variables, I get the following measurement equation:

$$Y_{t+1} = \hat{X}_{t+1} \log \gamma_{t+1} + \alpha_1' z_t + \varepsilon_{t+1} \tag{16}$$

where $Y_{t+1} = r_{m,t+1} - \exp(\log \gamma_{t+1|t})\sigma_{m,t+1} + \exp(\log \gamma_{t+1|t})\sigma_{m,t+1} \log \gamma_{t+1|t}$, $\hat{X}_{t+1} = \exp(\log \gamma_{t+1|t})\sigma_{m,t+1}$.

Without heteroskedasticity, I could use the usual Kalman filtering to conduct a maximum likelihood estimation. However, I must address how to estimate GARCH specification. I include ε_{t+1} in transition equation following Harvey, Ruiz, and Sentana (1992).[8] In matrix

[8]See chapter 3,5,and 6 of Kim and Nelson (1999) for the more detail explanation.

forms, the specified state space models can be written as the following compact forms.

$$\begin{aligned} Y_{t+1} &= \tilde{X}_{t+1}\tilde{\beta}_{t+1} + \alpha_1' z_t \\ \tilde{\beta}_{t+1} &= \mu_t + F\tilde{\beta}_t + \tilde{v}_{t+1}, \tilde{v}_{t+1} \sim N(0, \tilde{Q}_{t+1}) \end{aligned}$$

where $\tilde{X}_{t+1} = \left[\hat{X}_{t+1}, 1\right], \tilde{\beta}_{t+1} = \begin{bmatrix} \log\gamma_{t+1} \\ \varepsilon_{t+1} \end{bmatrix}$, $\mu_t = \begin{bmatrix} \phi_0 + \phi_2' x_t \\ 0 \end{bmatrix}$, $F = \begin{bmatrix} \phi_1 & 0 \\ 0 & 0 \end{bmatrix}$, $\tilde{v}_{t+1} = \begin{bmatrix} \nu_{t+1} \\ \varepsilon_{t+1} \end{bmatrix}$ and $\tilde{Q}_{t+1} = \begin{pmatrix} \sigma_\nu^2 & 0 \\ 0 & h_{t+1} \end{pmatrix}$. At each iteration of the Kalman filter, I obtain a linear approximation of the model around $\log\gamma_{t+1} = \log\gamma_{t+1|t}$,and calculate Y_{t+1} and $\tilde{X}_{t+1}$ for the following Kalman filter.

$$\begin{aligned} &\tilde{\beta}_{t+1|t} = F\tilde{\beta}_{t|t} + \mu_t, p_{t+1|t} = Fp_{t|t}F' + \tilde{Q}_{t+1} \\ &l_{t+1|t} = Y_{t+1} - \tilde{X}_{t+1}'\beta_{t+1|t} - \alpha_1' z_t, H_{t+1|t} = \tilde{X}_{t+1}' p_{t+1|t}\tilde{X}_{t+1} \\ &\tilde{\beta}_{t+1|t+1} = \tilde{\beta}_{t+1|t} + p_{t+1|t}\tilde{X}_{t+1}H_{t+1|t}^{-1} l_{t+1|t}, p_{t+1|t+1} = p_{t+1|t} - p_{t+1|t}\tilde{X}_{t+1}H_{t+1|t}^{-1}\tilde{X}_{t+1}p_{t+1|t} \end{aligned} \tag{17}$$

where Ψ_t is the information set up to time t, $\tilde{\beta}_{t+1|t}$ is conditional estimate of $\tilde{\beta}_{t+1}$ on information up to t($E[\tilde{\beta}_{t+1}|\Psi_t]$), $\tilde{\beta}_{t+1|t+1}$ is conditional estimate of $\tilde{\beta}_{t+1}$ on information up to t+1 ($E[\tilde{\beta}_{t+1}|\Psi_{t+1}]$), $p_{t+1|t}$ is covariance matrix of $\tilde{\beta}_{t+1}$ conditional on information up to t($E[(\tilde{\beta}_{t+1} - \tilde{\beta}_{t+1|t})(\tilde{\beta}_{t+1} - \tilde{\beta}_{t+1|t})']$), $p_{t+1|t+1}$ is covariance matrix of $\tilde{\beta}_{t+1}$ conditional on information up to t+1($E[(\tilde{\beta}_{t+1} - \tilde{\beta}_{t+1|t+1})(\tilde{\beta}_{t+1} - \tilde{\beta}_{t+1|t+1})']$) and $H_{t+1|t}$ is conditional variance of prediction error.($E[l_{t+1|t}^2]$) To process the above Kalman filter, I need ε_t^2 term to calculate GARCH(h_{t+1}) in $\tilde{Q}_{t+1}$ matrix. As in Harvey, Ruiz, and Sentana (1992), the term ε_t^2 is approximated by $E[\varepsilon_t^2|\Psi_t]$, where Ψ_t is information up to time t. To get the form of $E[\varepsilon_t^2|\Psi_t]$,

$$E[\varepsilon_t^2|\Psi_t] = E[\varepsilon_t|\Psi_t]^2 + E\left[(\varepsilon_t - E[\varepsilon_t|\Psi_t])^2\right] \tag{18}$$

where $E\left[\varepsilon_t|\Psi_t\right]$ is obtained from the last element of $\tilde{\beta}_{t|t}$ and its mean squared error $E\left[(\varepsilon_t - E\left[\varepsilon_t|\Psi_t\right])^2\right]$ is given by the last diagonal element of $p_{t|t}$. As by-products of the above Kalman filter, I obtain the prediction error $\eta_{t+1|t}$ and its variance $H_{t+1|t}$. Based on this prediction error decomposition, the approximate log likelihood can easily be calculated as

$$\ln L(Y_{t+1}|\sigma_{m,t+1}) = -\frac{1}{2}\sum_{t=1}^{T}\ln((2\pi)|H_{t+1|t}|) - \frac{1}{2}\sum_{t=1}^{T} l_{t+1|t}' H_{t+1|t}^{-1} l_{t+1|t} \tag{19}$$

Finally, I explain how to estimate $E_t(\ln \hat{\sigma}_{m,t+1})$ and log likelihood function given in (19) jointly. While previously I assumed $E_t(\ln \hat{\sigma}_{m,t+1})$ as given, only a proxy is available. Therefore, I have a classical generated regressor problem. Without joint estimation, I would get biased standard errors, and all Kalman filter algorithm should be corrected because of endogeneity issue.[9] To avoid this bias, I use the following joint maximum log likelihood estimation based on Pagan (1984) and chapter 5 of Kim and Nelson (1999).

$$\ln L(Y_{t+1}, \sigma_{m,t+1}) = \ln L(Y_{t+1}|\sigma_{m,t+1}) + \ln L(\sigma_{m,t+1}) \tag{20}$$

where $\ln L(Y_{t+1}|\sigma_{m,t+1})$ is given in (19) and $\ln L(\sigma_{m,t+1})$ has the following form.

$$\ln L = -\frac{1}{2}\sum_{t=2}^{T} \ln(2\pi)|\sigma_\eta^2|) - \frac{1}{2}\sum_{t=2}^{T} (\eta_t)' \sigma_\eta^{-2}(\eta_t), \tag{21}$$

where $\eta_{t+1} = ln\hat{\sigma}_{m,t+1} - \delta_0 - \delta_1 ln\hat{\sigma}_{m,t} - \delta_2' u_t$. By plugging estimated $exp(E_t(ln\hat{\sigma}_{m,t}) + \frac{1}{2}\sigma_\eta^2)$ in (19), I jointly maximize the sum of log likelihood values of (19) and (21) with respect to all parameters.[10]

3. Data and Empirical Results

3.1 Data

In this study, I use quarterly data for the period 1957:1 to 2005:4. The beginning of the period is set to 1957:1 to get the surplus consumption ratio data(SURP). In addition to the surplus consumption ratio, I consider the following variables; the dividend price ratio on NYSE-AMEX-Nasdaq value-weighted stock return from CRSP(DP); the default premium(DEF), defined as the difference in yields between BAA and AAA corporate bonds; Lettau and Ludvigson (2001a)'s CAY without a look-ahead bias(CAYA); the difference between the risk-free rate and its average in the previous 4 quarters(RREL); the term premium, denoted as the yield spread between 10-year Treasury bonds and 3-month Treasury bills(TERM); the inflation, measured

[9] Refer to Kim (2006) for the details.

[10] I experiment with several starting values for each empirical model to ensure global convergence of the parameters. I use the GAUSS 7.0 and Optmum or CML procedure to numerically maximize the joint likelihood function with BFGS as a base optimization algorithm and utilize various numerical techniques such as transformation function techniques and penalty algorithms to limit the boundaries of parameters. I also apply parameter rescaling techniques for numerical stability to attain fast convergence.

by GDP deflator(INFLA); the real GDP growth with seasonal adjustment(REGD). Definitions and constructions of the data are provided in details in the appendix. Fig.1 plots these return predictors, with the shaded areas denoting business recessions dated by the National Bureau of Economic Research (NBER). All the variables except for REGD are quite persistent and exhibit strong cyclical patterns. While RREL, REGD,and SURP tend to decrease during business recessions, the other variables move countercyclically. The summary statistics presented in Table 1 also confirm these facts. Most of the variables are highly serially correlated, with the autocorrelation coefficients above 85 %. Fig.1 also presents the consumption wealth ratio(CAY) of Lettau and Ludvigson (2001a) along with the similar variable without a look-ahead bias(CAYA). Two variables have a similar time series pattern and their correlation is around 76 %.

In time series analysis, my stock return measure is the standard value-weighed return of NYSE-AMEX-NASDAQ index from CRSP. To compute excess equity returns, I subtract the lagged 3 month continuously compounded T-Bill yield earned over the same period. Consistent with quarterly data, I calculate the realized variance using the daily CRSP value-weighted stock returns and the pseudo daily risk-free rate by assuming that risk-free rate is constant within a quarter. The daily excess market return is calculated as the difference between the daily risk-free rate and the daily market return. Realized stock market variance (REVOL1) is defined as the variance of daily excess stock market returns in a quarter. To check the robustness of my results, I construct four different measures of realized variance series. For example, I replace the largest value in realized variance series with the second largest value following Guo and Whitelaw (2006)(REVOL2) and I use auto-correlation corrected measure of the realized variance following French, Schwert, and Stambaugh (1987).(REVOL1auto and REVOL2auto) Table 2 summarizes descriptive statistics for this four different versions of realized variance series. All series have similar sample statistics and their correlations are around 85%. Fig.2 plots 4 versions of realized variance along with the estimated GARCH(1,1) series. The figure shows that volatility moves countercyclically and also tends to increase dramatically during several crises such as the 1962 Cuban missile crisis, the 1987 stock market crash, the 1997 East Asia crisis, and the 1998 Russian bond default. Even though all four versions have similar sample characteristics, Fig.2 suggests that only REVOL2 and REVOL2auto have comparable magnitude with the estimated GARCH series. It seems reasonable since REVOL1 estimates the volatility of the current quarter with daily data in that quarter only which might get too extreme values in crash periods. REVOL2 removes the effects of this outlier.

In cross-sectional analysis, I use, as test assets, the returns on Fama-French 25 portfolios sorted by size and book-to-market and 30 industry portfolios. Even though the 25 portfolios have become the benchmark in testing competing asset pricing models, Lewellen, Nagel, and Shanken (2006) show that the 55 portfolios are the more appropriate to rigorously compare the models. All the portfolio returns and the Fama-French three-factors -the returns of the market portfolio(Rmrf), HML, and SMB are downloaded from French's website.

3.2 Empirical Results

3.2.1 Asset pricing models with time-varying RRA

In this section, I report estimation results for six different model specifications without hedging components. Previous studies assumed one or two variables could serve as the proxy for time-varying RRA without time-series specification tests. I fill this gap and develop direct tests to examine the determinants of RRA under a unified empirical framework and report the results. For models using realized variance, I report the estimation results only with one measure of realized variance(Revol1auto) since all other measures provide qualitatively similar results. All the exogenous variables are normalized to have mean of zero and standard deviation of one to facilitate the interpretations. Finally, instead of entertaining a "kitchen sink" regression, including all of the variables in the specification and searching for the correct form, I use an educated guess from theoretical arguments from Campbell and Cochrane (1999); I take "SURP" as the single crucial variable against which other variables are compared since the external habit formation specification addressed with this variable is the main theoretical motivation for conditional CAPMs.

First, I report estimation results for the realized-variance-in model(case 1 and 2). Since SURP, REGD and RREL in volatility equation($\ln \hat{\sigma}_{m,t+1}$) and α_0 and ϕ_1 are not statistically significant in the preliminary estimation, I re-estimate the model and report the results without these variables.[11] Table 3 presents parameter estimates in volatility equation across different cases. Since most of the estimates are qualitatively similar, I report one representative estimate for each case. In fact, all cases using realized volatility provide almost identical results. While past market volatility(δ_1),CAYA(δ_{21}),DEF(δ_{24}) and INFL(δ_{25}) have statisti-

[11] I re-estimate and report results in this way for all cases presented in this paper.

cally significant positive signs, DP(δ_{22}) and TERM(δ_{23}) have statistically significant negative signs. Panel A of Table 4 shows the results for case 1. After the estimating univariate specification for relative risk aversion, I re-estimate the same model with SURP and one of other possible candidates given from univariate specification tests to evaluate the importance of each conditioning variable. While SURP, CAYA,TERM and RREL are statistically significant in univariate specification tests, SURP drives out TERM and RREL in bivariate tests. Only CAYA retains statistical significance with positive sign. The implied risk aversion is countercyclical with positive coefficient of SURP and negative coefficient of CAYA since low surplus consumption ratio and high CAYA is typically interpreted as an indicator of recession or other bad states. Finally, Panel B of Table 4 reports the results with positivity restriction on relative risk aversion(case 2). Only SURP has a statistically significant negative coefficient.

Table 5 reports estimation results for the hybrid model with realized-volatility-in-mean and GARCH in error terms.(case 3 and 4) For realized volatility parameters, the results of the previous model are preserved such that the signs and magnitudes of coefficients are quite similar. For GARCH parameters, the estimated parameters are typically not persistent(0.55) and not statistically significant in all models using GARCH. These results confirm prior assertion that GARCH-in-mean models are probably not a good description of stock returns at quarterly horizon. For relative risk aversion specification, I find that consistent with Table 3, SURP(case 3 and 4) and CAYA(case 4) are statistically significant and have the same signs as before. All other variables do not survive the competition with SURP for relative risk aversion.

Finally, Table 6 shows the estimation results for case 5 and 6. The estimated signs and magnitudes of GARCH parameters precisely resemble those of previous cases. For relative risk specification, SURP(case 5 and 6) and RREL(case 5) are the two significant variables in this GARCH-in-mean specification. However, I don't further pursue RREL as a proxy for relative risk aversion for several reasons presented in the next section. Again, all other variables do not survive the competition with SURP for relative risk aversion. Lastly, the standard deviation parameter(σ_v) of relative risk aversion seem quite small in these cases compared with the numbers reported in other cases. It might indicate well known results that the time-varying parameter model can be an alternative model for GARCH. Or it could indicate possible identification issues with complex models. So, in unreported estimation, I re-estimate case 5 and 6 by fixing variance parameters σ_v as 0.01 and get the qualitatively same results.[12]

[12]The corresponding tables were included in the previous version of the paper and are available upon request.

I summarize my findings as follows. First, realized volatility specification seems better than GARCH specification because in most estimations, all the estimated parameters in realized volatility equations are quite significant and robust but GARCH parameters are either marginally significant or insignificant at all. Second, the surplus consumption ratio is always statistically significant with correct negative sign no matter which models I use. Third, CAYA seems to capture additional explanatory power on relative risk aversion while financial variables seem to forecast just volatility terms. Several interesting points are raised for empirical asset pricing models at this point. With direct comparison, only consumption related variables are important determinants of relative risk aversion and financial market variables typically used in conditional asset pricing studies do not look as primary instruments for it. Especially, the surplus consumption ratio motivated from the external habit formation model is the most important determinant for explaining the time-varying nature of relative risk aversion. These results seem to suggest a warning for asset pricing studies without consumption related variables. For example, typical bond market research imposes that market prices of risks or relative risk aversion for bond market are a function of yield variables only. My estimates suggest that the estimation of market price of risk or relative risk aversion might be difficult to be identified if we use only yield variables.

3.2.2 Robustness checks with hedging components

Merton (1973) points out that in addition to the stock market variance, hedging demand for time-varying investment opportunities is also an important determinant of the expected stock market risk premium. In empirical investigation of that idea, Scruggs (1998) and Guo and Whitelaw (2006) find that ignoring hedge components in the ICAPM might introduce a downward bias in the estimated risk-return relation(or the relative risk aversion) because the volatility and the hedge demand could be negatively correlated. This is classical omitted variable bias problem in which the set of predictor variables is misspecified. Especially, Guo, Wang, and Yang (2006) argue that relative risk aversion is constant once we correctly model the ICAPM with CAY. To test this hypothesis, I include each return forecasting variable as a proxy for hedging component and test that relative risk aversion is constant or not. Here I use the ICAPM specification of Hodrick and Zhang (2001),Guo and Whitelaw (2006) and Guo, Wang, and Yang (2006) and use contemporaneous values of the predictive variables rather than their innovations. I extend models in the previous sections with the hedging components.

Panel A of Table 7 report the estimated results for case 1 with additional hedging components.[13] Since SURP seems robust as a proxy for relative risk aversion, I include all the other variables except for SURP and check the robustness of the results. In summary, the surplus consumption ratio is always statistically significant and has a correct negative sign even after I include additional variables as hedging components. However, CAYA does not provide consistent results. First, three out of seven cases are significant at 5 % but are marginally significant for other three cases. Especially, with CAYA in hedging components, both terms lose statistical significance.[14] Finally, none of variables has any statistical significance as a hedging component. For other cases, several points deserve to be mentioned.(Table 8 and 9) First, SURP is almost always statistically significantly negative except for one occasion in case 5. Second, for case 4, CAYA in relative risk aversion specification is still significant as a proxy for relative risk aversion with any variable specified as the hedging component even when CAYA is also included. These results seem to suggest that CAYA would be better described as a proxy for relative risk aversion. Third, RREL is statistically significant as the hedging component for three cases.(case 2,4, and 5) All other variables are at most significant only in one case. Finally, while,in one of cases(case 5) reported in the previous section, RREL survives as a proxy for relative risk aversion, I don't report the results for the implied ICAPM and pursue that interpretation further for several reasons. First, in unreported estimation, RREL lost its significance as a proxy for risk aversion when I also include RREL into hedging components. Moreover RREL is statistically significant as a hedging component as indicated in Table 9. Given the results from other cases, RREL seems to be better described as a proxy for a hedging component.

In summary, these tables strongly indicate that relative risk aversion is indeed time-varying with or without a correct modeling of hedging components. Among other things, the surplus consumption ratio(SURP) is almost always statistically significant with the negative sign. Second, the consumption-wealth ratio without a look ahead bias,(CAYA) seems to capture relative risk aversion. Often CAY is used as proxy for relative risk aversion(Lettau and Ludvigson (2001b)) but hedging components interpretation is also frequently utilized(Guo and Whitelaw (2006)). The estimated results in this paper seem to favor relative risk aversion interpretation. Third, RREL has some explanatory power as a proxy for hedging components while TERM is

[13] For the parameters of realized volatility equation and GARCH, I don't report results further since their signs and magnitudes are quite close to the corresponding models provided in the previous section.

[14] In unreported tables, if I put just SURP in relative risk aversion specification, then CAYA in a hedging component becomes marginally significant.

insignificant in most cases even though it is widely used either a conditioning variable or a proxy for a hedging component. In fact, several recent studies find that the yield spread(TERM) is not a very good predictor of economic activity after 1985. Notably, Ang, Piazzesi, and Wei (2006), after imposing no arbitrage restrictions, find that the short term interest rate, not the term spread is the main forecasting instrument to future economic activity. Also, Ang and Bekaert (2006) confirms that after extensive statistical analysis, only the short term interest rate strongly negatively predicts excess returns among chosen predictability variables. Since Merton (1980), it has been well known that the interest rate accurately describes the changing investor opportunity set. Finally, other return forecasting variables do not have any statistical power to explain both relative risk aversion or hedging components while some of the variables forecast market volatility.

3.2.3 Robustness checks with sub-sample analysis

In this section, I report estimation results using data sampled from 1982:01 to 2005:04. Fig.1 seems to suggest a possible regime shift in the several predictability variables.(e.g. inflation series) Without addressing this issue properly, empirical results from the full sample analysis might be misleading. However, it is probably infeasible to develop a regime shift nonlinear state space model. Instead, I set the break point at 1982:01 following a regime switching literature in monetary policy and conduct time-series specification tests.[15]

Empirical results for conditional CAPMs and ICAPMs with realized volatility(case 1 and 2) are presented in Table 10 and 11.[16] Overall, the results reported from the full sample analysis are preserved. For case 1 and case 2 only SURP is statistically significant and has a correct negative sign while all other variables are not significant either individually or along with SURP.

[15] This change of monetary policy would be a main reason to observe a low volatility regime in economic variables until the recent financial crisis. In addition to that, I tried 1980:01 and 1984:01 as break points and obtained qualitatively similar results.

[16] While I also tried to estimate other cases, there seems to be convergence issues. The primary suspect is the interaction of GARCH terms with time-varying risk aversion. This complex structure seems to request more samples to be identified. In unreported experimentation, I find that by fixing one of two terms as constants, the estimation converges quite fast.

3.2.4 The filtered estimates of RRA

In this section, I report the filtered estimates of the relative risk aversion from the two models with positivity restriction since qualitative implications are similar across the models with slight difference in magnitudes.[17] Since relative risk aversion relates to SURP and CAYA, both of which are strong cyclical indicators of economic conditions, it is reasonable to suspect a business cycle pattern in risk aversion. Fig.3 plots estimates of relative risk aversion from the conditional CAPM with SURP and from the conditional ICAPM with SURP and CAYA as instruments for risk aversion and RREL as a proxy for hedging components along with shade indicating NBER business cycle contraction. I find that the relative risk aversions implied by both models are mostly countercyclical even though they miss the short recessions around 1970 and 1974. Intuitively, we expect periods of strong economic conditions to be associated with low or falling risk aversion, while recessions are associated with high or rising risk aversion. Table 12 presents that the filtered relative risk aversion is around 2 on average with a standard deviation of 3, which is consistent with sensible estimates that many economists are willing to accept. It appears to capture the turbulent financial markets during 1990s in which the relative risk aversion could be high not because of the recession but because of extremely volatile movements in international financial markets. Recently Chue (2005) argues that the time-varying relative risk aversion with surplus consumption ratio could be important to understand the financial crises or contagion.

3.2.5 Cross-sectional implications

I have shown that the relative risk aversion identified with the surplus consumption ratio and the consumption wealth ratio moves countercyclically and such a relation is still statistically significant even after I control for the hedging component and time-varying market volatility. These results appear to be robust because I reach the same conclusion using several different specifications. However, in time series asset pricing analysis, I extract all the implications from just one variable, excess returns estimation. Without further verification, it looks premature to conclude that time-varying relative risk aversion is really important for asset pricing applications. To further elaborate on the results, in this section, I follow Lettau and Wachter (2006)'s suggestion and investigate the models' implications for the cross-section of

[17] Since I am using a complex nonlinear state space model with GARCH, it is not feasible to use the usual Kalman smoothing algorithm. So, I report filtered estimates of relative risk aversion.

stock returns following precisely the testing methods suggested in Petkova (2006) to compare empirical models. Fama (1991) conjectures that we should relate the cross-section properties of expected returns to the variation of expected returns through time. Usually, two different approaches have been suggested. We can use conditional versions of unconditional single factor models, such as conditional CAPM or conditional consumption CAPM while unconditional multi-factor models are also frequently used. From my time-series specification tests, I find that probably we need both terms to fully understand the risk premium in stock market. Consumption-related variables are significant determinants for relative risk aversion but the short term interest rate has some explanatory power as the hedging component.

Conditional models are appealing because unconditional models may not capture time-varying risk premiums appropriately. Theoretically, Hansen and Richard (1987) show that, even if the unconditional versions of some models fail, the corresponding conditional models with correctly specified information sets could be perfectly valid for capturing the dynamics of risk premiums and they will outperform the unconditional versions of the models. However, as Ghysels (1998) argues, if the model's implied time-varying risk premiums are misspecified due to the wrong conditioning variable without any specification test, then these conditional models may have bigger pricing errors than their counterparts in unconditional specification. In this sense, current risk-return trade-off research seems to have problems since they just focus on time-series information. Therefore, it seems natural to conduct cross-sectional verifications of my time-series models.

In this paper, as test assets, I first use Fama-French 25 portfolios. It has become standard practice in the cross-sectional asset-pricing literature to evaluate models based on how well they explain average returns on size- and book-to-market-sorted portfolios. In addition to that, I use 55 portfolios with Fama-French 25 portfolios and 30 industry portfolios. As Lewellen, Nagel, and Shanken (2006) suggest, many models are proposed to capture the value premium but they typically fails to match the risk premium implied by 55 portfolios.[18] Here I show that my empirically chosen models are comparable to the Fama-French three factor model in explaining the value premium and seem to capture part of this industry premium better than the Fama-French three factor model does. Fama and French (1993) argue that HML and SMB represent compensations for risk consistent with Merton (1973)'s ICAPM. However, it

[18]See their Table 1 for the details. Almost all recently suggested models are not better than Fama-French three factor model after extensive simulations and various robustness checks.

is still not clear whether the HML and SMB factors have specific economic interpretations. Cochrane (2001) argues that asset pricing models that use portfolio returns as factors may be successful in describing asset returns, but those models will never be able to explain portfolio returns in economic sense since these models leave unanswered the question of what explains the return-based factors themselves. Therefore, I expect that the conditional ICAPM suggested in this paper might shed some lights on this issue since part of premium could be attributed to time-varying relative risk aversion or hedging components.

To determine whether the suggested empirical models can account for the cross section of returns on the 25 Fama-French size and B/M sorted portfolios for the period from 1957:1 to 2005:4, I utilize the Fama and MacBeth (1973) procedure. I use this Fama-Macbeth type beta pricing approach since the excess returns on the test assets commonly chosen in empirical work often exhibit high contemporaneous correlations and this can make some of the numerical calculations of the standard GMM approach unstable for a large cross-section of assets typically with small span of data set.(Lettau and Ludvigson (2001b) In the first stage time series regression, I regress the portfolio returns on the market excess return, and several additional variables specified from the model to obtain the betas. As in Lettau and Ludvigson (2001b), the full-sample loadings, which are the independent variables in the second stage regressions, are computed in one multiple time-series regression. My empirical asset pricing models(model 1,2, and 3) are based on the time series analysis in previous sections. To better evaluate the performances of the conditional models, I also estimate and report results for the simple unconditional CAPM, and the Fama-French three-factor model. The first-stage regression for model 1 is specified as follows.[19]

$$R_{i,t} - R_{f,t} = \alpha_i + (\beta_{iM} + \beta_{i2}\mathrm{SURP}_{t-1} + \beta_{i3}\mathrm{CAYA}_{t-1})(R_{M,t} - R_{f,t}) + \beta_{i4}Revol_{t-1} + \varepsilon_{it} \quad (22)$$

where $R_{i,t}$ is portfolio returns;$R_{f,t}$ is treasury bill returns; $R_{M,t}$ is market returns. Model 2 and model 3 add RREL_{t-1} and CAYA_{t-1} respectively. Estimated betas from the first-stage regressions are subsequently used as independent variables in the second-stage cross-sectional regression for all time periods. Hence, the risk premium estimates in the second-stage regression are subject to an errors-in-variables bias. To correct for this problem, I adjust the standard errors from the second stage regressions as proposed in Shanken (1992). However, I also

[19] I use the market excess return as the market factor and include a realized variance as an additional variable to directly compare with the results of other conditional asset pricing studies.

report the Fama-MacBeth standard errors since Jagannathan and Wang (1998) show that with conditional heteroskedasticity, the standard errors produced by the Fama-MacBeth procedure do not necessarily overstate the precision of the risk premium estimates. The second-stage regression can be presented as follows.

$$R_{i,t} - R_{f,t} = \lambda_0 + \lambda_M \widehat{\beta_{iM}} + \lambda_2 \widehat{\beta_{i2}} + \lambda_3 \widehat{\beta_{i3}} + \lambda_4 \widehat{\beta_{i4}} + \lambda_5 \widehat{\beta_{i5}} + u_{i,t} \tag{23}$$

where λ stands for the risk price. Following Fama and MacBeth, I run this cross-sectional regressions each quarter, generating time-series of estimates for risk prices(λ). Means, standard errors, and t-statistics are then computed from these time series in the usual manner. It is well known that security returns are cross-sectionally correlated, due to the common market and industry factors, and also heteroscedastic. As a result, the usual formulas for standard errors are not appropriate for the OLS cross-sectional regressions(CSR). Fama-Macbeth approach can be interpreted as a remedy for this phenomenon. Since the true variance of each quarterly estimator depends on the covariance matrix of returns, cross-sectional correlation and heteroskedasticity are reflected in the time series of quarterly estimates.

To judge the goodness of fit of the suggested empirical models, I use the cross-sectional R^2 measure employed first by Jagannathan and Wang (1996). This R^2 shows the fraction of cross-sectional variation in average returns that is explained by the model. This measure is calculated as

$$R^2 = \frac{\sigma_C^2(\bar{R}) - \sigma_C^2(\bar{e})}{\sigma_C^2(\bar{R})} \tag{24}$$

where σ_C^2 represents the in-sample cross-sectional variance,$\bar{R}$ is a vector of average excess returns, and $\bar{e}$ stands for the vector of average residuals in cross-sectional regression. I also report the root mean square of pricing errors(α) in cross-sectional regression(RMSE) as another intuitive diagnostic to compare the models. I use $\sqrt{\frac{1}{25}\sum_{i=1}^{25} \alpha_i^2} = \sqrt{\frac{1}{N}\alpha'\alpha}$ for all the models. This simple RMSE could be more informative against Hansen-Jagannathan(HJ) distance measure if the original portfolios were primary concerns and the second moment matrix of the test assets is quite close to singular since the HJ distance places too much weight on pricing near-riskless portfolios rather than pricing the original assets. In fact, Lewellen, Nagel, and Shanken (2006) suggest that Fama-French 25 size and B/M sorted portfolios have essentially three degree of freedom. Finally, Lewellen, Nagel, and Shanken (2006) suggest to report Shanken (1985)'s Hotelling T^2 statistics since the cross-sectional R^2 is not invariant to portfolio formation.

Following Petkova (2006), I compute and report the transformed Hotelling T^2 statistic which is adjusted for the errors-in variables problem and has an approximate F-distribution in small samples. The transformed test statistic is computed as

$$Q = \frac{T\bar{e}'\bar{\Sigma}^{-1}\bar{e}}{(1+c)} \tag{25}$$

where T is the number of time-series observations, $\bar{e}$ stands for the average residual vector in the cross section, and $\hat{\Sigma}$ is the estimated covariance matrix of the residuals in the first-stage time series regression and c is the Shanken correction term.

Table 13 reports the estimated coefficients, Fama-MacBeth(FM) and Shanken-corrected standard errors and the degrees of freedom-adjusted R^2 and the RMSE and F-statistics for the cross-sectional regressions using the excess returns on 25 portfolios sorted by book-to-market and size. First, in most cases, the market factor receives a negative and statistically insignificant risk premium consistent with the previous findings.(Fama and French (1992) and Lettau and Ludvigson (2001b)) While it appears to be a severe problem for the CAPM, the negative market risk premium has not been understood yet. Since that issue is beyond the scope of this paper, I defer it for future studies.

Second, the proposed conditional models indicate clear improvements over CAPM. All models deliver much higher cross-sectional R^2 around 65%, respectively and smaller RMSE than CAPM does. These results show that it is likely for CAPM to hold conditionally since as Lettau and Ludvigson (2001b) argue, if the CAPM holds conditionally, but not unconditionally, better performance may obtain if the CAPM is scaled by variables that capture relevant conditioning information. However, the take-away point is that a large number of macroeconomic variables can be added to ad-hoc linear factor models($M_{t+1} = a - bf_{t+1}$) in this way to price the Fama-French 25 portfolios. Here I want to emphasize the difference of my conditional models from the models proposed by Lettau and Ludvigson (2001b) or Ferson and Harvey (1999). In this paper, I get conditioning variables with non-ad-hoc time-series specification tests with several robustness checks. Lettau and Ludvigson (2001b) and Ferson and Harvey (1999) also do not try differentiate hedging components with risk aversion components or volatility components. Therefore, I argue that my models are subject to data snooping issue clearly in a lesser degree than other models do.

Third, the results from the conditional models indicate that the cross-sectional R^2 and

RMSE are slightly worse than the Fama-French model. However, this result might be spurious. If I omit a constant term in the second stage regression, model 2(66%) and 3(63%) have in fact bigger R^2 than the Fama-French model does(59%). Finally, all models are statistically rejected at 1% level. This rejection is largely from the smallest growth portfolio(11) as usual. Fig.4 plots the realized versus predicted returns of the models examined of the selected models. The numbers on the x-axis are the portfolios' names. The first digit number in a portfolio name is the size group it belongs to, and the second digit is the B/m group it belongs to. Both the size groups and the B/M groups are in ascending order. The closer a portfolio lies to the 45-degree line, the better the model explains the returns of that portfolio. It can be seen from the graph that the conditional models explains the value effect comparable to Fama-French three-factor model: In general, the fitted expected returns on value portfolios (larger second digit) are higher than the fitted expected returns on growth portfolios (smaller second digit).

The value premium has been an important but controversial subject in the asset pricing literature. Consistent with Fama and French's ICAPM conjecture, Liew and Vassalou (2000) find that the value premium forecasts output growth. Brennan, Wang, and Xia (2004) and Petkova (2006) also show that the value premium is correlated with their measures of investment opportunities. However, there are alternative explanations in the conditional CAPM literature for the value premium. In particular, Lettau and Ludvigson (2001b) find that the conditional CAPM with CAY helps explain the value premium and argue that the Fama-French factors are mimicking portfolios for risk factors associated with time-variation in market price of risk(or risk aversion).[20] The estimation results in Table 13 shed light on the on-going debate about the value premium since I develop the cross-sectional asset pricing models based on more thorough time-series specification tests. First, the selected conditional CAPM with SURP and CAYA indeed explains the strong value premium for 1957 to 2005. Likewise, once augmented with proxies for hedging components, the proposed models also seem to capture the value premium comparable to the Fama-French three-factor model.

Recently, Lewellen, Nagel, and Shanken (2006) argue that the proposed models for the value premium do not seem to explain premium of industry portfolios. Typically, they find that almost all models are worse than the Fama-French three factor model in explaining industry premium. Therefore, Lewellen, Nagel, and Shanken (2006) recommend that when three factors

[20] Zhang (2005) also develops equilibrium model with adjustment costs for investment to explain the value premium when relative risk aversion is high.

explain nearly all of the time-series variation in returns of size-B/M portfolios, we should augment them with 30 industry portfolios which don't correlate with SMB and HML as much for correct comparison of the models. Furthermore, since there are essentially three degrees of freedom in Fama-French 25 portfolios, Cochrane (2006) suggests that asset pricing models with more than three factors, should be carefully investigated even though those models tend to explain Fama-French 25 portfolios.[21] Following the suggestions of Lewellen, Nagel, and Shanken (2006), I test the robustness of the proposed empirical models by examining the ability of the competing models to price industrial portfolios. I expect that selected models should describe these asset returns better than the Fama-French model does. Table 14 reports the cross-sectional regression results on the 55 portfolios returns, and Fig.5 plots the realized versus predicted returns of the models examined of the selected models. The conditional models appear to perform better than the Fama-French three factor model in explaining the test assets in terms of the intuitive measures(both R^2 and RMSE).

In summery, the selected conditional models with time-varying relative risk aversion and hedging components are not only comparable to Fama-French three factor model in explaining the value premium but also satisfy the robustness criteria of Lewellen, Nagel, and Shanken (2006) since they have a higher explanatory power in terms of the 55 portfolios. However, none of the models seems to price industry portfolios sufficiently. Lettau and Wachter (2006) argue that the external habit formation model need an extra hedging component(cash flow state variables) to explain asset returns. While I include RREL as a candidate for that extra term, it seems not clear whether we can have any incremental explanatory power with other specifications. My paper can be interpreted as a first step to find the complete empirical models since I obtain the determinants of relative risk aversion with extensive empirical analysis. In my future study, I will try to incorporate other variables for explaining hedging components more accurately.

4. Conclusion

This paper contributes to the asset pricing literature in several respects. Recent applications of the ICAPM try to avoid "fishing license problem" by employing return forecasting

[21] Brennan, Wang, and Xia (2004) also tests their model with this 55 portfolios and finds that their model is statistically rejected. However, they don't report any intuitive statistics.

variables. However, without understanding the nature of the forecastibility, it seems rather arbitrary to choose certain models. I develop novel time series methods to identify the determinants of stochastic risk aversion and hedging components separately under the unified framework of Merton (1973) ICAPM.

First, I find that only consumption related variables explain the time-varying relative risk aversion. The surplus consumption ratio motivated from the external habit formation model has the most successful explanatory power, with a correct sign, on time-varying relative risk aversion. Other return forecasting variables including dividend price ratio, default spread, term spread, short term interest rate, inflation and real GDP growth lose their statistical significance especially in the presence of the surplus consumption ratio. Consistent with Lettau and Ludvigson (2001b) CAY without a look-ahead bias seems to capture only part of relative risk aversion but not the hedging component suggested by Guo and Whitelaw (2006). Second, only RREL captures part of the changing investment opportunities argued by Merton (1973). Other return forecasting variables only explain the time-varying volatility and become statistically insignificant in other terms in the presence of consumption variables.

In addition, I also compare the cross-sectional implication of the selected conditional CAPMs and ICAPMs with several bench mark asset pricing models including Fama-French three-factor model. The models are compared on a common set of returns: either the Fama-French 25 size and B/M sorted portfolios alone or with 30 industry portfolios. I find that the carefully selected conditional models with time-varying relative risk aversion and hedging components are not only comparable to Fama-French three factor model in explaining the value premium and also have a higher explanatory power in terms of the 55 portfolios. However, the chosen models with stochastic risk aversion and a hedging component are not enough to explain industry risk premium.

Recently, Guo (2006) employs a version of Guo, Wang, and Yang (2006) to check the risk-return trade off in the international stock markets. While Fama and French (1998) find the value premium in the international stock markets and cast the doubt on the validity of the traditional international asset pricing models, Zhang (2006) finds that the world CAPM augmented with both exchange rate risk and the conditioning variable for describing world business cycle can explain parts of the premium. I expect that the cross-sectional implication of the changing risk aversion or hedging components identified from my paper could also shed light on the precise nature of the risk premium in the international stock market.

Appendix A. Data in details

In this section, I list all the variables used in the article and describe how they are computed from original data sources. I measure all variables at the quarterly frequency, and my base sample period extends from 1957:1 to 2005:4.[22]

A.1 CAY without a Look-ahead bias(CAYA)

Lettau and Ludvigson (2001a) constructed CAY using full sample estimation regression coefficients. For this reason, CAY is often criticized with a possible look-ahead bias. To avoid this bias, I follow Goyal and Welch (2006) and construct modified CAY using only the data up to the current periods by estimating parameters with rolling regressions such that the new measure of CAY(CAYA) does not use look-ahead estimation regression coefficients. I downloaded CAY and raw data(1951:4-2005:4) from Ludvigson's website. Figure 1 suggests that CAY and CAYA have similar patterns. They are highly correlated in my sample.(0.76)

$$c_t = \alpha + \beta_w^s w_t + \beta_y^s y_t + \sum_{t=-8}^{8} b_{w,i}^s \Delta w_{t-i} + \sum_{t=-8}^{8} b_{y,i}^s \Delta y_{t-i} + \varepsilon_t,\ t = 9, \ldots, s-8 \qquad (A.1)$$

where c_t is the aggregate consumption, w_t is the aggregate wealth, and y_t is the aggregate income. The superscript on the betas indicates that these are rolling estimates.

Using estimated coefficients from the above equation provides

$$C\widehat{AY}A_t = c_t - \beta_w^s w_t - \beta_y^s y_t, t = 1, ..., T \qquad (A.2)$$

A.2 Surplus consumption ratio

I follow Duffee (2005) and Wachter (2006)'s specification precisely and define a proxy for surplus consumption ratio at the quarterly frequency as

$$\mathrm{SURP}_t = \frac{1-\Psi}{1-\Psi^{40}} \sum_{j=0}^{39} \Psi^j \Delta c(t-j) \qquad (A.3)$$

where Ψ=0.96 and Δc refers to the log change in real per capita quarterly consumption on nondurables and services.

I downloaded all consumption and population data from Bureau of Economic Analysis from 1947:1 and constructed surplus consumption ratio series starting from 1957:1 since I need 40 quarters of data to construct the first observation. And I checked and verified my data with Duffee (2005)'s surplus consumption data for common periods.

[22] I am thankful to Sydney Ludvigson, Gregory Duffee, and Kenneth French for making their data publicly available.

A.3 Equity Market variables

1. Excess returns: My stock return measure is the standard value-weighed return of NYSE-AMEX-NASDAQ index from CRSP. To compute excess equity returns, I subtracted the lagged 3month continuously compounded T-Bill yield earned over the same period from CRSP.

2. Dividend Price Ratio: I follow Bekaert, Engstrom, and Xing (2006) by first calculating quarterly dividend yield series as,

$$DP_{t+1} = \left(\frac{P_{t+1}}{P_t}\right)^{-1} \left(\frac{P_{t+1} + D_{t+1}}{P_t} - \frac{P_{t+1}}{P_t}\right) \qquad (A.4)$$

   where $\frac{P_{t+1}+D_{t+1}}{P_t}$ and $\frac{P_{t+1}}{P_t}$are available directly from the CRSP as the value weighted stock return series including and excluding dividends respectively. I use the four-period moving average as dividend price ratio,

$$dp_t^f = \frac{1}{4}[\ln(1 + DP_t) + \ln(1 + DP_{t-1}) + \ln(1 + DP_{t-2}) + \ln(1 + DP_{t-3})]. \qquad (A.5)$$

3. Realized variance series: I use the daily CRSP value-weighted stock returns as a proxy for aggregate stock market returns consistent with my quarterly excess stock return measure. The quarterly risk-free rate is the lagged yield on 3 month T-bills and I constructed the daily risk-free rate by assuming that it is constant within a quarter. The excess stock market return is defined as the difference between the stock market return and the risk-free rate as usual. To check the robustness of my results, I constructed four different measures of realized variance series.

   - REVOL1 : the variance of the daily excess stock market returns in a quarter

$$\sigma_{m,t}^2 = \frac{1}{N_t} \sum_{i=1}^{N_t} [r_{i,t} - mean(r_{i,t})]^2. \qquad (A.6)$$

     where $r_{i,t}$: daily excess return , N_t: the number of trading days in a quarter

   - REVOL2 : The 1987 stock market crash has a confounding effect on my variance measure; following Guo and Whitelaw (2006), I replace REVOL1 for 1987:4 with the second-largest observation in my sample. Guo and Whitelaw (2006) argue that REVOL2 is more appropriate since the variable(REVOL1) rose dramatically during this crash period but reverted to the normal level shortly after.

   - REVOL1auto and REVOL2auto: Non-synchronous trading of securities causes daily portfolio returns to be autocorrelated, particularly at lag one. To take into account this autocorrelation, I construct two additional REVOL measures.

$$\sigma_{m,t}^2 = \sum_{i=1}^{N_t} r_{i,t}^2 + \sum_{i=1}^{N_t-1} r_{i,t} r_{i+1,t} \qquad (A.7)$$

4. Fama French Factors and Portfolios data: Fama French Factors and Fama French 25 size and B/M sorted portfolios and 30 industry portfolios are obtained from Kenneth French's Web site. The original returns on the portfolios are monthly. So, I computed quarterly returns by compounding the three monthly returns of each quarter. I denote the 25 size and B/M sorted portfolios as 11, 12, 13, ..., 55, where the first digit indicates the portfolios size group and the second digit the portfolios B/M ratio group. The number 1 refers to the smallest size (lowest B/M ratio) and the number 5 to the biggest size (highest B/M ratio).

A.4 Other variables

- Term spread(TERM): This is the difference between long-term and short-term government bond yields. The long-term government bond yield data are from the Federal Reserve Economic Database(FRED) and are based on a maturity of 10 years. The short-term yield is the 3-month Treasury bill rate (secondary market) and is also from the FRED. The original data are monthly. I obtained quarterly observations by averaging over the three months comprising a quarter.

- Default spread(DEF): This is the difference between the Moody's seasoned Baa corporate bond yield and the Moody's seasoned Aaa corporate bond yield. The corporate bond yield data are from the FRED. The original corporate bond yield data are monthly. I obtained quarterly observations by averaging over the three months comprising a quarter.

- Stochastically detrended short term interest rate(RREL): I computed RREL as the quarterly short-term interest rate in deviations from a four-quarter moving average consisting of the four previous quarters from the CRSP.

- Real GDP growth(REGD): I computed real GDP growth using the seasonally adjusted data on real GDP in billions of chained 2000 dollars. Quarterly real GDP is from the FRED.

- Inflation(INFL): I computed inflation series using GDP deflator with quarterly nominal and real GDP series from the FRED.

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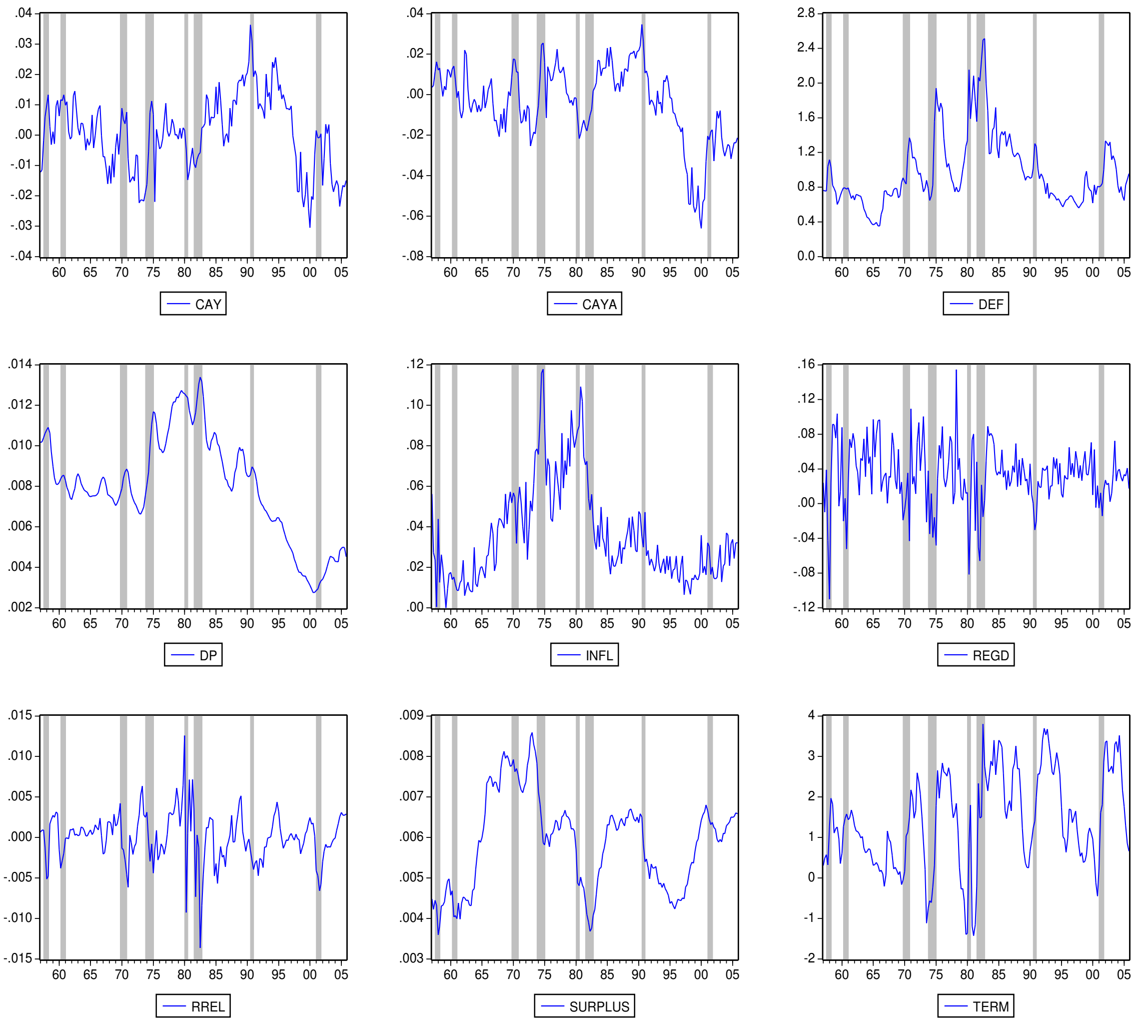
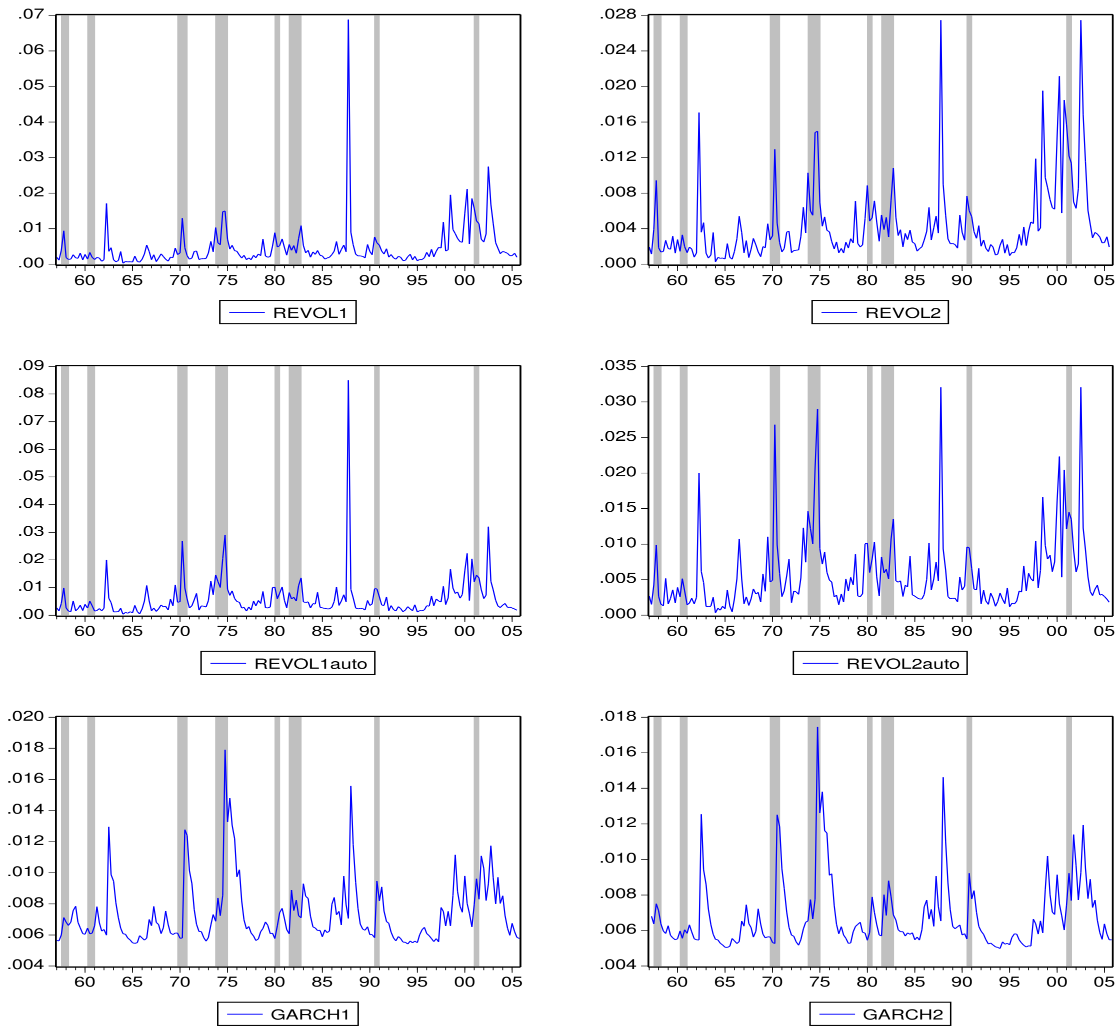


Note: CAY is the consumption-wealth ratio; CAYA is the consumption-wealth ratio without a look-ahead bias; DEF is the yield spread between Baa- and Aaa-rated corporate bonds; DP is the deseasonalized dividend over price ratio; INFL is the quarterly inflation rate measured by GDP deflator; REGD is the quarterly real GDP growth;RREL is the difference between the 3 month treasury bill rate and its average in the previous 4 quarters; SURP is the surplus consumption ratio; and TERM is the yield spread between 10-year treasury bonds and 3-month treasury bills. Shared areas indicate NBER business recessions.

Figure 1: Exogenous Variables and Business Cycles(1957:2-2005:4)



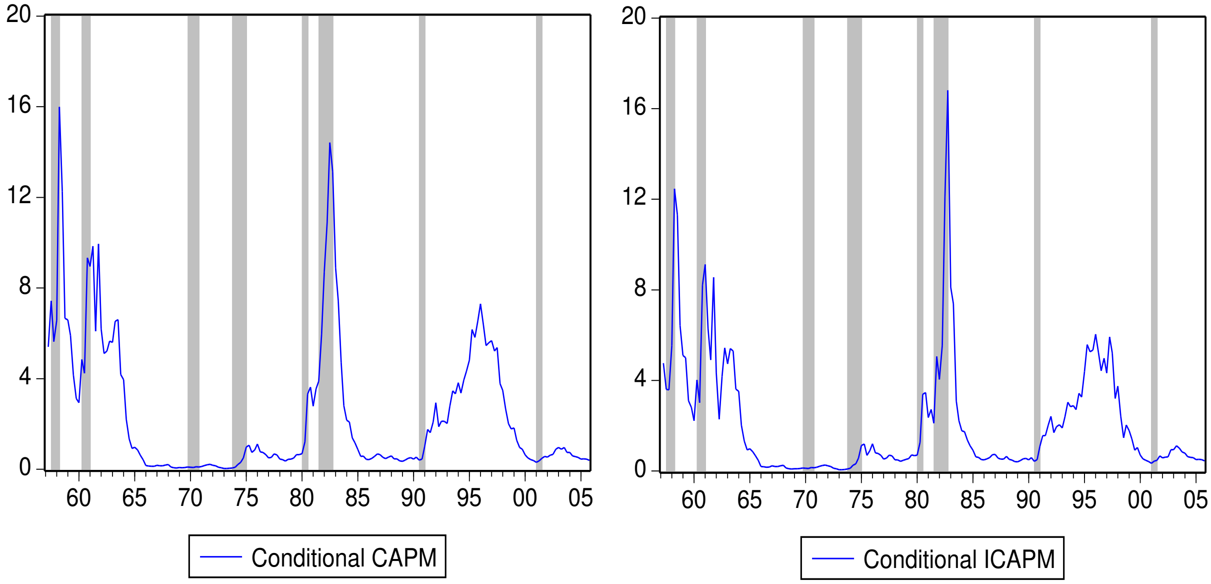
Note: Realized volatility(REVOL1) is defined in the data appendix; REVOL2 replaces a data point(1987:4) in REVOL1 with the second largest one; REVOL1auto is the autocorrelation-corrected measure of REVOL1; REVOL2auto replaces a data point(1987:4) in REVOL1auto with the second largest one; $r_{m,t+1}$ is the CRSP value-weighted stock return minus lagged 3-month treasure bill rate. GARCH1 is estimated with simple GARCH(1,1)-M model of the market excess return(Model1); GARCH2 is estimated with the conditional ICAPM model with SURP and RREL(case 4). All exogenous variables(SURP, RREL, and u_t) are normalized to have means of zero and standard deviations of one. u_t are entered as (CAYA_t,DP_t,TERM_t,DEF_t,INFL_t). All variables are defined in Fig 1. Shared areas indicate NBER business recessions.

$$\text{Model1}: r_{m,t+1} = \gamma_1 h_{t+1} + \varepsilon_{t+1},$$

$$\begin{aligned}\text{Model2}: r_{m,t+1} &= \exp(\log \gamma_{t+1}) \exp(E_t(\ln \hat{\sigma}_{m,t+1}) + \tfrac{1}{2}\sigma_\eta^2) + \alpha_1(\text{RREL})_t + \varepsilon_{t+1}, \\ \log \gamma_{t+1} &= \phi_0 + \phi_1(\text{SURP})_t + v_{t+1},\ \ln \hat{\sigma}_{m,t+1} = \delta_0 + \delta_1 \ln \hat{\sigma}_{m,t} + \delta_2' u_t + \eta_{t+1}\end{aligned}$$

where $\varepsilon_{t+1|t} \sim N(0, h_{t+1})$, $v_{t+1} \sim N(0, \sigma_v^2)$, $\eta_{t+1} \sim N(0, \sigma_\eta^2)$, $h_{t+1} = \omega + \beta_1 h_t + \beta_2 \varepsilon_t^2$

Figure 2: Realized Volatility and GARCH(1957:2-2005:4)



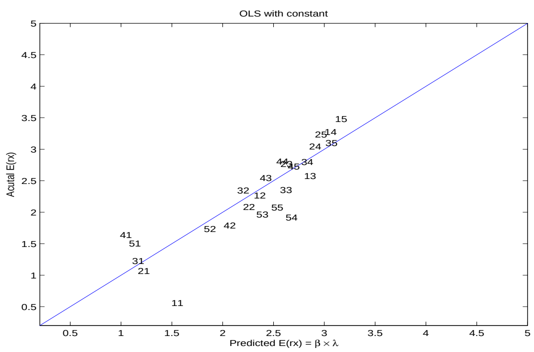
This figure plots the quarterly time series of relative risk aversion series($\exp(\gamma_{t+1})$) implied by conditional CAPM with SURP(Model1) and conditional ICAPM with SURP and CAYA as instruments for relative risk aversion and RREL as a proxy for the hedging component(Model2). All exogenous variables(SURP,RREL, and u_t) are normalized to have means of zero and standard deviations of one. u_t are entered as (CAYA_t,DP_t,TERM_t,DEF_t,INFL_t). All variables are defined in Fig 1. Shared areas indicate NBER business recessions.

$$\text{Model1}: \; r_{m,t+1} = \exp(\log\gamma_{t+1})\exp(E_t(\ln\hat{\sigma}_{m,t+1}) + \tfrac{1}{2}\sigma_\eta^2) + \varepsilon_{t+1},$$

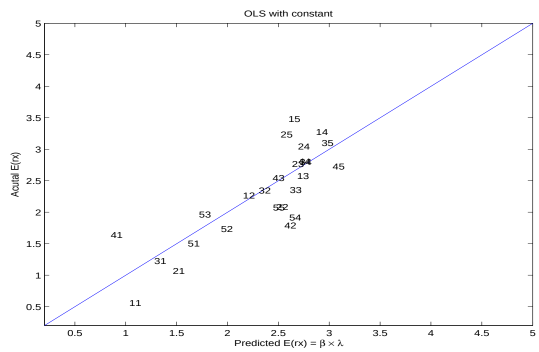
$$\text{Model2}: \; r_{m,t+1} = \exp(\log\gamma_{t+1})\exp(E_t(\ln\hat{\sigma}_{m,t+1}) + \tfrac{1}{2}\sigma_\eta^2) + \alpha_1(\mathrm{RREL})_t + \varepsilon_{t+1},$$
$$\log\gamma_{t+1} = \phi_0 + \phi_1(\mathrm{SURP})_t + v_{t+1}, \; \ln\hat{\sigma}_{m,t+1} = \delta_0 + \delta_1\ln\hat{\sigma}_{m,t} + \delta_2' u_t + \eta_{t+1}$$

where $\varepsilon_{t+1|t} \sim N(0,h_{t+1})$, $v_{t+1} \sim N(0,\sigma_v^2)$, $\eta_{t+1} \sim N(0,\sigma_\eta^2)$, $h_{t+1} = \omega + \beta_1 h_t + \beta_2\varepsilon_t^2$

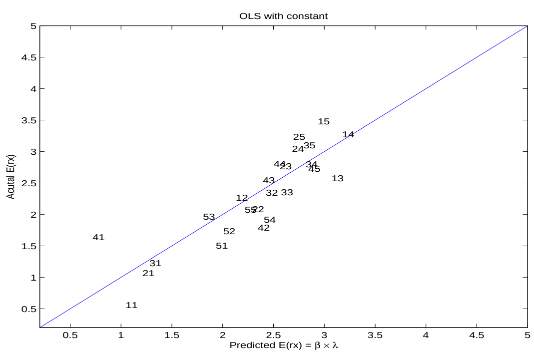
Figure 3: Time-series of relative risk aversion.(1957:2-2005:4)



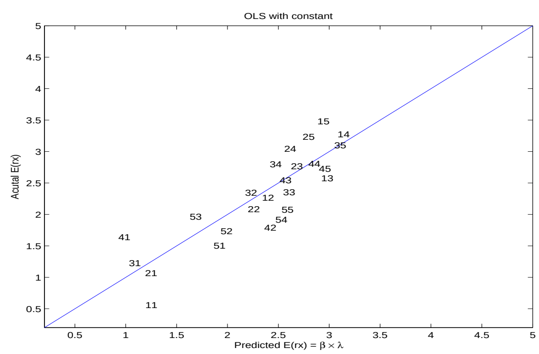
(a) Fama-French Three-factor model



(b) Model1



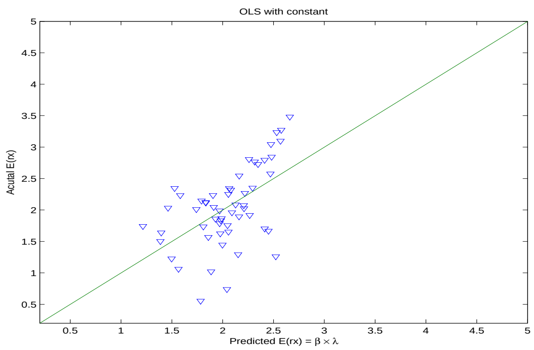
(c) Model2



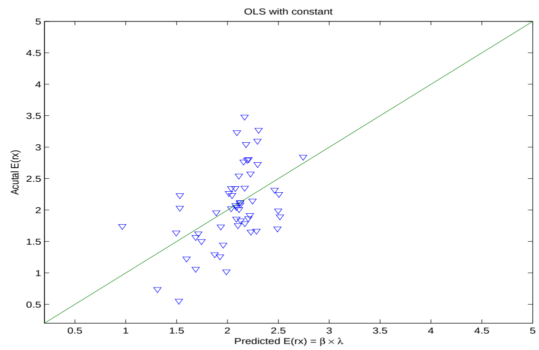
(d) Model3

The plot shows realized average returns (in percent) on the vertical axis and fitted expected returns (in percent) on the horizontal axis for 25 size and book-to-market sorted portfolios. The first digit refers to the size quintile (1 being the smallest and 5 the largest), while the second digit refers to the book-to-market quintile (1 being the lowest and 5 the highest). For each portfolio, the realized average return is the time-series average of the portfolio return and the fitted expected return is the fitted value for the expected return from the corresponding model. The straight line is the 45-degree line from the origin. All models are defined in section *3.2.5*.

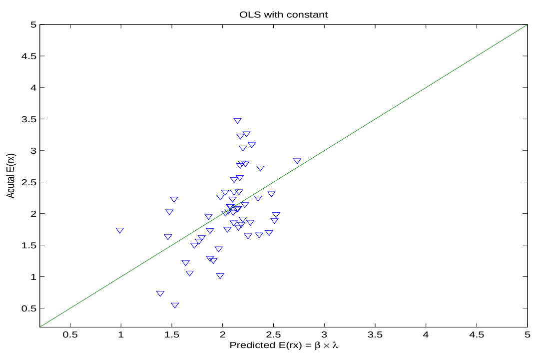
Figure 4: Fitted Expected Returns Versus Average Realized Returns for the Fama French 25 portfolios(1957:2-2005:4)



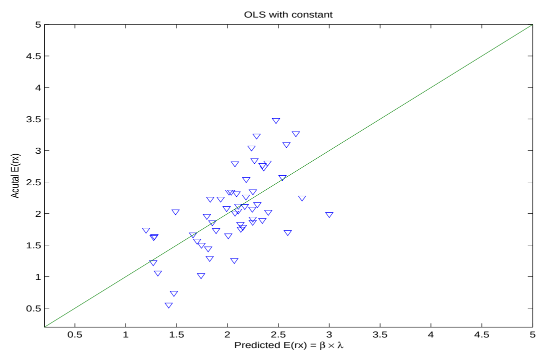
(a) Fama-French Three-factor model



(b) Model1



(c) Model2



(d) Model3

The plot shows realized average returns (in percent) on the vertical axis and fitted expected returns (in percent) on the horizontal axis for 25 size and book-to-market sorted portfolios and 30 industry portfolios. For each portfolio, the realized average return is the time-series average of the portfolio return and the fitted expected return is the fitted value for the expected return from the corresponding model. The straight line is the 45-degree line from the origin. All models are defined in section *3.2.5*.

Figure 5: Fitted Expected Returns Versus Average Realized Returns for the Fama French 25 portfolios and 30 Industry portfolios(1957:2-2005:4)

Table 1: Summary Statistics

Data is sampled quarterly from 1957:2 to 2005:4. The Auto(1) give the first autocorrelation. Note: EXCESS is the CRSP value-weighted stock return minus lagged 3-month treasury bill rate;CAYA is the consumption-wealth ratio without a look-ahead bias; DEF is the yield spread between Baa- and Aaa-rated corporate bonds; DP is the deseasonalized dividend price ratio; INFL is the quarterly inflation rate measured by GDP deflator; REGD is the quarterly real GDP growth;RREL is the difference between the 3 month treasury bill rate and its average in the previous 4 quarters; SURP is the surplus consumption ratio; and TERM is the yield spread between 10-year treasury bonds and 3-month treasury bills.

	EXCESS	CAYA	DEF	DP	INFL	REGD	RREL	SURP	TERM
	Panel A: Correlation Matrix								
EXCESS	1.000								
CAYA	-0.140	1.000							
DEF	0.120	0.171	1.000						
DP	0.061	0.641	0.527	1.000					
INFL	-0.126	0.194	0.435	0.563	1.000				
REGD	0.026	-0.088	-0.238	-0.097	-0.227	1.000			
RREL	-0.179	-0.091	-0.358	-0.002	0.162	0.289	1.000		
SURP	-0.154	-0.038	-0.138	-0.152	0.303	0.084	0.193	1.000	
TERM	0.167	0.141	0.260	-0.081	-0.300	0.117	-0.441	-0.196	1.000
	Panel B:Univariate Summary Statistics								
Mean	0.011	-0.004	0.975	0.008	0.036	0.032	0.000	0.006	1.421
Std. Dev.	0.085	0.019	0.411	0.003	0.024	0.036	0.003	0.001	1.185
Skewness	-0.850	-0.863	1.367	-0.115	1.161	-0.390	-0.342	0.109	-0.074
Kurtosis	4.412	3.823	4.948	2.404	3.910	4.555	6.013	2.161	2.382
Auto(1)	0.030	0.909	0.921	0.985	0.865	0.293	0.530	0.975	0.874

Table 2: Summary Statistics for Realized Variance and GARCH

Data is sampled quarterly from 1957:2 to 2005:4. Note: $r_{m,t+1}$ is the CRSP value-weighted stock return minus lagged 3-month treasury bill rate;Realized volatility(REVOL1) is defined in the data appendix; REVOL2 replaces a data point(1987:4) in REVOL1 with the second largest one; REVOL1auto is the autocorrelation-corrected measure of REVOL1; REVOL2auto replaces a data point(1987:4) in REVOL1auto with the second largest one; GARCH1 is estimated with simple GARCH(1,1) model of the market excess return(Model1); GARCH2 is estimated with the conditional ICAPM model with surplus consumption ratio(SURP) and RREL(Model2). All exogenous variables(SURP,RREL,and u_t) are normalized to have means of zero and standard deviations of one.u_t are entered as (CAYA_t,DP_t,TERM_t,DEF_t,INFL_t). Definitions of all variables are provided in Table1.

Model1 : $r_{m,t+1} = \gamma_1 h_{t+1} + \varepsilon_{t+1}$,

Model2 : $r_{m,t+1} = \exp(\log \gamma_{t+1}) \exp(E_t(\ln \hat{\sigma}_{m,t+1}) + \frac{1}{2}\sigma_\eta^2) + \alpha_1(\mathrm{RREL})_t + \varepsilon_{t+1}$,

$$\log \gamma_{t+1} = \phi_0 + \phi_1(\mathrm{SURP})_t + v_{t+1}, \ln \hat{\sigma}_{m,t+1} = \delta_0 + \delta_1 \ln \hat{\sigma}_{m,t} + \delta_2' u_t + \eta_{t+1}$$

where $\varepsilon_{t+1|t} \sim N(0, h_{t+1})$, $v_{t+1} \sim N(0, \sigma_v^2)$, $\eta_{t+1} \sim N(0, \sigma_\eta^2)$, $h_{t+1} = \omega + \beta_1 h_t + \beta_2 \varepsilon_t^2$

	REVOL1	REVOL2	REVOL1auto	REVOL2auto	GARCH1	GARCH2
Panel A : Correlation Matrix						
REVOL1	1.000					
REVOL2	0.896	1.000				
REVOL1auto	0.963	0.841	1.000			
REVOL2auto	0.836	0.927	0.884	1.000		
GARCH1	0.224	0.319	0.236	0.342	1.000	
GARCH2	0.239	0.340	0.253	0.366	0.977	1.000
Panel B : Univariate Summary Statistics						
Mean	0.005	0.004	0.006	0.006	0.007	0.007
Std. Dev.	0.006	0.004	0.008	0.005	0.002	0.002
Skewness	6.408	2.657	6.505	2.564	2.185	2.293
Kurtosis	61.443	11.346	63.255	11.073	8.940	9.424

Table 3: Realized Variance and GARCH estimates

This table shows the representative parameter estimates for the Realized variance and the GARCH for all cases specified in section (*2.1.3*). Note: $r_{m,t+1}$ is the CRSP value-weighted stock return minus lagged 3-month treasury bill rate;Realized volatility($\hat{\sigma}_{m,t+1}$) is defined in the data appendix; All exogenous variables(X_{1t} , X_{2t}, and u_t) are normalized to have means of zero and standard deviations of one to facilitate the interpretation.u_t are entered as (CAYA_t,DP_t,TERM_t,DEF_t,INFL_t). All variables are defined in Table 1.

$$\text{Model}: r_{m,t+1} = \gamma_{t+1} v_t(r_{m,t+1}) + \alpha_1 z_t + \varepsilon_{t+1}$$
$$f(\gamma_{t+1}) = \phi_0 + \phi_1 X_{1t} + \phi_2 X_{2t} + v_{t+1}, \ln \hat{\sigma}_{m,t+1} = \delta_0 + \delta_1 \ln \hat{\sigma}_{m,t} + \delta_2' u_t + \eta_{t+1}$$

where $f(\gamma_{t+1}) = \gamma_{t+1}$ or $\log \gamma_{t+1}$ and $v_t(r_{m,t+1}) = \exp(E_t(\ln \hat{\sigma}_{m,t+1}) + \frac{1}{2}\sigma_\eta^2)$ or h_{t+1},
$$h_{t+1} = \omega + \beta_1 h_t + \beta_2 \varepsilon_t^2, \varepsilon_{t+1|t} \sim N(0, v_t(r_{m,t+1})),\ v_{t+1} \sim N(0, \sigma_v^2),\ \eta_{t+1} \sim N(0, \sigma_\eta^2)$$

	δ_0	δ_1	δ_{21}	δ_{22}	δ_{23}	δ_{24}	δ_{25}	σ_η	ω	β_1	β_2
Case 1)	-3.6815	0.3271	0.1749	-0.4455	-0.1688	0.3236	0.1711	0.6002			
tstats	-10.5990	5.2242	3.1167	-5.6917	-3.3949	4.9391	3.1471	19.5642			
Case 2)	-3.6717	0.3278	0.1573	-0.4444	-0.1691	0.3254	0.1699	0.6021			
tstats	-10.4894	5.1990	2.6772	-5.6374	-3.3754	4.9358	3.1060	19.3885			
Case 3)	-3.6630	0.3319	0.1908	-0.4699	-0.1653	0.3321	0.1819	0.5976	0.0014	0.5138	< 0.0001
tstats	-10.3790	5.1924	3.3092	-5.7279	-3.2945	4.9633	3.2681	19.6733	0.0190	0.0201	< 0.0001
Case 4)	-3.5472	0.3531	0.1590	-0.4402	-0.1552	0.3378	0.1759	0.5972	0.0022	0.5119	0.1960
tstats	-9.4546	5.1898	2.5126	-4.9915	-2.8643	4.6547	2.9229	19.6973	2.2202	2.9758	1.5720
Case 5)									0.0020	0.5707	0.1431
tstats									2.0871	3.5435	1.6511
Case 6)									0.0020	0.5850	0.1393
tstats									2.1204	3.7695	1.7053

Table 4: Time-series Specification Tests: Time-varying RRA(Case 1 & 2)

This table shows the estimation results of several different specifications of conditional CAPM. Note: $r_{m,t+1}$ is the CRSP value-weighted stock return minus lagged 3-month treasury bill rate; Realized volatility($\hat{\sigma}_{m,t+1}$) is defined in the data appendix; All exogenous variables(X_{1t} , X_{2t}, and u_t) are normalized to have means of zero and standard deviations of one to facilitate the interpretation.u_t are entered as (CAYA$_t$,DP$_t$,TERM$_t$,DEF$_t$,INFL$_t$). All variables are defined in Table 1.

Model : $r_{m,t+1} = \gamma_{t+1} \exp(E_t(\ln \hat{\sigma}_{m,t+1}) + \frac{1}{2}\sigma_\eta^2) + \varepsilon_{t+1}$,

$$f(\gamma_{t+1}) = \phi_0 + \phi_1 X_{1t} + \phi_2 X_{2t} + v_{t+1}, \ln \hat{\sigma}_{m,t+1} = \delta_0 + \delta_1 \ln \hat{\sigma}_{m,t} + \delta_2' u_t + \eta_{t+1},$$

where $\varepsilon_{t+1|t} \sim N(0, E_t(\hat{\sigma}_{m,t+1}))$, $v_{t+1} \sim N(0, \sigma_v^2)$, $\eta_{t+1} \sim N(0, \sigma_\eta^2)$, $f(\gamma_{t+1}) = \gamma_{t+1}$ or $\log \gamma_{t+1}$ for Panel A & B.

Panel A.	Case 1			Panel B.	Case 2	
X_{1t}	ϕ_0	ϕ_1	σ_v	ϕ_0	ϕ_1	σ_v
SURP	2.5013	-3.3545	5.2620	0.3669	-1.2214	0.6274
tstats	2.3725	-3.1058	2.4164	0.4551	-2.0671	0.7531
CAYA	2.2740	1.7884	5.7095	0.7765	0.4991	1.9701
tstats	2.1351	1.8231	2.6753	1.6726	1.1184	1.4295
DEF	2.0244	0.6876	6.0808	0.6915	-0.4044	3.2877
tstats	1.8446	0.6867	2.9867	1.1840	-0.9811	1.7522
DP	2.2345	1.2438	5.9445	0.7989	0.0900	2.7060
tstats	2.0853	1.2840	2.8805	1.6590	0.3492	1.6903
INFL	2.4983	-1.6601	6.1708	0.6227	-1.1152	1.3156
tstats	2.2824	-1.7192	3.1518	1.0392	-1.6196	1.6121
REGD	2.2188	0.2665	6.1874	0.7443	-0.0960	2.8764
tstats	2.0348	0.2501	3.0902	1.4491	-0.4757	1.7924
RREL	1.9888	-2.1858	5.6632	0.4377	-0.6319	< 0.0001
tstats	1.8633	-2.2324	2.6763	0.8026	-3.3673	< 0.0001
TERM	2.3311	2.1218	5.5713	0.8224	0.4535	1.6108
tstats	2.2002	2.1455	2.5964	1.8246	1.1189	1.4515

X_{1t}, X_{2t}	ϕ_0	ϕ_1	ϕ_2	σ_v	ϕ_0	ϕ_1	ϕ_2	σ_v
SURP,CAYA	2.6035	-3.3365	1.7878	4.5890				
tstats	2.5109	-3.1502	1.8952	1.8766				
SURP,RREL	2.3215	-3.0056	-1.6883	4.8218	0.3011	-0.9277	-0.1955	< 0.0001
tstats	2.2153	-2.7772	-1.7507	2.0678	0.8311	-2.0392	-1.1557	< 0.0001
SURP,TERM	2.5947	-3.0019	1.5891	4.7715				
tstats	2.4928	-2.7734	1.6270	2.0283				

Table 5: Time-series Specification Tests: Time-varying RRA(Case 3 & 4)

This table shows the estimation results of several different specifications of conditional CAPM. Note: $r_{m,t+1}$ is the CRSP value-weighted stock return minus lagged 3-month treasury bill rate; Realized volatility($\hat{\sigma}_{m,t+1}$) is defined in the data appendix; All exogenous variables(X_{1t} , X_{2t}, and u_t) are normalized to have means of zero and standard deviations of one to facilitate the interpretation.u_t are entered as (CAYA$_t$,DP$_t$,TERM$_t$,DEF$_t$,INFL$_t$). All variables are defined in Table 1.

Model : $r_{m,t+1} = \gamma_{t+1} \exp(E_t(\ln \hat{\sigma}_{m,t+1}) + \frac{1}{2}\sigma_\eta^2) + \varepsilon_{t+1}$,

$$f(\gamma_{t+1}) = \phi_0 + \phi_1 X_{1t} + \phi_2 X_{2t} + v_{t+1}, \ln \hat{\sigma}_{m,t+1} = \delta_0 + \delta_1 \ln \hat{\sigma}_{m,t} + \delta_2' u_t + \eta_{t+1},$$

where $\varepsilon_{t+1|t} \sim N(0, h_{t+1})$, $h_{t+1} = \omega + \beta_1 h_t + \beta_2 \varepsilon_t^2$, $v_{t+1} \sim N(0, \sigma_v^2)$, $\eta_{t+1} \sim N(0, \sigma_\eta^2)$, $f(\gamma_{t+1}) = \gamma_{t+1}$ or $\log \gamma_{t+1}$ for Panel A & B.

Panel A.	Case 3			Panel B.	Case 4	
X_{1t}	ϕ_0	ϕ_1	σ_v	ϕ_0	ϕ_1	σ_v
SURP	2.5071	-3.3306	10.0146	0.4694	-1.1704	< 0.0001
tstats	2.3358	-3.0281	6.3192	0.6707	-2.3556	< 0.0001
CAYA	0.0625	1.4754	10.1146	0.4038	0.8772	< 0.0001
tstats	0.4672	1.5303	5.9144	1.7193	2.9072	< 0.0001
DEF	0.0086	1.1143	9.9157	-0.3497	0.7435	< 0.0001
tstats	0.0213	1.0212	5.8932	-0.6799	2.5452	< 0.0001
DP	2.1793	1.1491	10.3201	-0.9794	2.1329	< 0.0001
tstats	1.9906	1.1697	6.3079	-42.7984	4.7644	< 0.0001
INFL	2.4428	-1.8335	10.5142	-0.2588	-2.0354	< 0.0001
tstats	2.2195	-1.8177	6.6817	-0.6921	-3.5880	< 0.0001
REGD	2.1645	0.3423	10.4367	0.9898	-0.4377	< 0.0001
tstats	1.9472	0.3151	6.4459	163.5672	-6.9241	< 0.0001
RREL	1.9338	-2.1689	10.2330	0.1706	-0.7020	< 0.0001
tstats	1.7624	-2.1986	6.3346	0.7505	-5.5164	< 0.0001
TERM	2.2046	2.0618	10.0876	0.8328	0.2667	< 0.0001
tstats	2.0379	2.0395	6.1271	4.1328	1.2562	< 0.0001

X_{1t}, X_{2t}	ϕ_0	ϕ_1	ϕ_2	σ_v	ϕ_0	ϕ_1	ϕ_2	σ_v
SURP,CAYA	2.6356	-3.3413	1.6284	9.7328	0.2457	-0.7801	1.0564	< 0.0001
tstats	2.4713	-3.0987	1.7064	6.0087	0.7582	-2.0416	2.8171	< 0.0001
SURP,DEF					0.4576	-0.9560	-0.1307	< 0.0001
tstats					1.4773	-1.8844	-0.9781	< 0.0001
SURP,DP					0.4121	-1.0143	-0.1646	< 0.0001
tstats					0.9538	-1.4284	-0.8875	< 0.0001
SURP,INFL					0.2046	-1.1906	-0.5343	< 0.0001
tstats					0.4012	-1.7251	-1.0922	< 0.0001
SURP,REGD					-0.2376	-1.8830	0.1594	< 0.0001
tstats					-0.3853	-2.3459	0.8033	< 0.0001
SURP,RREL	2.3293	-2.9626	-1.6293	9.8526	0.1970	-0.9267	-0.2427	< 0.0001
tstats	2.1688	-2.6958	-1.6615	6.1713	0.4787	-1.6354	-1.0172	< 0.0001
SURP,TERM	2.5419	-2.9930	1.4927	9.7612				
tstats	2.3613	-2.7161	1.4835	6.0345				

Table 6: Time-series Specification Tests: Time-varying RRA(Case 5 & 6)

This table shows the estimation results of several different specifications of conditional CAPM. Note: $r_{m,t+1}$ is the CRSP value-weighted stock return minus lagged 3-month treasury bill rate; Realized volatility($\hat{\sigma}_{m,t+1}$) is defined in the data appendix; All exogenous variables(X_{1t} , X_{2t}, and u_t) are normalized to have means of zero and standard deviations of one to facilitate the interpretation.u_t are entered as (CAYA$_t$,DP$_t$,TERM$_t$,DEF$_t$,INFL$_t$). All variables are defined in Table 1.

Model : $r_{m,t+1} = \gamma_{t+1} h_{t+1} + \varepsilon_{t+1},, f(\gamma_{t+1}) = \phi_0 + \phi_1 X_{1t} + \phi_2 X_{2t} + v_{t+1}$

where $\varepsilon_{t+1|t} \sim N(0, h_{t+1})$, $v_{t+1} \sim N(0, \sigma_v^2)$, $h_{t+1} = \omega + \beta_1 h_t + \beta_2 \varepsilon_{t+1}^2$, $f(\gamma_{t+1}) = \gamma_{t+1}$ or $\log \gamma_{t+1}$ for Panel A & B.

Panel A.	Case 5			Panel B.	Case 6
X_{1t}	ϕ_0	ϕ_1	σ_v	ϕ_1	σ_v
SURP	2.2711	-2.0264	< 0.0001	-1.2159	< 0.0001
tstats	2.5817	-2.2175	< 0.0001	-5.8229	< 0.0001
CAYA	2.1829	1.1093	< 0.0001	1.0735	< 0.0001
tstats	2.5720	1.3425	0.0001	3.7815	< 0.0001
DEF	2.2114	0.6745	< 0.0001	0.6526	< 0.0001
tstats	2.5647	0.8177	0.0001	4.4015	< 0.0001
DP	2.2755	0.8277	< 0.0001	1.0183	< 0.0001
tstats	2.6633	0.9952	< 0.0001	4.1038	< 0.0001
INFL	2.3547	-0.8541	< 0.0001	0.2846	10.5760
tstats	2.7278	-1.0766	< 0.0001	1.5560	0.9327
REGD	2.2806	-0.3068	< 0.0001	-0.6181	< 0.0001
tstats	2.6902	-0.4021	< 0.0001	-2.7971	< 0.0001
RREL	2.0703	-1.9762	< 0.0001	-0.7053	< 0.0001
tstats	2.3703	-2.1775	< 0.0001	-7.0341	< 0.0001
TERM	2.1334	1.1776	< 0.0001	0.6697	< 0.0001
tstats	2.4226	1.2530	0.0001	1.6139	< 0.0001

X_{1t}, X_{2t}	ϕ_0	ϕ_1	ϕ_2	σ_v	ϕ_1	ϕ_2	σ_v
SURP,CAYA					-0.9959	0.7332	< 0.0001
tstats					-1.8097	0.8674	< 0.0001
SURP,DEF					-1.2691	-0.0793	< 0.0001
tstats					-5.3486	-0.3451	< 0.0001
SURP,DP					-1.4001	-0.3607	< 0.0001
tstats					-6.0207	-1.0012	< 0.0001
SURP,INFL					-1.1862	-0.3289	< 0.0001
tstats					-4.4763	-0.9453	< 0.0001
SURP,REGD					-1.2588	0.0633	< 0.0001
tstats					-5.2204	0.3008	< 0.0001
SURP,RREL	2.0889	-1.8983	-1.8249	< 0.0001	-0.9728	-0.3002	< 0.0001
tstats	2.3367	-2.0715	-2.0196	< 0.0001	-2.9105	-1.6275	0.0002

Table 7: Time-series Specification Tests: Time-varying RRA and a hedging component(Case 1 & 2)

This table shows the estimation results of several different specifications of conditional ICAPM. Note: $r_{m,t+1}$ is the CRSP value-weighted stock return minus lagged 3-month treasury bill rate; Realized volatility($\hat{\sigma}_{m,t+1}$) is defined in the data appendix; All exogenous variables(X_{1t} , X_{2t}, and u_t) are normalized to have means of zero and standard deviations of one to facilitate the interpretation.u_t are entered as (CAYA$_t$,DP$_t$,TERM$_t$,DEF$_t$,INFL$_t$). All variables are defined in Table 1.

Model : $r_{m,t+1} = \gamma_{t+1} \exp(E_t(\ln \hat{\sigma}_{m,t+1}) + \frac{1}{2}\sigma_\eta^2) + \alpha_1 z_t + \varepsilon_{t+1}$,

$$f(\gamma_{t+1}) = \phi_0 + \phi_1(\text{SURP})_t + \phi_2(\text{CAYA})_t + v_{t+1}, \ln \hat{\sigma}_{m,t+1} = \delta_0 + \delta_1 \ln \hat{\sigma}_{m,t} + \delta_2' u_t + \eta_{t+1},$$

where $\varepsilon_{t+1|t} \sim N(0, E_t(\hat{\sigma}_{m,t+1}))$, $v_{t+1} \sim N(0, \sigma_v^2)$, $\eta_{t+1} \sim N(0, \sigma_\eta^2)$, $f(\gamma_{t+1}) = \gamma_{t+1}$ or $\log \gamma_{t+1}$ for Panel A & B.

Panel A.	Case 1					Panel B.	Case 2		
z_t	α_1	ϕ_0	ϕ_1	ϕ_2	σ_v	α_1	ϕ_0	ϕ_1	σ_v
CAYA	-0.0026	2.6317	-3.3528	2.1838	4.5517	0.0098	0.3776	-1.1995	0.5232
tstats	-0.1798	2.5110	-3.1571	0.9129	1.8376	1.7546	0.4490	-1.9659	0.5092
DEF	-0.0025	2.5947	-3.3898	1.8496	4.5337	-0.0005	0.3511	-1.2342	0.6060
tstats	-0.4435	2.5092	-3.1830	1.9427	1.8356	-0.0933	0.4143	-1.9833	0.6745
DP	-0.0031	2.6278	-3.4123	2.0810	4.5095	0.0044	0.4808	-1.1116	0.7611
tstats	-0.4202	2.5306	-3.1784	1.7732	1.8120	0.7477	0.6629	-2.0082	0.9407
INFL	-0.0105	2.4961	-2.7048	2.0803	3.9995	-0.0094	0.0467	-1.3728	< 0.0001
tstats	-1.7593	2.4473	-2.4651	2.2055	1.4572	-1.7188	0.1186	-4.0486	< 0.0001
REGD	0.0020	2.5979	-3.3692	1.8124	4.5348	0.0024	0.2882	-1.2889	0.5475
tstats	0.3949	2.5102	-3.1741	1.9186	1.8362	0.4695	0.3129	-1.9243	0.5732
RREL	-0.0098	2.5838	-2.9933	1.6707	4.2775	-0.0107	0.4755	-1.0673	0.4870
tstats	-1.6766	2.5090	-2.8003	1.7844	1.6602	-1.8687	0.6529	-1.9850	0.3901
TERM	0.0060	2.5594	-3.1173	1.6677	4.3951	0.0091	0.1943	-1.3229	0.3498
tstats	1.0853	2.4858	-2.9107	1.7641	1.7338	1.7413	0.1964	-1.9316	0.2299

Table 8: Time-series Specification Tests: Time-varying RRA and a hedging component(Case 3 & 4)

This table shows the estimation results of several different specifications of conditional ICAPM. Note: $r_{m,t+1}$ is the CRSP value-weighted stock return minus lagged 3-month treasury bill rate; Realized volatility($\hat{\sigma}_{m,t+1}$) is defined in the data appendix; All exogenous variables(X_{1t} , X_{2t}, and u_t) are normalized to have means of zero and standard deviations of one to facilitate the interpretation.u_t are entered as (CAYA$_t$,DP$_t$,TERM$_t$,DEF$_t$,INFL$_t$). All variables are defined in Table 1.

$$\text{Model}: r_{m,t+1} = \gamma_{t+1}\exp(E_t(\ln\hat{\sigma}_{m,t+1}) + \tfrac{1}{2}\sigma_\eta^2) + \alpha_1 z_t + \varepsilon_{t+1},$$
$$f(\gamma_{t+1}) = \phi_0 + \phi_1(\text{SURP})_t + \phi_2(\text{CAYA})_t + v_{t+1}, \ln\hat{\sigma}_{m,t+1} = \delta_0 + \delta_1\ln\hat{\sigma}_{m,t} + \delta_2' u_t + \eta_{t+1},$$

where $\varepsilon_{t+1|t} \sim N(0, h_{t+1})$, $h_{t+1} = \omega + \beta_1 h_t + \beta_2\varepsilon_t^2$, $v_{t+1} \sim N(0, \sigma_v^2)$, $\eta_{t+1} \sim N(0, \sigma_\eta^2)$, $f(\gamma_{t+1}) = \gamma_{t+1}$ or $\log\gamma_{t+1}$ for Panel A & B.

Panel A.	Case 3				Panel B.	Case 4			
z_t	α_1	ϕ_0	ϕ_1	σ_v	α_1	ϕ_0	ϕ_1	ϕ_2	σ_v
CAYA	0.0089	2.5172	-3.2808	9.9275	-0.0016	0.2543	-0.7712	1.0620	< 0.0001
tstats	1.5453	2.3678	-3.0336	6.2502	-0.2021	0.7930	-2.0618	2.8440	< 0.0001
DEF	-0.0009	2.5100	-3.3542	10.0052	0.0010	0.2469	-0.7741	1.0566	< 0.0001
tstats	-0.1481	2.3366	-3.0480	6.3260	0.1610	0.7626	-2.0353	2.8267	< 0.0001
DP	0.0036	2.5028	-3.2379	10.0380	-0.0005	0.2467	-0.7818	1.0559	< 0.0001
tstats	0.6085	2.3379	-2.9508	6.3089	-0.0757	0.7626	-2.0492	2.8154	< 0.0001
INFL	-0.0106	2.4819	-2.9619	10.1547	-0.0129	0.1628	-0.7356	1.2321	< 0.0001
tstats	-1.7584	2.3738	-2.6129	7.0147	-2.0562	0.5191	-1.9389	3.2684	< 0.0001
REGD	0.0019	2.5080	-3.3727	9.9688	0.0065	0.2302	-0.8081	1.1176	< 0.0001
tstats	0.3433	2.3424	-3.0802	6.2864	1.0496	0.7668	-2.1290	3.2386	< 0.0001
RREL	-0.0102	2.4834	-2.9256	9.9296	-0.0114	0.2299	-0.7068	1.0912	< 0.0001
tstats	-1.7225	2.3252	-2.6528	6.2684	-1.9303	0.7016	-1.9823	3.0064	< 0.0001
TERM	0.0067	2.4357	-3.0759	9.9324	0.0121	0.1551	-0.8107	1.1921	< 0.0001
tstats	1.1875	2.2801	-2.7891	6.2358	2.0712	0.4537	-2.0466	3.1224	< 0.0001

Table 9: Time-series Specification Tests: Time-varying RRA and a hedging component(Case 5 & 6)

This table shows the estimation results of several different specifications of conditional ICAPM. Note: $r_{m,t+1}$ is the CRSP value-weighted stock return minus lagged 3-month treasury bill rate; Realized volatility($\hat{\sigma}_{m,t+1}$) is defined in the data appendix; All exogenous variables(X_{1t} , X_{2t}, and u_t) are normalized to have means of zero and standard deviations of one to facilitate the interpretation.u_t are entered as (CAYA$_t$,DP$_t$,TERM$_t$,DEF$_t$,INFL$_t$). All variables are defined in Table 1.

Model : $r_{m,t+1} = \gamma_{t+1}h_{t+1} + +\alpha_1 z_t + \varepsilon_{t+1},\ f(\gamma_{t+1}) = \phi_0 + \phi_1 X_{1t} + \phi_2 X_{2t} + v_{t+1}$

where $\varepsilon_{t+1|t} \sim N(0, h_{t+1}),\ v_{t+1} \sim N(0, \sigma_v^2),\ h_{t+1} = \omega + \beta_1 h_t + \beta_2 \varepsilon_{t+1}^2,\ f(\gamma_{t+1}) = \gamma_{t+1}$ or $\log \gamma_{t+1}$ for Panel A & B.

Panel A.	Case 5				Panel B.	Case 6	
z_t	α_1	ϕ_0	ϕ_1	σ_v	α_1	ϕ_1	σ_v
CAYA	0.0058	2.1778	-2.0588	0.0028	0.0060	-1.2146	< 0.0001
tstats	0.8672	2.4048	-2.2227	0.0110	0.9058	-5.5819	< 0.0001
DEF	0.0025	2.2438	-2.0004	< 0.0001	0.0014	-1.2027	< 0.0001
tstats	0.4007	2.5386	-2.1938	< 0.0001	0.2159	-5.4448	< 0.0001
DP	0.0028	2.2333	-1.9897	< 0.0001	0.0016	-1.2009	< 0.0001
tstats	0.4502	2.5249	-2.1795	< 0.0001	0.2444	-5.4039	< 0.0001
INFL	-0.0083	2.2869	-1.6442	0.0029	-0.0089	-1.1880	< 0.0001
tstats	-1.2556	2.6216	-1.7164	0.0113	-1.3967	-5.0927	< 0.0001
REGD	0.0005	2.2694	-2.0368	< 0.0001	0.0021	-1.2371	< 0.0001
tstats	0.0850	2.5845	-2.2193	< 0.0001	0.3558	-5.8334	< 0.0001
RREL	-0.0105	2.2373	-1.8417	0.0000	-0.0099	-1.1362	< 0.0001
tstats	-1.8233	2.4655	-1.9843	0.0002	-1.6875	-4.6121	< 0.0001
TERM	0.0086	2.1541	-1.9274	0.0001	0.0100	-1.2165	< 0.0001
tstats	1.4627	2.4321	-2.1099	0.0006	1.7241	-5.6368	< 0.0001

Table 10: Time-series Specification Tests: Time-varying RRA(Case 1 & 2) from 1982:01 to 2005:04

This table shows the estimation results of several different specifications of conditional CAPM using data from 1982:1 to 2005:4. Note: $r_{m,t+1}$ is the CRSP value-weighted stock return minus lagged 3-month treasury bill rate; Realized volatility($\hat{\sigma}_{m,t+1}$) is defined in the data appendix; All exogenous variables(X_{1t} , X_{2t}, and u_t) are normalized to have means of zero and standard deviations of one to facilitate the interpretation.u_t are entered as (CAYA$_t$,DP$_t$,TERM$_t$,DEF$_t$,INFL$_t$). All variables are defined in Table 1.

Model : $r_{m,t+1} = \gamma_{t+1} \exp(E_t(\ln \hat{\sigma}_{m,t+1}) + \frac{1}{2}\sigma_\eta^2) + \varepsilon_{t+1}$,

$$f(\gamma_{t+1}) = \phi_0 + \phi_1 X_{1t} + \phi_2 X_{2t} + v_{t+1}, \ln \hat{\sigma}_{m,t+1} = \delta_0 + \delta_1 \ln \hat{\sigma}_{m,t} + \delta_2' u_t + \eta_{t+1},$$

where $\varepsilon_{t+1|t} \sim N(0, E_t(\hat{\sigma}_{m,t+1}))$, $v_{t+1} \sim N(0, \sigma_v^2)$, $\eta_{t+1} \sim N(0, \sigma_\eta^2)$, $f(\gamma_{t+1}) = \gamma_{t+1}$ or $\log \gamma_{t+1}$ for Panel A & B.

Panel A.	Case 1			Panel B.	Case 2	
X_{1t}	ϕ_0	ϕ_1	σ_v	ϕ_0	ϕ_1	σ_v
SURP	3.0847	-2.7899	2.9701	0.9024	-0.5991	< 0.0001
tstats	2.2531	-2.0159	0.6693	1.6046	-1.8823	< 0.0001
CAYA	3.0978	2.0294	3.5893	0.9577	0.6453	1.1839
tstats	2.2107	1.5210	0.9463	1.6426	1.1929	1.0742
DEF	2.7532	0.1347	4.5128	1.0145	0.0254	1.6317
tstats	1.9208	0.1057	1.4467	1.8842	0.0428	1.2627
DP	3.0184	1.6578	3.5060	0.9121	-0.4887	< 0.0001
tstats	2.1667	1.3177	0.8900	1.5386	-1.2302	< 0.0001
INFL	2.7598	-1.1902	4.7687	0.9644	-0.4326	1.5370
tstats	1.9283	-0.8436	1.6184	1.6212	-0.7046	1.5845
REGD	2.9783	1.4637	4.2755	1.0443	0.2077	1.0714
tstats	2.1003	1.1003	1.3295	2.0752	0.2655	0.3222
RREL	2.5901	-1.2073	4.2810	0.5850	-0.5233	< 0.0001
tstats	1.8141	-0.8820	1.3233	0.7458	-1.8081	< 0.0001
TERM	2.8651	1.0059	4.4227	0.9791	0.4132	1.4724
tstats	2.0157	0.7374	1.4085	1.7259	0.8118	1.4270

X_{1t}, X_{2t}	ϕ_1	ϕ_2	σ_v	ϕ_1	ϕ_2	σ_v
SURP,RREL				-0.8698	-0.1829	< 0.0001
tstats				-2.2108	-0.6184	< 0.0001

Table 11: Time-series Specification Tests: Time-varying RRA and a hedging component(Case 1 & 2) from 1982:01 to 2005:04

This table shows the estimation results of several different specifications of conditional ICAPM using data from 1982:1 to 2005:4. Note: $r_{m,t+1}$ is the CRSP value-weighted stock return minus lagged 3-month treasury bill rate; Realized volatility($\hat{\sigma}_{m,t+1}$) is defined in the data appendix; All exogenous variables(X_{1t} , X_{2t}, and u_t) are normalized to have means of zero and standard deviations of one to facilitate the interpretation.u_t are entered as (CAYA_t,DP_t,TERM_t,DEF_t,INFL_t). All variables are defined in Table 1.

Model : $r_{m,t+1} = \gamma_{t+1} \exp(E_t(\ln \hat{\sigma}_{m,t+1}) + \frac{1}{2}\sigma_\eta^2) + \alpha_1 z_t + \varepsilon_{t+1}$,

$$f(\gamma_{t+1}) = \phi_0 + \phi_1(\text{SURP})_t + \phi_2(\text{CAYA})_t + v_{t+1}, \ln \hat{\sigma}_{m,t+1} = \delta_0 + \delta_1 \ln \hat{\sigma}_{m,t} + \delta_2' u_t + \eta_{t+1},$$

where $\varepsilon_{t+1|t} \sim N(0, E_t(\hat{\sigma}_{m,t+1}))$, $v_{t+1} \sim N(0, \sigma_v^2)$, $\eta_{t+1} \sim N(0, \sigma_\eta^2)$, $f(\gamma_{t+1}) = \gamma_{t+1}$ or $\log \gamma_{t+1}$ for Panel A & B.

Panel A.	Case 1					Panel B.	Case 2	
z_t	α_1	ϕ_0	ϕ_1	σ_v	α_1	ϕ_0	ϕ_1	σ_v
CAYA	0.0109	3.0721	-2.9015	2.1573	0.0105	0.9097	-0.6026	< 0.0001
tstats	1.3883	2.2867	-2.1219	0.3618	1.3532	1.6324	-1.9171	< 0.0001
DEF	-0.0075	3.0634	-2.9082	2.7166	-0.0104	0.7704	-0.7363	< 0.0001
tstats	-0.8763	2.2568	-2.1082	0.5684	-1.1522	1.0951	-1.8552	< 0.0001
DP	0.0025	3.0705	-2.7066	2.9279	0.0023	0.9151	-0.5759	< 0.0001
tstats	0.2923	2.2447	-1.9155	0.6513	0.2597	1.6511	-1.7577	< 0.0001
INFL	-0.0124	3.0466	-2.7778	2.4018	-0.0153	0.7281	-0.7623	< 0.0001
tstats	-1.5812	2.2499	-2.0353	0.4612	-1.8935	0.9778	-1.8576	< 0.0001
REGD	0.0093	3.0658	-2.8895	2.3656	0.0112	0.8242	-0.6958	< 0.0001
tstats	1.1572	2.2750	-2.1099	0.4429	1.3786	1.2949	-1.9518	< 0.0001
RREL	-0.0012	3.0842	-2.7593	2.9547	-0.0013	0.9080	-0.5903	< 0.0001
tstats	-0.1474	2.2507	-1.9705	0.6643	-0.1672	1.6231	-1.8359	< 0.0001
TERM	0.0032	3.0748	-2.7346	2.9170	0.0043	0.8970	-0.6015	< 0.0001
tstats	0.4392	2.2486	-1.9696	0.6506	0.5973	1.5792	-1.8662	< 0.0001

Table 12: Summary Statistics for the estimated Time-varying Risk Aversion

Summary statistics for the estimated risk aversion from 1957:2 to 2005:4. The Auto(1) give the first autocorrelation. This table shows descriptive statistics of the estimated risk aversion series(exp(log γ_{t+1})) from conditional CAPM with the surplus consumption ratio(Model1) and conditional ICAPM with the surplus consumption ratio and the consumption-wealth ration as instruments for relative risk aversion and RREL as a proxy for hedging component(Model2). Note: $r_{m,t+1}$ is the CRSP value-weighted stock return minus lagged 3-month treasury bill rate;Realized volatility(REVOL1) is defined in the data appendix; All exogenous variables(SURP$_t$,RREL$_t$,and u_t) are normalized to have means of zero and standard deviations of one. u_t are entered as (CAYA$_t$,DP$_t$,TERM$_t$,DEF$_t$,INFL$_t$). All variables are defined in Table 1.

$$\text{Model1}: r_{m,t+1} = \exp(\log\gamma_{t+1})\exp(E_t(\ln\hat{\sigma}_{m,t+1}) + \tfrac{1}{2}\sigma_\eta^2) + \varepsilon_{t+1},$$
$$\text{Model2}: r_{m,t+1} = \exp(\log\gamma_{t+1})\exp(E_t(\ln\hat{\sigma}_{m,t+1}) + \tfrac{1}{2}\sigma_\eta^2) + \alpha_1(\text{RREL})_t + \varepsilon_{t+1},$$
$$\log\gamma_{t+1} = \phi_0 + \phi_1(\text{SURP})_t + v_{t+1},\ \ln\hat{\sigma}_{m,t+1} = \delta_0 + \delta_1\ln\hat{\sigma}_{m,t} + \delta_2' u_t + \eta_{t+1}$$

where $\varepsilon_{t+1|t} \sim N(0, h_{t+1})$, $v_{t+1} \sim N(0, \sigma_v^2)$, $\eta_{t+1} \sim N(0, \sigma_\eta^2)$, $h_{t+1} = \omega + \beta_1 h_t + \beta_2\varepsilon_t^2$

	Risk Aversion(C-CAPM)	Risk Aversion(C-ICAPM)
Mean	2.388	2.070
Median	0.771	0.850
Maximum	15.994	16.801
Minimum	0.035	0.055
Std. Dev.	3.020	2.580
Skewness	1.835	2.342
Kurtosis	6.544	10.271
Auto(1)	0.906	0.852
Corr	0.964	

Table 13: Cross-Sectional Tests of Asset Pricing Models on Fama French 25 portfolios(1957:2-2005:4)

The table presents the estimated results of Fama and MacBeth (1973) cross-sectional regression using the excess returns on 25 portfolios sorted by book-to-market and size. The full-sample factor loadings, which are the independent variables in the regressions, are computed in one multiple time-series regression following Lettau and Ludvigson (2001b). The Adjusted R^2 follows the specification of Jagannathan and Wang (1996). Adj.$R^2(2)$ is calculated from Fama-Macbeth regression without a constarnt. The first set of standard errors, indicated by FM, stands for the Fama-MacBeth estimates. The second set, indicated by Shanken, adjusts for erros-in-variables and follows Shanken (1992). Approximate F-statistics is the transformed Hotelling T^2-statistics for the small sample test that the pricing errors in the model are jointly zero by Shanken (1985) and 1 percent critical value is given below the F-statistics. The last column reports the root mean squared pricing errors of the model. Note: Rmrf, SMB, and HML are the Fama and French (1993)'s market and size and B/M factors;CAYA is the consumption-wealth ratio without a look ahead bias; RREL is the difference between the 3 month treasury bill rate and its average in the previous 4 quarters; SURP is the surplus consumption ratio; and TERM is the yield spread between 10-year Treasury bonds and 3-month treasure bills. All exogenous variables(SURP,CAYA, RREL, and TERM) are normalized to have means of zero and standard deviations of one. All models are defined in section *3.2.5*.

Panel A

	const	Rmrf	SMB	HML				Adj.R^2	F-test	RMSE	Adj.$R^2(2)$
CAPM	0.0401	-0.0163						0.1781	2.9598	0.0064	-0.8402
FM	0.0083	0.0104							1.9209		
Shanken	0.0084	0.0105									
Fama-French	0.0459	-0.0296	0.0034	0.0150				0.7369	2.5218	0.0035	0.5909
FM	0.0099	0.0119	0.0043	0.0047					1.9634		
Shanken	0.0108	0.0127	0.0043	0.0047							

Panel B

	const	Rmrf	SURP*Rmrf	CAYA*Rmrf	REVOL	RREL	CAYA	Adj.R^2	F-test	RMSE	Adj.$R^2(2)$
Model 1	0.0239	-0.0086	0.0267	0.0741	0.0023			0.6059	3.2304	0.0042	0.5687
FM	0.0075	0.0097	0.0153	0.0201	0.0013				1.9873		
Shanken	0.0104	0.0121	0.0205	0.0273	0.0017						
Model 2	0.0203	0.0010	-0.0127	0.0742	0.0005	-1.1724		0.6824	2.8692	0.0036	0.6571
FM	0.0079	0.0106	0.0175	0.0185	0.0006	0.3923			2.0132		
Shanken	0.0137	0.0163	0.0294	0.0310	0.0011	0.6787					
Model 3	0.0239	-0.0078	0.0259	0.0624	0.0001		-0.8816	0.6769	1.9347	0.0037	0.6336
FM	0.0075	0.0098	0.0145	0.0182	0.0006		0.2801		2.0132		
Shanken	0.0115	0.0131	0.0209	0.0267	0.0009		0.4175				

Table 14: Cross-Sectional Tests of Asset Pricing Models on Fama French 25 size-B/M and 30 industry portfolios(1957:2-2005:4)

The table presents the estimated results of Fama and MacBeth (1973) cross-sectional regression using the excess returns on 25 portfolios sorted by book-to-market and size together with 30 industry portfolios. The full-sample factor loadings, which are the independent variables in the regressions, are computed in one multiple time-series regression following Lettau and Ludvigson (2001b). The Adjusted R^2 follows the specification of Jagannathan and Wang (1996). Adj.$R^2(2)$ is calculated from Fama-Macbeth regression without a constarnt. The first set of standard errors, indicated by FM, stands for the Fama-MacBeth estimates. The second set, indicated by Shanken, adjusts for erros-in-variables and follows Shanken (1992). Approximate F-statistics is the transformed Hotelling T^2-statistics for the small sample test that the pricing errors in the model are jointly zero by Shanken (1985) and 1 percent critical value is given below the F-statistics. The last column reports the root mean squared pricing errors of the model. Note: Rmrf, SMB, and HML are the Fama and French (1993)'s market and size and B/M factors;CAYA is the consumption-wealth ratio without a look ahead bias; RREL is the difference between the 3 month treasury bill rate and its average in the previous 4 quarters; SURP is the surplus consumption ratio; and TERM is the yield spread between 10-year Treasury bonds and 3-month treasure bills. All exogenous variables(SURP,CAYA, RREL, and TERM) are normalized to have means of zero and standard deviations of one. All models are defined in section *3.2.5*.

Panel A

	const	Rmrf	SMB	HML	Adj.R2	F-test	RMSE	Adj.R^2(2)
CAPM	0.0275	-0.0068			0.0372	2.7245	0.0060	-0.7234
FM	0.0070	0.0094				(1.6587)		
Shanken	0.0070	0.0095						
Fama-French	0.0325	-0.0153	0.0029	0.0087	0.2583	2.5700	0.0052	0.0296
FM	0.0082	0.0104	0.0044	0.0048		1.6686		
Shanken	0.0085	0.0106	0.0044	0.0048				

Panel B

	const	Rmrf	SURP*Rmrf	CAYA*Rmrf	REVOL	RREL	CAYA	Adj.R2	F-test	RMSE	Adj.R^2(2)
Model 1	0.0226	-0.0051	0.0079	0.0255	0.0013			0.2121	2.8826	0.0053	0.0403
FM	0.0068	0.0095	0.0131	0.0138	0.0010				1.6738		
Shanken	0.0073	0.0099	0.0139	0.0146	0.0011						
Model 2	0.0227	-0.0053	0.0091	0.0252	0.0021	0.0368		0.1868	2.5351	0.0053	0.0270
FM	0.0066	0.0093	0.0134	0.0136	0.0018	0.2157			1.6791		
Shanken	0.0070	0.0097	0.0142	0.0144	0.0019	0.2298					
Model 3	0.0287	-0.0121	0.0231	0.0276	0.0006		-0.6388	0.3506	1.9864	0.0047	0.0801
FM	0.0067	0.0093	0.0127	0.0136	0.0016		0.2032		1.6791		
Shanken	0.0084	0.0108	0.0153	0.0163	0.0020		0.2494				