Consumption Betas and the Cross-Section of Option Returns

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Preliminary

January 2018

Abstract

We show that time variation in both conditional mean and volatility of consumption growth affects option returns. We estimate the conditional moments of consumption growth from a Markov-switching process. Using option portfolio returns in cross-sectional pricing tests, we show that loadings on consumption growth and expected consumption growth significantly positively forecast delta-hedged returns and those on consumption growth volatility significantly negatively forecast delta-hedged returns. Applying an alternative empirical specification, we confirm that exposure to consumption growth is a positively priced source of risk in both simple and delta-hedged option returns. Our findings lend strong support for a preference for early resolution of uncertainty.

JEL Classification: G11; G12.

Keywords: Asset pricing, Cross-sectional option return, Consumption beta

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§We thank Michael Brennan for helpful comments. Any remaining errors are ours.

1 Introduction

It has been widely studied how moments of consumption growth are priced in stock returns. Surprisingly, the impact of moments of consumption growth on option returns has received little attention in empirical tests of consumption-based pricing models. The contribution of this paper is to show that exposures to consumption growth, expected consumption growth and consumption growth volatility lead to risk premiums in cross-sectional delta-hedged option returns. Options exposed more to consumption growth risk and expected consumption growth risk, and less to consumption volatility risk require higher expected delta-hedged returns. More importantly, this empirical result strongly supports that investors prefer to resolve uncertainty sooner than later.

To guide the empirical exercise, we adopt the model framework of Kandel and Stambaugh (1991), Bansal and Yaron (2004) and Lettau, Ludvigson, and Wachter (2008). The representative agent has recursive Epstein and Zin (1989) preferences, and the conditional first and second moments of consumption growth follow two independent two-state Markov chains with unobservable states. The model setting implies that the agent's beliefs in those unobservable consumption states or the agent's estimates of the conditional first and second moments of consumption growth are priced. When the elasticity of intertemporal substitution (EIS) is greater than the inverse of the relative risk aversion (RRA), the agent prefers that intertemporal risk from unobservable Markov states be resolved sooner than later. Consequently, the agent demands positive and negative prices of risk for shocks to the conditional expectation and volatility of consumption growth respectively.

Following Hamilton (1994), we estimate a Markov chain for the first and second moments of consumption growth. We retain the common assumption that the representative agent has preferences over total consumption, defined as the sum of nondurable and service consumption expenditures. Following Cao and Han (2013), we calculate simple and delta-hedged call option returns. And we form 10 equally-weighted option portfolios based on lag-one-period moneyness, defined as underlying stock price divided by option strike price. To exclude the influence of time-to-maturity, we specify the range of lag-one-period time-to-maturities of call options before forming portfolios.

Our first set of empirical evidence on the pricing of moments of consumption is based on market prices of risk obtained from regressions of option portfolio returns on estimated loadings on log consumption growth, as well as changes in the perceived mean and volatility of consumption growth. For delta-hedged returns, empirical analysis shows no evidence that changes in the expected consumption growth are priced. However, consumption growth and consumption growth volatility are robustly priced in the cross-section of delta-hedged returns. Importantly, the price of consumption volatility risk is negative, consistent with preference for early resolution of uncertainty. This is a crucial assumption in the long-run risk framework of Bansal and Yaron (2004) and our finding strongly supports it. For simple returns, risk loading on consumption growth is not priced. But mean and volatility of consumption growth are positively priced in the cross-section. Positive price of consumption expectation risk implies preference for early resolution of risk, while positive price of consumption volatility risk implies preference for late resolution of risk. Contradictory results occur in simple call option returns.

Applying an alternative numerical approximation, we have an alternative empirical test specification. We run rolling quarterly time-series regressions of option portfolio returns on consumption growth as well as log changes in the perceived mean and volatility of consumption growth to obtain time-varying risk loadings. We study the relation between risk loadings and future returns. Consistent with former results in delta-hedged returns, price for consumption growth risk and price for consumption volatility risk are positive and negative respectively. Moreover, loadings on expected consumption growth significantly positively forecast cross-sectional differences in delta-hedged returns. That provides further evidence that the representative agent prefers to resolve uncertainty early. More importantly, we can even decide the value of EIS and RRA with three significant risk premiums. Inconsistent with former results in simple returns, market prices for consumption growth risk and consumption mean risk are positive and negative respectively. And no evidence shows that consumption volatility risk is priced in the cross-section of simple call option returns. The inconsistency between results from different empirical specifications makes it difficult to draw inferences on model parameters from simple call option returns.

To figure out why empirical results are different for simple and delta-hedged returns, we use the third empirical test specification. To estimate risk loadings, we run rolling quarterly time-series regressions of option portfolio returns on consumption growth as well as changes in beliefs in high mean-low variance, high mean-high variance, and low mean-low variance consumption states.

Similarly, we study the relation between risk loadings and future returns. For both simple and delta-hedged returns, consumption growth is robustly priced in the cross-section and the market price of consumption growth risk is positive. With the EIS larger than the inverse of RRA, risk premiums for loadings on beliefs in high mean-low variance, high mean-high variance, and low mean-low variance consumption states should all be positive. However, empirical evidence shows that the market price for loading on belief in high mean-high variance is negative for simple option returns. The mispricing of belief in high mean-high variance consumption state causes the mispricing of consumption volatility risk in the first set of empirical results in simple returns. We have not found the reason for the mispricing.

Pricing of volatilities in cross-sectional option returns has received attention in the literature recently. Cao and Han (2013) presents a robust new finding that delta-hedged equity option return decreases monotonically with an increase in the idiosyncratic volatility of the underlying stock. Aretz, Lin, and Poon (2016) use a model of the stochastic discount factor to show that the expected returns of European options are not unambiguously related to their underlying asset's volatility. Hu and Jacobs (2017) show that returns on call (put) option portfolios decrease (increase) with underlying stock volatility in the cross-section of stock option returns. These papers study the relation between underlying stock volatility and cross-sectional option returns.

Motivated by the long-run risk model of Bansal and Yaron (2004), several important papers study the relation between consumption volatility and prices. Bansal, Khatchatrian, and Yaron (2005) find that measures of economic uncertainty (conditional consumption volatility) predict and are predicted by valuation ratios at long horizons. Lettau, Ludvigson, and Wachter (2008) estimate a Markov model with learning to show that learning about declining consumption volatility can explain the decrease in equity risk premium during the 1990s. Calvet and Fisher (2007) introduce a parsimonious equilibrium model with regime shifts of heterogeneous durations in fundamentals and estimate specifications with up to 256 states on daily aggregate returns. We extend this literature by studying the cross-section of option returns rather than aggregate valuation ratios.

Papers closely related to our work are Jagannathan and Wang (2007), Bansal, Kiku, and Yaron (2007), Romeo (2013) and Boguth and Kuehn (2013). Jagannathan and Wang (2007) point out that the consumption-based asset pricing model (CCAPM) explains the cross-section of stock returns as well as the Fama and French (1993) three-factor model when consumption betas are computed using year-over-year consumption growth based upon the fourth quarter. Bansal, Kiku, and Yaron (2007) empirically evaluate the ability of the long-run risks model to explain asset returns. They highlight the importance of low-frequency movements and time-varying uncertainty in economic growth for understanding risk-return tradeoffs in financial markets. Romeo (2013) shows that changes in consumption volatility are the key driver for explaining major asset pricing anomalies across risk horizons. Boguth and Kuehn (2013) show that consumption volatility is a negatively priced source of risk for a wide variety of test portfolios and exposure to consumption volatility risk predicts future returns at the firm level. These studies investigate the pricing of moments of consumption growth in stock returns while our work in option returns.

Recent extensions to the long-run risk framework that study the pricing implications of time-varying uncertainty include the following papers. Drechsler and Yaron (2011) extend the long-run risks model. They demonstrate that time-varying economic uncertainty and a preference for early resolution of uncertainty are required to generate a positive time-varying variance premium that predicts excess stock market returns. Bansal and Shaliastovich (2011) model optimal decisions of investors to learn the unobserved state. Their model predicts that income volatility predicts future jump periods while income growth does not. Bollerslev et al. (2009) study the pricing implications from a stylized self-contained general equilibrium model incorporating the effects of time-varying economic uncertainty. While we also study the effect of time-varying uncertainty in a framework with Epstein-Zin preferences, we focus on cross-sectional pricing.

The remainder of the paper is organized as follows. In Section 2, we describe the theoretical framework which motivates our empirical analysis in Section 3. In Section 3, we test whether loadings on consumption growth and its conditional moments forecast returns in the cross-section. Section 4 concludes. The Appendix contains derivations and additional results.

2 Model

In this section, we describe the consumption-based asset pricing model developed by Lettau, Ludvigson, and Wachter (2008). In the model, the consumption growth rate follows a Markov-switching process, and the representative agent has recursive preferences of Epstein and Zin (1989).

We then follow Boguth and Kuehn (2013) and linearize the pricing kernel to derive an equation of expected returns for empirical testing.

2.1 Consumption

We assume that the log of consumption growth follows a Markov-switching process in which the conditional mean and volatility states follow two independent Markov chains. To be specific, log consumption growth, Δc_{t+1}, follows

$$\Delta c_{t+1} \equiv \ln\left(\frac{C_t}{C_{t-1}}\right) = \mu_t + \sigma_t \epsilon_{t+1}, \quad \epsilon_{t+1} \sim N(0,1),$$

where μ_t represents the conditional expectation and σ_t the conditional standard deviation. We assume two states for the mean, $\mu_t \in \{\mu_l, \mu_h\}$, and two for the volatility, $\sigma_t \in \{\sigma_l, \sigma_h\}$. The transition matrices for the mean and volatility states are $\boldsymbol{P}^{\mu}$ and $\boldsymbol{P}^{\sigma}$ respectively, given by

$$\boldsymbol{P}^{\mu} = \begin{bmatrix} p_{\mu}^{hh} & 1-p_{\mu}^{ll} \\ 1-p_{\mu}^{hh} & p_{\mu}^{ll} \end{bmatrix} \quad \boldsymbol{P}^{\sigma} = \begin{bmatrix} p_{\sigma}^{hh} & 1-p_{\sigma}^{ll} \\ 1-p_{\sigma}^{hh} & p_{\sigma}^{ll} \end{bmatrix}. \tag{1}$$

Since the mean and volatility states switch independently, the joint transition matrix is the product of the marginal transition probabilities for mean and volatility states and can be fully characterized by p_{μ}^{ll}, p_{μ}^{hh}, p_{σ}^{ll}, and p_{σ}^{hh}. As stated by Boguth and Kuehn (2013), independent switching for mean and volatility states do not imply that the beliefs about mean and volatility states are independent.

We assume that the representative agent does not observe the state of the economy and must infer it from observable consumption data. The posterior belief that the economy is in specific states at date $t+1$ conditional on observations obtained through date t is denoted by the vector $\boldsymbol{\xi}_{t+1|t}$. The Bayesian inference implies that the belief vector evolves according to

$$\boldsymbol{\xi}_{t+1|t} = \boldsymbol{P}\frac{\left(\boldsymbol{\xi}_{t|t-1} \odot \boldsymbol{\eta}_t\right)}{\mathbf{1}'\left(\boldsymbol{\xi}_{t|t-1} \odot \boldsymbol{\eta}_t\right)}. \tag{2}$$

where $\boldsymbol{\eta}_t$ is a vector of conditional Gaussian densities, $\odot$ represents element-by-element multiplication, $\boldsymbol{P} = \boldsymbol{P}^{\mu} \otimes \boldsymbol{P}^{\sigma}$ denotes the joint transition matrix, and $\otimes$ is the symbol for the Kronecker product.

2.2 Model Framework

We apply a standard asset pricing model with a representative agent and recursive preferences as in Epstein and Zin (1989) and Weil (1989). The indirect utility at time t, U_t is given by

$$U_t = \left[(1-\delta) C_t^{1-\frac{1}{\psi}} + \delta \left[E_t \left(U_{t+1}^{1-\gamma} \right) \right]^{\frac{1-\frac{1}{\psi}}{1-\gamma}} \right]^{\frac{1}{1-\frac{1}{\psi}}}. \tag{3}$$

C_t is consumption, δ is the time discount factor, γ determines the degree of relative risk aversion, and ψ is the elasticity of intertemporal substitution (EIS). And parameters γ and ψ are required to satisfy $\gamma > 0$, $\psi > 0$ and $\psi \neq 1$. For $\gamma = \frac{1}{\psi}$ the representative agent has standard CRRA preferences. $\gamma > \frac{1}{\psi}$ indicates a preference for the early resolution of uncertainty and $\gamma < \frac{1}{\psi}$ indicates a preference for late resolution. The general asset pricing equation to price any asset i is given by

$$E_t \left[M_{t+1} R_{i,t+1} \right] = 1. \tag{4}$$

And the stochastic discount factor is

$$M_{t+1} = \delta^{\frac{1-\gamma}{1-\frac{1}{\psi}}} \left(\frac{C_{t+1}}{C_t} \right)^{-\gamma} \left(\frac{Z_{t+1}}{Z_t - 1} \right)^{\frac{\frac{1}{\psi}-\gamma}{1-\frac{1}{\psi}}}, \tag{5}$$

and $Z_t = \frac{W_t}{C_t}$, denotes the wealth-consumption ratio. A log-linear approximation of the pricing kernel implied by (5) is

$$m_{t+1} \approx \left(\frac{1-\gamma}{1-\frac{1}{\psi}} \right) \ln \delta - \gamma \Delta c_{t+1} + \left(\frac{\frac{1}{\psi}-\gamma}{1-\frac{1}{\psi}} \right) \Delta z_{t+1}. \tag{6}$$

In an endowment economy where the consumption growth is only driven by independent and identically distributed (i.i.d.) shocks, the wealth-consumption ratio is constant. We assume that the conditional expectation and volatility of consumption growth follow a Markov chain. Under this setting, the agent's posterior beliefs over the moments characterize the state of the economy due to the unobservability of the Markov states. Consequently, the wealth-consumption ratio is a function of the agent's beliefs, $Z_t = Z(\boldsymbol{\xi}_{t+1|t})$.

2.3 Numerical Approximation

Define the posterior belief that the mean or volatility state is high tomorrow conditional on the current information set $\mathcal{F}_t$ by

$$b_{\mu,t} = P\left(\mu_{t+1} = \mu_h | \mathcal{F}_t\right) \quad b_{\sigma,t} = P\left(\sigma_{t+1} = \sigma_h | \mathcal{F}_t\right). \tag{7}$$

And define the perceived first and second moments of consumption growth as belief-weighted averages

$$\hat{\mu}_t = b_{\mu,t}\mu_h + \left(1 - b_{\mu,t}\right)\mu_l \quad \hat{\sigma}_t = b_{\sigma,t}\sigma_h + \left(1 - b_{\sigma,t}\right)\sigma_l. \tag{8}$$

The corresponding changes in the perceived moments are denoted by

$$\Delta\hat{\mu}_t = \hat{\mu}_t - \hat{\mu}_{t-1} \quad \Delta\hat{\sigma}_t = \hat{\sigma}_t - \hat{\sigma}_{t-1}, \tag{9}$$

and log changes in the perceived moments are

$$\Delta \ln \hat{\mu}_t = \ln \hat{\mu}_t - \ln \hat{\mu}_{t-1} \quad \Delta \ln \hat{\sigma}_t = \ln \hat{\sigma}_t - \ln \hat{\sigma}_{t-1}. \tag{10}$$

To conduct empirical analyses, we we assume that changes in the log wealth-consumption ratio can be approximated by changes or log changes in perceived moments of consumption growth linearly.

$$\Delta z_t \approx \kappa_1 + A_1\Delta\hat{\mu}_t + A_2\Delta\hat{\sigma}_t, \tag{11}$$

$$\Delta z_t \approx \kappa_2 + B_1\Delta \ln \hat{\mu}_t + B_2\Delta \ln \hat{\sigma}_t. \tag{12}$$

Also we assume that changes in the log wealth-consumption ratio are approximately affine in the changes of beliefs, that is

$$\Delta z_t \approx \kappa_3 + C_1\Delta\xi_{1,t} + C_2\Delta\xi_{2,t} + C_3\Delta\xi_{3,t}. \tag{13}$$

$\Delta\xi_1$, $\Delta\xi_2$ and $\Delta\xi_3$ are changes in beliefs for high mean-low variance, high mean-high variance and low mean-low variance consumption growth states respectively.

As presented in Table 1, changes in the log wealth-consumption ratio are proportional to changes in beliefs, changes in the perceived moments and log changes in the perceived moments. That can be confirmed by high R^2 in each panel. Panel A displays the situation where the RRA is greater than the inverse of EIS and the EIS is greater than 1 while panel B presents when EIS is smaller than 1. Panel C and panel D show the opposite cases for panel A and panel B respectively, namely when the RRA is smaller than the inverse of the EIS. In panel A and panel C, coefficients of changes in beliefs ($\Delta\xi_1$, $\Delta\xi_2$ and $\Delta\xi_3$) are all positive. Meanwhile, coefficients of $\Delta\hat{\mu}$ and $\Delta\ln\hat{\mu}$ are positive, whereas those of $\Delta\hat{\sigma}$ and $\Delta\ln\hat{\sigma}$ are negative. In contrast, in panel B and panel D, coefficients of $\Delta\xi_1$, $\Delta\xi_2$ and $\Delta\xi_3$ are all negative and those of $\Delta\hat{\mu}$ and $\Delta\ln\hat{\mu}$ are negative while those for $\Delta\hat{\sigma}$ and $\Delta\ln\hat{\sigma}$ are positive.

Insert Table 1 here

2.4 Asset Pricing Implications

We have shown that changes in the log wealth-consumption ratio can be linearly approximated by changes in beliefs. From an empirical asset pricing perspective, this implies that changes in beliefs about the conditional moments of consumption growth are priced in the cross-section since they affect the wealth-consumption ratio.

To test the model in the cross-section of returns, it is convenient to restate the Euler equation in terms of betas[1],

$$E_t\left[R_{i,t+1}\right] - R_t^f \approx \beta_{c1,t}^i \lambda_{c1,t} + \beta_{\mu,t}^i \lambda_{\mu,t} + \beta_{\sigma,t}^i \lambda_{\sigma,t}. \tag{14}$$

R_t^f is the risk-free rate, $\beta_{c1,t}^i$, $\beta_{\mu,t}^i$, $\beta_{\sigma,t}^i$ denote risk loadings of asset i at date t with respect to consumption growth and changes in the perceived first and second moments of consumption growth, and $\lambda_{c1,t}$, $\lambda_{\mu,t}$, $\lambda_{\sigma,t}$ are market prices of those betas.

[1] Detailed derivations for equations (14), (15) and (16) are shown in the Appendix.

Also we have

$$E_t\left[R_{i,t+1}\right] - R_t^f \approx \beta_{c2,t}^i \lambda_{c2,t} + \beta_{\ln\mu,t}^i \lambda_{\ln\mu,t} + \beta_{\ln\sigma,t}^i \lambda_{\ln\sigma,t}, \tag{15}$$

similarly, $\beta_{c2,t}^i$, $\beta_{\ln\mu,t}^i$, $\beta_{\ln\sigma,t}^i$ are risk loadings of asset i at date t with respect to consumption growth and log changes in the perceived first and second moments of consumption growth, and $\lambda_{c2,t}$, $\lambda_{\ln\mu,t}$, $\lambda_{\ln\sigma,t}$ are market prices of those betas.

Alternatively we have

$$E_t\left[R_{i,t+1}\right] - R_t^f \approx \beta_{c3,t}^i \lambda_{c3,t} + \beta_{\xi_1,t}^i \lambda_{\xi_1,t} + \beta_{\xi_2,t}^i \lambda_{\xi_2,t} + \beta_{\xi_3,t}^i \lambda_{\xi_3,t}. \tag{16}$$

$\beta_{c3,t}^i$, $\beta_{\xi_1,t}^i$, $\beta_{\xi_2,t}^i$, $\beta_{\xi_3,t}^i$ denote risk loadings of asset i at date t with respect to consumption growth and changes in beliefs of high mean-low variance, high mean-high variance and low mean-low variance consumption growth states, and $\lambda_{c3,t}$, $\lambda_{\xi_1,t}$, $\lambda_{\xi_2,t}$, $\lambda_{\xi_3,t}$ are market prices of those betas.

The model always predicts a positive risk premium for the consumption growth beta, since the RRA (γ) is positive. Table 2 reports signs of risk premiums when EIS is greater than and less than the inverse of the RRA. When EIS is greater than the inverse of the RRA, λ_μ, $\lambda_{\ln\mu}$, λ_{ξ_1}, λ_{ξ_2}, and λ_{ξ_3} are positive while λ_σ and $\lambda_{\ln\sigma}$ are negative. Those signs go opposite if EIS is less than the inverse of the RRA.

Insert Table 2 here.

The main cross-sectional implications of the model are summarized here. Assuming that the EIS is greater than the inverse of RRA ($\psi > \frac{1}{\gamma}$), the agent requires higher expected excess returns for options that load more on changes in expected consumption growth and less on changes in consumption growth volatility. In this case, the agent prefers that intertemporal risk due to the unobservable Markov states to be resolved sooner than later. Thus the agent likes positive shocks to expected consumption growth and requires a positive market price of risk. Meanwhile, she dislikes positive shocks to the conditional volatility of consumption growth and requires a negative market price of risk.

3 Empirical Tests

In this section, we estimate the Markov model and investigate the pricing implications of changes in consumption moments and beliefs of consumption states cross-sectionally.

3.1 Estimating Consumption Dynamics

Total consumption is defined as the sum of nondurable and services consumption expenditures. To estimate the model, we obtain data on quarterly per capita real consumption expenditures on nondurable goods and services from the Bureau of Economic Analysis (BEA). It is observed that consumption behavior in the United States following World War II is systematically different from later years. Following Yogo (2006), Lettau, Ludvigson, and Wachter (2008), and Boguth and Kuehn (2013), we restrict our time series from the first quarter of 1952 to the fourth quarter of 2016.

The parameter estimates of the Markov chains are reported in Table 3. Panel A shows that expected consumption growth is always positive and is 0.0844% and 0.5741% in low and high states respectively. State-conditional consumption volatilities are $\sigma_l = 0.2151\%$ and $\sigma_h = 0.4894\%$. The probability of remaining in a given regime for the mean is 0.87 in the low state and 0.96 in the high state. Both volatility regimes are persistent, with probabilities of 0.94 in the low state and 0.95 in the high state. Our estimates differ from those presented by Lettau, Ludvigson, and Wachter (2008). They present volatilities in both states to be more persistent, 0.991 and 0.994 respectively. Since there are differences in the consumption measure, uncertainty after the financial crisis in our analysis greatly reduces the persistence of volatility regimes.

[Insert Table 3 here]

[Insert Figure 1 here]

Figure 1 shows the filtered beliefs for the regimes. The upper panel depicts the belief dynamics for mean consumption growth, $b_{\mu,t}$, and the lower panel for the standard deviation, $b_{\sigma,t}$. Shown in those graphs, the mean regimes are more persistent than the volatility regimes. The parameter estimates of transition probabilities from high to high state for the mean regimes and the volatility regimes are 0.96 and 0.95 respectively. Imply that high mean states last 25 quarters whereas high volatility states last 20 quarters on average. Furthermore, a shift towards low volatility regimes from 1990s onward can be easily observed, as pointed out by Kim and Nelson (1999) and Boguth and Kuehn (2013). However, the 2000 dot-com and the 2008 financial crisis periods prove that the shift is not permanent.

3.2 Cross-Sectional Return Predictability

3.2.1 Data

We use data from the US equity option market. For the January 1996 to April 2016 sample period, we obtain call option data on US individual stock options from the Ivy DB database provided by OptionMetrics. The data fields include daily closing bid and ask quotes, trading volume, strike price, and expiration date of each option, and the option's delta computed by OptionMetrics based on standard market conventions. Also, we obtain the close prices and dividend distribution of underlying stocks of options and risk-free rates from OptionMetrics.

3.2.2 Sorting Portfolios

We calculate quarterly and monthly simple returns as well as delta-hedged returns for each option. To calculate monthly and quarterly simple option returns, we first keep end of month and quarter option prices. And apply several filters to the extracted option data, following Cao and Han (2013). First, we exclude an option if the underlying stock paid a dividend during the remaining life of the option. Second, we exclude call options that violate obvious no-arbitrage bounds such as $S \geq C \geq \max(0, S - Ke^{-rT})$, where C is the call option price, S is the underlying stock price, K is the strike price, T is time to maturity of the option, and r is the risk-free rate. Third, to avoid microstructure-related bias, we only retain options that have positive trading volume and positive bid quotes, with the bid price strictly smaller than the ask price, and the midpoint of bid and ask prices being at least 1/8. We only keep the options whose last trade dates match the record dates and whose option price dates match the underlying stock price dates.

Following Cao and Han (2013), we also calculate quarterly and monthly delta-hedged option returns. First, define delta-hedged option gain, which is change in the value of a self-financing portfolio consisting of a long call option, hedged by a short position in the underlying stock. This portfolio is not sensitive to stock price movement and the net investment earns risk-free rate. Following Bakshi and Kapadia (2003), consider a call option that is hedged discretely N times over a period $[t, t+\tau]$, where the hedge is rebalanced at each of the dates t_n, $n = 0, 1 \ldots, N-1$ (where we define $t_0 = t$, $t_N = t + \tau$). The discrete delta-hedged call option gain is given by

$$\begin{aligned} \Pi(t, t+\tau) = C_{t+\tau} - C_t - \sum_{n=0}^{N-1} \Delta_{c,t_n} \left[S(t_{n+1}) - S(t_n) \right] \\ - \sum_{n=0}^{N-1} \frac{a_n r_{t_n}}{365} \left[C(t_n) - \Delta_{C,t_n} S(t_n) \right], \end{aligned} \tag{17}$$

where C_t is the call option price on date t, Δ_{C,t_n}, $S(t_n)$ and r_{t_n} are the delta of the call option, the annualized risk-free rate and the underlying stock price on date t_n. a_n is the number of calendar days between t_n and t_{n+1}. The delta-hedged call option return is given by the scaled delta-hedged call option gain, $\Pi(t, t+\tau) / (\Delta_t S_t - C_t)$ and we hedge call options on a daily basis.

To exclude the influence of time-to-maturity, we keep observations with lag-one-period time-to-maturity between 30 to 90 days for monthly returns and 106 to 176 days for quarterly returns. Observations with those lag-one-period time-to-maturities account for around 47.87% and 47.94% for simple returns and 49.56% and 51.12% for delta-hedged returns among total monthly and quarterly observations. And we sort both simple and delta-hedged option returns into 10 equally-weighted portfolios based on lag-one-period moneyness. Portfolios are rebalanced each period. Moneyness is defined as the underlying stock price divided by the strike price of an option.

[Insert Table 4 here]

Table 4 reports the average returns of equally-weighted decile portfolios as well as a long-short strategy that each period invests $1 into decile 10 (high moneyness) and sells $1 of decile1 (low moneyness). In panel A, portfolios are formed with simple option returns. Both quarterly and monthly portfolio returns drop as moneyness increases, as what has been pointed out by Coval and Shumway (2001). Low-moneyness portfolios are more risky, and thus should be compensated with higher returns. The H-L portfolio has a quarterly return of -1.8509 and a monthly return of -0.9568. Panel B displays delta-hedged return portfolios. In contrast, both quarterly and monthly portfolio returns increase as moneyness increases. The quarterly and monthly returns for the long-short strategy are 0.0257 and 0.0135 respectively.

3.2.3 Risk Loadings

Based on numerical approximations in section 2, we specify two time-series regressions to obtain risk loadings. The first specification is regressing quarterly option portfolio returns on log consumption growth, Δc_t, and changes in the perceived conditional mean, $\Delta\hat{\mu}_t$, and volatility of consumption growth, $\Delta\hat{\sigma}_t$. We use log changes of the perceived conditional mean, $\Delta\ln\hat{\mu}_t$, and volatility of consumption growth, $\Delta\ln\hat{\sigma}_t$, in the second specification. In particular, for each option portfolio, we estimate factor loadings in a quarter t^* using the previous 10 years of quarterly observations from

$$R^i_{Q,t} = \alpha^i_{1,t^*} + \beta^i_{c1,t^*}\Delta c_t + \beta^i_{\mu,t^*}\Delta\hat{\mu}_t + \beta^i_{\sigma,t^*}\Delta\hat{\sigma}_t + \epsilon^i_{1,t}, \tag{18}$$

$$R^i_{Q,t} = \alpha^i_{2,t^*} + \beta^i_{c2,t^*}\Delta c_t + \beta^i_{\ln\mu,t^*}\Delta\ln\hat{\mu}_t + \beta^i_{\ln\sigma,t^*}\Delta\ln\hat{\sigma}_t + \epsilon^i_{2,t}, \tag{19}$$

where $R^i_{Q,t}$ denotes quarterly option portfolio returns and $t \in \{t^* - 39, t^*\}$.

Figure 2 [2] presents time-series average of $\hat{\beta}^i_{c1}$, $\hat{\beta}^i_{\mu}$, $\hat{\beta}^i_{\sigma}$, $\hat{\beta}^i_{c2}$, $\hat{\beta}^i_{\ln\mu}$, and $\hat{\beta}^i_{\ln\sigma}$ for each portfolio formed with simple option returns. As observed from Figure 2, there does not exist a very clear pattern in $\hat{\beta}^i_{\mu}$, $\hat{\beta}^i_{\sigma}$, $\hat{\beta}^i_{\ln\mu}$ or $\hat{\beta}^i_{\ln\sigma}$. In terms of consumption mean betas, $\hat{\beta}^i_{\mu}$ tends to decrease as moneyness of portfolios increases and $\hat{\beta}^i_{\ln\mu}$ is quite stable among portfolios, if those of portfolio 1 are excluded. At the same time, $\hat{\beta}^i_{\sigma}$ and $\hat{\beta}^i_{\ln\sigma}$ are quite volatile among portfolios. But we can observe from the graph that low-moneyness portfolios have relatively higher consumption growth betas ($\hat{\beta}^i_{c1}$ and $\hat{\beta}^i_{c2}$) and high-moneyness portfolios have lower consumption growth betas. That is to say, low-moneyness portfolios have higher consumption growth risks. However, different situation applies in risk loadings for delta-hedged option portfolio returns, as shown in Figure 3 [3]. Low-moneyness portfolios tend to have larger negative consumption growth betas ($\hat{\beta}^i_{c1}$ and $\hat{\beta}^i_{c2}$). For delta-hedged returns, low-moneyness portfolios also load more on consumption growth risks than high-moneyness portfolios. For consumption mean betas, both $\hat{\beta}^i_{\mu}$ and $\hat{\beta}^i_{\ln\mu}$ display a sharp drop

[2] Data used in Figure 2 are presented in Table 7 in the Appendix.
[3] Data used in Figure 3 are presented in Table 8 in the Appendix.

from portfolio 1 to portfolio 2 and stay relatively stable among other portfolios. As for consumption volatility betas, both $\hat{\beta}^i_\sigma$ and $\hat{\beta}^i_{\ln\sigma}$ increase sharply from portfolio 1 to portfolio 4 and drop slightly from portfolio 4 to portfolio 10.

[Insert Figure 2 here.]

[Insert Figure 3 here.]

3.2.4 Fama-MacBeth Regressions

As in Boguth and Kuehn (2013), we cross-sectionally regress monthly option portfolio returns on their latest available risk loadings:

$$R^i_{M,t+1} = \varphi_{0,t+1} + \varphi_{1,t+1}\hat{\beta}^i_{c1,t} + \varphi_{2,t+1}\hat{\beta}^i_{\mu,t} + \varphi_{3,t+1}\hat{\beta}^i_{\sigma,t} + \eta^i_{1,t+1}, \tag{20}$$

$$R^i_{M,t+1} = \phi_{0,t+1} + \phi_{1,t+1}\hat{\beta}^i_{c2,t} + \phi_{2,t+1}\hat{\beta}^i_{\ln\mu,t} + \phi_{3,t+1}\hat{\beta}^i_{\ln\sigma,t} + \eta^i_{2,t+1}. \tag{21}$$

$R^i_{M,t+1}$ is monthly option portfolio return. The risk loadings $\hat{\beta}^i_{c1,t}$, $\hat{\beta}^i_{\mu,t}$, $\hat{\beta}^i_{\sigma,t}$, $\hat{\beta}^i_{c2,t}$, $\hat{\beta}^i_{\ln\mu,t}$ and $\hat{\beta}^i_{\ln\sigma,t}$ are estimated from the first-pass regression (18) and (19).

[Insert Table 5 here]

The results of the Fama-MacBeth regressions are presented in Table 5. Panel A displays Fama-MacBeth regression coefficient estimates of two specifications for simple option portfolio returns. In specification 1, risk loading on consumption growth do not predict cross-sectional differences in returns, as indicated by the insignificant average coefficient on $\beta^i_{c1,t}$. $\beta^i_{\mu,t}$ and $\beta^i_{\sigma,t}$ have significantly positive cross-sectional risk premiums at the same time, which is not consistent with the theoretical prediction. Because risk premiums for $\beta^i_{\mu,t}$ and $\beta^i_{\sigma,t}$ should have opposite signs no matter whether EIS is greater than or less than the inverse of RRA. Coefficient estimations of specification 2 are completely different with those of specification 1. Risk premiums for $\beta^i_{c2,t}$ and $\beta^i_{\ln\mu,t}$ are significantly positive and negative. And risk loading on log change of perceived consumption volatility, $\beta^i_{\ln\sigma,t}$, can not predict variations in cross-sectional returns. The inconsistency of significant cross-sectional risk premiums between specification 1 and 2 makes it difficult to draw reliable inferences on model parameters.

Panel B demonstrates estimates for delta-hedged option portfolio returns. Different from results shown in panel A, estimations of specification 1 and 2 are consistent, which provides strong evidence to infer model parameters described in Section 2. In both specifications, consumption growth betas ($\beta^i_{c1,t}$ and $\beta^i_{c2,t}$) have a strong power to predict cross-sectional variations in returns. Portfolios with high consumption growth betas will have higher returns next period, which is consistent with the theoretical prediction. And portfolios with high consumption volatility betas will have lower returns next period, as indicated by significantly negative risk premiums of $\beta^i_{\sigma,t}$ and $\beta^i_{\ln\sigma,t}$. Moreover, $\beta^i_{\ln\mu,t}$ has a positive risk premium at the same time. The estimated price of consumption growth risk, expected consumption growth risk and consumption volatility risk are significantly positive and negative, suggesting that EIS should be greater than the inverse of RRA. This empirical finding strongly supports the long-run risk model of Bansal and Yaron (2004), and with those three significant risk premiums for $\beta^i_{c2,t}$, $\beta^i_{\ln\mu,t}$ and $\beta^i_{\ln\sigma,t}$, we can even infer the value range of γ and ψ.

3.2.5 Pricing of Changes in Prior Beliefs

The theory outlined in Section 2 implies that changes in beliefs about consumption growth states are priced sources of risk, and thus exposure to these risks should predict a spread in future returns. To examine how changes in beliefs are priced, similarly, we use two-pass regressions. First, for each portfolio, we estimate risk loadings from a time-series regression of quarterly portfolio returns on consumption growth (Δc_t), and changes in beliefs about high mean-low variance ($\Delta\xi_{1,t}$), high mean-high variance ($\Delta\xi_{2,t}$), and low mean-low variance ($\Delta\xi_{3,t}$) consumption growth states. In the second pass, the prices of risk are estimated by cross-sectionally regressing monthly portfolio returns on first-pass loadings. The exact empirical specification is given by

$$R^i_{Q,t} = \alpha^i_{3,t^*} + \beta^i_{c3,t^*}\Delta c_t + \beta^i_{\xi_1,t^*}\Delta\xi_{1,t} + \beta^i_{\xi_2,t^*}\Delta\xi_{2,t} + \beta^i_{\xi_3,t^*}\Delta\xi_{3,t} + \epsilon^i_{3,t}, \tag{22}$$

$$R^i_{M,t+1} = \omega_{0,t+1} + \omega_{1,t+1}\hat{\beta}^i_{c3,t} + \omega_{2,t+1}\hat{\beta}^i_{\xi_1,t} + \omega_{3,t+1}\hat{\beta}^i_{\xi_2,t} + \omega_{4,t+1}\hat{\beta}^i_{\xi_3,t} + \eta^i_{3,t+1}. \tag{23}$$

where $\hat{\beta}^i_{c3,t}$, $\hat{\beta}^i_{\xi_1,t}$, $\hat{\beta}^i_{\xi_2,t}$ and $\hat{\beta}^i_{\xi_3,t}$ are estimated from the first pass regression (22) and $t \in \{t^* - 39, t^*\}$.

[Insert Table 6 here]

The Fama-MacBeth regression estimations are reported in Table 6. Panel A presents estimates for simple option portfolio return, and panel B for delta-hedged option portfolio return. In panel B, risk premiums for $\beta^i_{c3,t}$ and $\beta^i_{\xi_3,t}$ are significantly positive, which is consistent with empirical results in Section 3.2.4 and supports that EIS is greater than the inverse of RRA. In panel A, risk premiums for $\beta^i_{c3,t}$, $\beta^i_{\xi_1,t}$ and $\beta^i_{\xi_3,t}$ are significantly positive, however, $\beta^i_{\xi_2,t}$ has a significantly negative risk premium. Risk premiums for $\beta^i_{c3,t}$, $\beta^i_{\xi_1,t}$, $\beta^i_{\xi_2,t}$ and $\beta^i_{\xi_3,t}$ should all be positive, assuming that EIS is larger than the inverse of RRA. With these results, we can figure out that the mispricing of changes in beliefs of high mean-high variance consumption growth state caused the mispricing of $\beta^i_{\sigma,t}$ in Section 3.2.4. More importantly, for both simple and delta-hedged option returns, consumption growth beta has a strong power to predict returns next period.

4 Conclusion

We follow Lettau, Ludvigson, and Wachter (2008), who generalize Bansal and Yaron (2004) to account for the latent nature of the conditional first and second moments of consumption growth. In the model, we identify conditional mean and volatility of consumption growth as two variables that affect the wealth-consumption ratio and thus asset prices.

To test theoretical predictions, we estimate a Markov model with two states for the conditional mean and two states for the conditional volatility of consumption growth. Using estimated beliefs and parameters from the Markov model, we empirically test the pricing implications for the cross-section of simple and delta-hedged option returns. We sort simple and delta-hedged option returns with specified time-to-maturities into 10 equally weighted portfolios based on moneyness. Using option portfolio returns in cross-sectional pricing tests, we show that loadings on consumption growth and changes in expected consumption growth significantly positively forecast delta-hedged returns and those on consumption growth volatility significantly negatively forecast delta-hedged returns. However, no clear evidence shows how consumption mean beta and consumption volatility beta are priced in the cross-section of simple option returns.

To figure out what caused the inconsistency between empirical evidences in simple and delta-hedged returns, we apply the third empirical test specification. We confirm that exposure to consumption growth is a positively priced source of risk in both simple and delta-hedged option returns. The mispricing of beliefs in high mean-high variance consumption growth state leads to the mispricing of changes in expected consumption growth and consumption volatility in simple option returns. In the context of our model, our findings lend strong support for the long-run risk model of Bansal and Yaron (2004), in particular, preference for early resolution of uncertainty.

Table 1: Change of Wealth-Consumption Ratio

We simulate 500 economies for 150 years at the quarterly frequency. Panel A displays regression results when $\gamma > \frac{1}{\psi}$ and $\psi > 1$, panel B when $\gamma > \frac{1}{\psi}$ and $\psi < 1$, panel C when $\gamma < \frac{1}{\psi}$ and $\psi > 1$ and panel D when $\gamma < \frac{1}{\psi}$ and $\psi < 1$. In all the panels, the representative agent has a rate of time preference of 0.995. The first, second and third regressions are regression (13), regression (11) and regression (12) respectively. We report the average regression coefficient and average R^2. We do not report the intercepts since they are very close to 0.

$\Delta\xi_1$	$\Delta\xi_2$	$\Delta\xi_3$	$\Delta\hat{\mu}$	$\Delta\hat{\sigma}$	$\Delta\ln\hat{\mu}$	$\Delta\ln\hat{\sigma}$	R^2
Panel A: $\gamma > \frac{1}{\psi}$, $\psi > 1$							
$\gamma = 10$, $\psi = 1.5$							
0.0104	0.0100	0.0006					0.9982
			2.0196	-0.1684			0.9981
					0.0067	-0.0015	0.9280
Panel B: $\gamma > \frac{1}{\psi}$, $\psi < 1$							
$\gamma = 10$, $\psi = 0.5$							
-0.0301	-0.0289	-0.0016					0.9983
			-5.8516	0.4784			0.9982
					-0.0195	0.0043	0.9285
Panel C: $\gamma < \frac{1}{\psi}$, $\psi > 1$							
$\gamma = 0.65$, $\psi = 1.5$							
0.0092	0.0092	0.0001					0.9999
			1.8696	-0.0255			0.9999
					0.0063	-0.0009	0.9472
Panel D: $\gamma < \frac{1}{\psi}$, $\psi < 1$							
$\gamma = 1.9$, $\psi = 0.5$							
-0.0272	-0.0270	-0.0005					0.9999
			-5.4822	0.1205			0.9999
					-0.0184	0.0028	0.9450

Table 2: Signs of Risk Premiums

This table reports signs of risk premiums (λ_μ, λ_σ, $\lambda_{\ln\mu}$, $\lambda_{\ln\sigma}$, λ_{ξ_1}, λ_{ξ_2}, and λ_{ξ_3}) when EIS is greater than and less than the inverse of the RRA.

	λ_μ	λ_σ	$\lambda_{\ln\mu}$	$\lambda_{\ln\sigma}$	λ_{ξ_1}	λ_{ξ_2}	λ_{ξ_3}
$\psi > \frac{1}{\gamma}$	$+$	$-$	$+$	$-$	$+$	$+$	$+$
$\psi < \frac{1}{\gamma}$	$-$	$+$	$-$	$+$	$-$	$-$	$-$

Table 3: Markov Model of Consumption Growth

This table reports parameter estimates of the Markov model for log consumption growth,

$$\Delta c_{t+1} = \mu_t + \sigma_t \epsilon_{t+1},$$

where μ_t denotes the conditional mean, σ_t denotes the conditional standard deviation and ϵ_{t+1} is standard normal. The conditional first and second moments of the consumption growth process switch jointly with transition matrices $\boldsymbol{P}^\mu$ and $\boldsymbol{P}^\sigma$, respectively, given by

$$\boldsymbol{P}^\mu = \begin{bmatrix} p_\mu^{hh} & 1-p_\mu^{ll} \\ 1-p_\mu^{hh} & p_\mu^{ll} \end{bmatrix} \quad \boldsymbol{P}^\sigma = \begin{bmatrix} p_\sigma^{hh} & 1-p_\sigma^{ll} \\ 1-p_\sigma^{hh} & p_\sigma^{ll} \end{bmatrix}.$$

The estimation procedure follows Hamilton (1994). We use quarterly per capita real consumption expenditure for nondurable goods and services for the years 1952.Q1 to 2016.Q4. t-statistics are reported in parentheses.

Panel A: Total Consumption Growth (%)			
μ_l	μ_h	σ_l	σ_h
0.0844	0.5741	0.2151	0.4894
(1.44)	(14.31)	(7.85)	(8.99)
Panel B: Marginal Transition Probabilities			
p_μ^{ll}	p_μ^{hh}	p_σ^{ll}	p_σ^{hh}
0.87	0.96	0.94	0.95
(14.89)	(42.72)	(18.96)	(20.75)

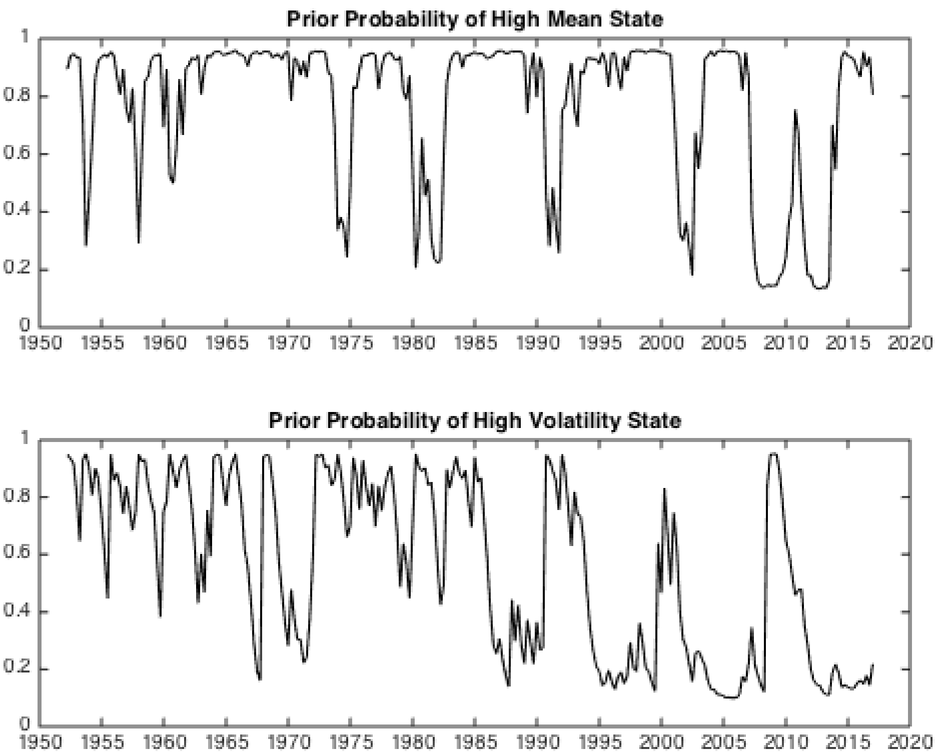

Figure 1: Bayesian Beliefs about the Mean and Volatility State

This figure displays the estimated Bayesian belief processes for being in the high expected growth rate state (top figure) and high volatility state (bottom figure). The estimation procedure follows Hamilton (1994). We use quarterly per capita real consumption expenditure for nondurable goods and services for the years 1952.Q1 to 2016.Q4.

Table 4: Portfolios Formed on Moneyness

This table reports average equally-weighted quarterly and monthly returns of independent univariate sorts based on lag-one-period moneyness. Lag-one-period time-to-maturities for quarterly and monthly returns are 106 to 176 days and 30 to 90 days respectively. Panel A are portfolios formed with simple option returns and panel B with delta-hedged option returns. t-statistics are reported in parentheses. The sample period is 1996.Q1 to 2016.Q1 for quarterly returns and January 1996 to April 2016 for monthly returns.

		Panel A: Simple Returns		Panel B: Delta-Hedged Returns	
Moneyness	Portfolio	Quarterly	Monthly	Quarterly	Monthly
Low	1	1.4862	0.7414	-0.0357	-0.0174
		(6.71)	(13.54)	(-8.65)	(-15.38)
	2	0.6039	0.4906	-0.0305	-0.0143
		(6.33)	(10.77)	(-7.02)	(-12.13)
	3	0.2686	0.3170	-0.0229	-0.0113
		(3.82)	(8.64)	(-5.38)	(-9.96)
	4	0.1930	0.2049	-0.0216	-0.0098
		(2.60)	(6.10)	(-5.35)	(-9.44)
	5	0.0396	0.0865	-0.0177	-0.0083
		(0.71)	(2.93)	(-4.77)	(-8.41)
	6	-0.0712	-0.0048	-0.0167	-0.007
		(-1.60)	(-0.18)	(-4.62)	(-7.81)
	7	-0.1477	-0.088	-0.0149	-0.0067
		(-3.49)	(-3.77)	(-4.46)	(-7.56)
	8	-0.236	-0.1400	-0.0141	-0.0055
		(-5.96)	(-6.89)	(-4.34)	(-6.66)
	9	-0.3017	-0.1772	-0.0132	-0.0047
		(-8.92)	(-9.78)	(-4.15)	(-5.90)
High	10	-0.3647	-0.2153	-0.0099	-0.0039
		(-11.68)	(-14.03)	(-3.57)	(-5.24)
H-L	10-1	-1.8509	-0.9568	0.0257	0.0135
		(-9.00)	(-21.25)	(8.58)	(17.02)

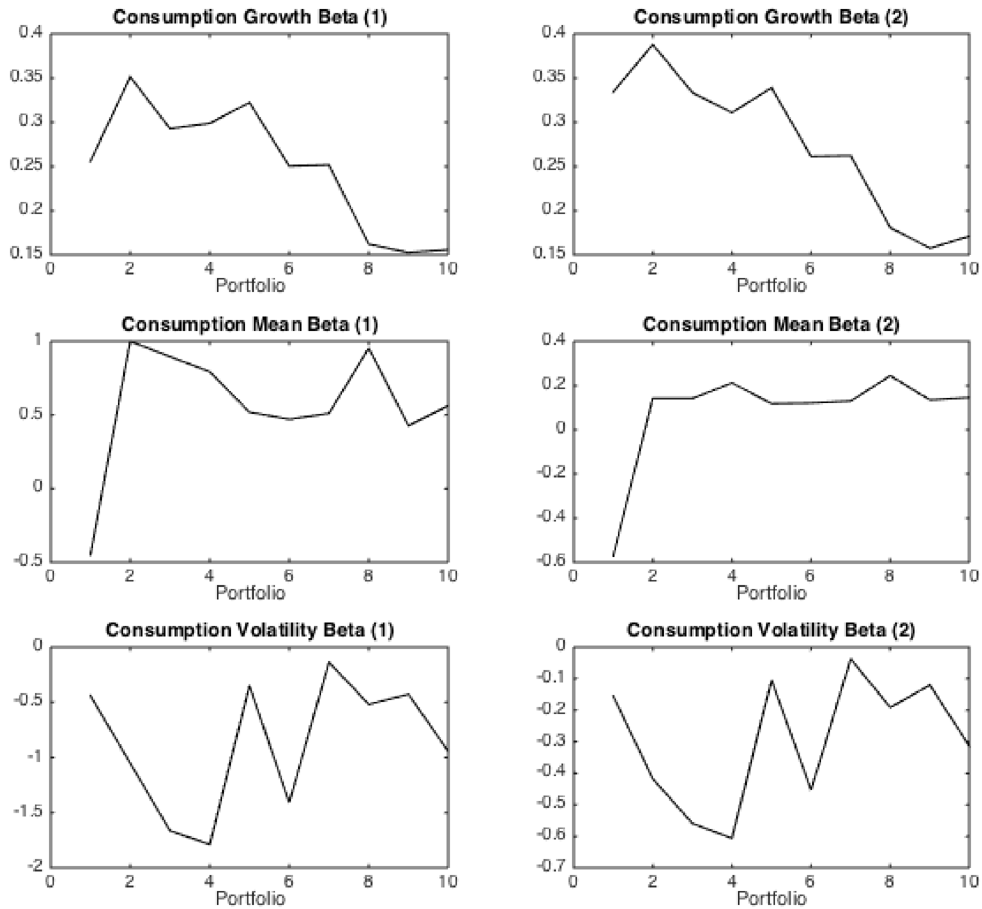

Figure 2: Risk Loadings for Simple Option Portfolio Returns

This graph displays time-series average of $\hat{\beta}^i_{c1}$, $\hat{\beta}^i_{\mu}$, $\hat{\beta}^i_{\sigma}$, $\hat{\beta}^i_{c2}$, $\hat{\beta}^i_{\ln\mu}$ and $\hat{\beta}^i_{\ln\sigma}$ for each portfolio formed with simple option returns. $\hat{\beta}^i_{c1}$, $\hat{\beta}^i_{\mu}$ and $\hat{\beta}^i_{\sigma}$ are estimated from regression (18), and $\hat{\beta}^i_{c2}$, $\hat{\beta}^i_{\ln\mu}$ and $\hat{\beta}^i_{\ln\sigma}$ are from regression (19). In the graph, consumption growth beta (1) represents $\hat{\beta}^i_{c1}$, and consumption growth beta (2) represents $\hat{\beta}^i_{c2}$. Similarly, consumption mean beta (1) and (2) denote $\hat{\beta}^i_{\mu}$ and $\hat{\beta}^i_{\ln\mu}$, and consumption volatility beta (1) and (2) represent $\hat{\beta}^i_{\sigma}$ and $\hat{\beta}^i_{\ln\sigma}$ respectively. The sample period is 1996.Q1 to 2016.Q1.

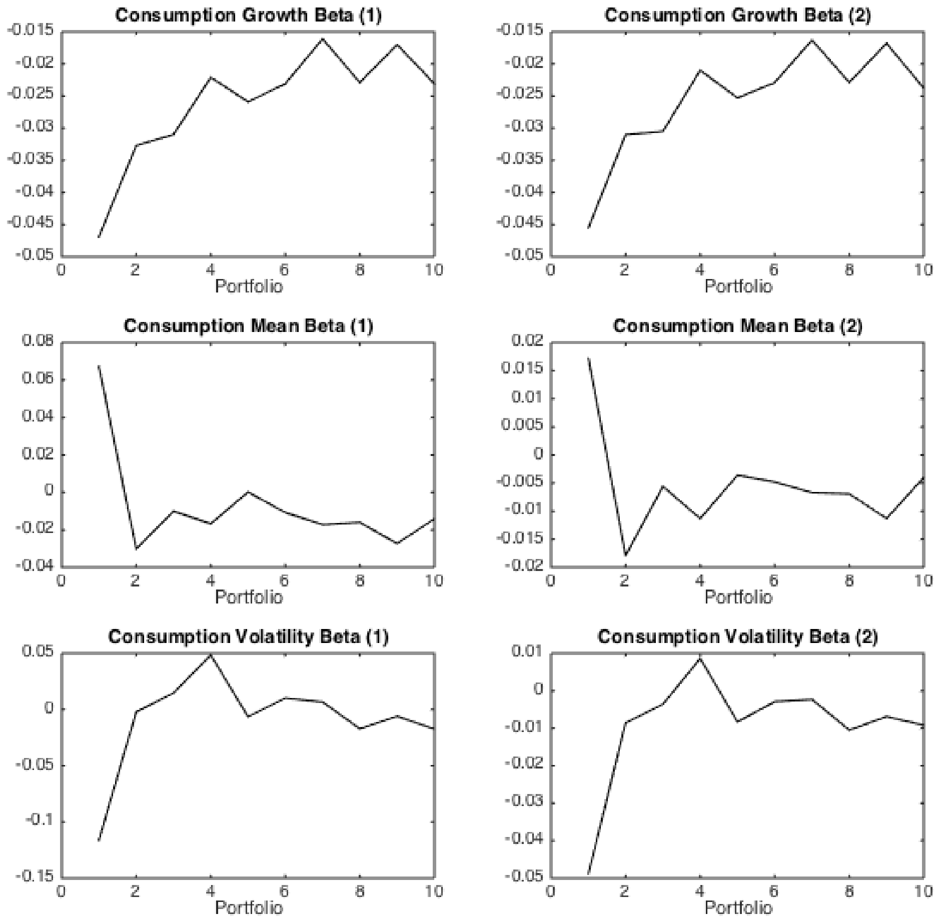

Figure 3: Risk Loadings for Delta-Hedged Option Portfolio Returns

This graph displays time-series average of $\hat{\beta}^i_{c1}$, $\hat{\beta}^i_{\mu}$, $\hat{\beta}^i_{\sigma}$, $\hat{\beta}^i_{c2}$, $\hat{\beta}^i_{\ln\mu}$ and $\hat{\beta}^i_{\ln\sigma}$ for each portfolio formed with delta-hedged option returns. $\hat{\beta}^i_{c1}$, $\hat{\beta}^i_{\mu}$ and $\hat{\beta}^i_{\sigma}$ are estimated from regression (18), and $\hat{\beta}^i_{c2}$, $\hat{\beta}^i_{\ln\mu}$ and $\hat{\beta}^i_{\ln\sigma}$ are from regression (19). In the graph, consumption growth beta (1) represents $\hat{\beta}^i_{c1}$, and consumption growth beta (2) represents $\hat{\beta}^i_{c2}$. Similarly, consumption mean beta (1) and (2) denote $\hat{\beta}^i_{\mu}$ and $\hat{\beta}^i_{\ln\mu}$, and consumption volatility beta (1) and (2) represent $\hat{\beta}^i_{\sigma}$ and $\hat{\beta}^i_{\ln\sigma}$ respectively. The sample period is 1996.Q1 to 2016.Q1.

Table 5: Fama-MacBeth Regressions

This table reports cross-sectional regressions of monthly returns on lagged estimated risk loadings. The first set of risk loadings is obtained from 10-year rolling time-series regressions of quarterly simple and delta-hedged portfolio returns on log consumption growth, $\beta^i_{c1,t}$, and changes in the perceived conditional mean, $\beta^i_{\mu,t}$, and volatility of consumption growth, $\beta^i_{\sigma,t}$. The second set of risk loadings is estimated from regressing on log consumption growth, $\beta^i_{c2,t}$, and log changes in the perceived conditional mean, $\beta^i_{\ln\mu,t}$, and volatility of consumption growth, $\beta^i_{\ln\sigma,t}$. We report Fama-MacBeth regression coefficients. t-statistics are reported in parentheses. The sample period is May 2006 to April 2016.

Intercept	$\beta^i_{c1,t}$	$\beta^i_{\mu,t}$	$\beta^i_{\sigma,t}$	$\beta^i_{c2,t}$	$\beta^i_{\ln\mu,t}$	$\beta^i_{\ln\sigma,t}$
Panel A: Simple Option Portfolio Return						
-0.1071	-0.0410	0.0957	0.1210			
(-2.30)	(-0.25)	(2.40)	(5.96)			
-0.1589				0.6713	-0.6084	0.0080
(-3.71)				(3.97)	(-4.92)	(1.12)
Panel B: Delta-Hedged Option Portfolio Return						
0.0033	0.4240	0.0104	-0.0193			
(2.37)	(8.66)	(1.12)	(-3.21)			
0.0040				0.4424	0.0565	-0.0548
(2.81)				(8.36)	(2.25)	(-2.87)

Table 6: Pricing of Changes in Beliefs

This table reports cross-sectional regressions of monthly returns on lagged estimated risk loadings. Risk loadings are obtained from 10-year rolling time-series regressions of quarterly simple and delta-hedged portfolio returns on log consumption growth ($\beta^i_{c3,t}$), and changes in the prior beliefs of high mean-low variance ($\beta^i_{\xi_1,t}$), high mean-high variance ($\beta^i_{\xi_2,t}$) and low mean-low variance ($\beta^i_{\xi_3,t}$) consumption growth states. We report Fama-MacBeth regression coefficients. t-statistics are reported in parentheses. The sample period is May 2006 to April 2016.

Intercept	$\beta^i_{c3,t}$	$\beta^i_{\xi_1,t}$	$\beta^i_{\xi_2,t}$	$\beta^i_{\xi_3,t}$
Panel A: Simple Option Portfolio Return				
-0.2151	1.1741	0.0830	-0.2673	0.1871
(-6.16)	(6.06)	(2.15)	(-8.75)	(3.78)
Panel B: Delta-Hedged Option Portfolio Return				
0.0016	0.3365	-0.0188	-0.0047	0.0711
(0.97)	(7.20)	(-1.12)	(-0.46)	(2.86)

5 Appendix

To test the model in the cross-section of returns, it is convenient to restate the Euler equation in terms of betas,

$$
\begin{aligned}
E_t\left[R^e_{i,t+1}\right] &\approx -\mathrm{Cov}_t\left(R_{i,t+1}, m_{t+1}\right) \\
&= \gamma \mathrm{Cov}_t\left(R_{i,t+1}, \Delta c_{t+1}\right) - \left(\frac{\frac{1}{\psi}-\gamma}{1-\frac{1}{\psi}}\right)\mathrm{Cov}_t\left(R_{i,t+1}, \Delta z_{t+1}\right) \\
&= \gamma \mathrm{Cov}_t\left(R_{i,t+1}, \Delta c_{t+1}\right) - \left(\frac{\frac{1}{\psi}-\gamma}{1-\frac{1}{\psi}}\right)\left[A_1 \mathrm{Cov}_t\left(R_{i,t+1}, \Delta \hat{\mu}_{t+1}\right)\right. \\
&\left. + A_2 \mathrm{Cov}_t\left(R_{i,t+1}, \Delta \hat{\sigma}_{t+1}\right)\right] \\
&= \beta^i_{c1,t}\lambda_{c1,t} + \beta^i_{\mu,t}\lambda_{\mu,t} + \beta^i_{\sigma,t}\lambda_{\sigma,t} \qquad (24)
\end{aligned}
$$

with

$$
\beta^i_{c1,t} = \frac{\mathrm{Cov}_t\left(R_{i,t+1}, \Delta c_{t+1}\right)}{\mathrm{Var}_t\left(\Delta c_{t+1}\right)} \quad \beta^i_{\mu,t} = \frac{\mathrm{Cov}_t\left(R_{i,t+1}, \Delta \hat{\mu}_{t+1}\right)}{\mathrm{Var}_t\left(\Delta \hat{\mu}_{t+1}\right)} \quad \beta^i_{\sigma,t} = \frac{\mathrm{Cov}_t\left(R_{i,t+1}, \Delta \hat{\sigma}_{t+1}\right)}{\mathrm{Var}_t\left(\Delta \hat{\sigma}_{t+1}\right)},
$$

and

$$
\lambda_{c1,t} = \gamma \mathrm{Var}_t\left(\Delta c_{t+1}\right) \quad \lambda_{\mu,t} = A_1\left(\frac{\gamma-\frac{1}{\psi}}{1-\frac{1}{\psi}}\right)\mathrm{Var}_t\left(\Delta \hat{\mu}_{t+1}\right) \quad \lambda_{\sigma,t} = A_2\left(\frac{\gamma-\frac{1}{\psi}}{1-\frac{1}{\psi}}\right)\mathrm{Var}_t\left(\Delta \hat{\sigma}_{t+1}\right),
$$

$\beta^i_{c1,t}$, $\beta^i_{\mu,t}$, $\beta^i_{\sigma,t}$ denote risk loadings of asset i at date t with respect to consumption growth and changes in the perceived first and second moments of consumption growth, and $\lambda_{c1,t}$, $\lambda_{\mu,t}$, $\lambda_{\sigma,t}$ are market prices of those betas.

Or

$$
\begin{aligned}
&= \gamma \mathrm{Cov}_t\left(R_{i,t+1}, \Delta c_{t+1}\right) - \left(\frac{\frac{1}{\psi}-\gamma}{1-\frac{1}{\psi}}\right)\left[B_1 \mathrm{Cov}_t\left(R_{i,t+1}, \Delta \ln \hat{\mu}_{t+1}\right)\right. \\
&\left. + B_2 \mathrm{Cov}_t\left(R_{i,t+1}, \Delta \ln \hat{\sigma}_{t+1}\right)\right] \\
&= \beta^i_{c2,t}\lambda_{c1,t} + \beta^i_{\ln \mu,t}\lambda_{\ln \mu,t} + \beta^i_{\ln \sigma,t}\lambda_{\ln \sigma,t} \qquad (25)
\end{aligned}
$$

with

$$\beta^i_{c2,t} = \frac{\text{Cov}_t\left(R_{i,t+1}, \Delta c_{t+1}\right)}{\text{Var}_t\left(\Delta c_{t+1}\right)} \quad \beta^i_{\ln\mu,t} = \frac{\text{Cov}_t\left(R_{i,t+1}, \Delta \ln \hat{\mu}_{t+1}\right)}{\text{Var}_t\left(\Delta \ln \hat{\mu}_{t+1}\right)}$$
$$\beta^i_{\ln\sigma,t} = \frac{\text{Cov}_t\left(R_{i,t+1}, \Delta \ln \hat{\sigma}_{t+1}\right)}{\text{Var}_t\left(\Delta \ln \hat{\sigma}_{t+1}\right)},$$

and

$$\lambda_{c2,t} = \gamma \text{Var}_t\left(\Delta c_{t+1}\right) \quad \lambda_{\ln\mu,t} = B_1\left(\frac{\gamma - \frac{1}{\psi}}{1 - \frac{1}{\psi}}\right)\text{Var}_t\left(\Delta \ln \hat{\mu}_{t+1}\right)$$
$$\lambda_{\ln\sigma,t} = B_2\left(\frac{\gamma - \frac{1}{\psi}}{1 - \frac{1}{\psi}}\right)\text{Var}_t\left(\Delta \ln \hat{\sigma}_{t+1}\right),$$

similarly, $\beta^i_{c2,t}$, $\beta^i_{\ln\mu,t}$, $\beta^i_{\ln\sigma,t}$ are risk loadings of asset i at date t with respect to consumption growth and log changes in the perceived first and second moments of consumption growth, and $\lambda_{c2,t}$, $\lambda_{\ln\mu,t}$, $\lambda_{\ln\sigma,t}$ are market prices of those betas.

Or

$$\begin{aligned}
&= \gamma \text{Cov}_t\left(R_{i,t+1}, \Delta c_{t+1}\right) - \left(\frac{\frac{1}{\psi} - \gamma}{1 - \frac{1}{\psi}}\right)\big[C_1 \text{Cov}_t\left(R_{i,t+1}, \Delta\xi_{1,t+1}\right) \\
&+ C_2 \text{Cov}_t\left(R_{i,t+1}, \Delta\xi_{2,t+1}\right) + C_3 \text{Cov}_t\left(R_{i,t+1}, \Delta\xi_{3,t+1}\right)\big] \\
&= \beta^i_{c3,t}\lambda_{c3,t} + \beta^i_{\xi_1,t}\lambda_{\xi_1,t} + \beta^i_{\xi_2,t}\lambda_{\xi_2,t} + \beta^i_{\xi_3,t}\lambda_{\xi_3,t},
\end{aligned} \tag{26}$$

with

$$\beta^i_{c3,t} = \frac{\text{Cov}_t\left(R_{i,t+1}, \Delta c_{t+1}\right)}{\text{Var}_t\left(\Delta c_{t+1}\right)} \quad \beta^i_{\xi_1,t} = \frac{\text{Cov}_t\left(R_{i,t+1}, \Delta\xi_{1,t+1}\right)}{\text{Var}_t\left(\Delta\xi_{1,t+1}\right)}$$
$$\beta^i_{\xi_2,t} = \frac{\text{Cov}_t\left(R_{i,t+1}, \Delta\xi_{2,t+1}\right)}{\text{Var}_t\left(\Delta\xi_{2,t+1}\right)} \quad \beta^i_{\xi_3,t} = \frac{\text{Cov}_t\left(R_{i,t+1}, \Delta\xi_{3,t+1}\right)}{\text{Var}_t\left(\Delta\xi_{3,t+1}\right)}$$

and

$$\lambda_{c3,t} = \gamma \text{Var}_t \left(\Delta c_{t+1} \right) \quad \lambda_{\xi_1,t} = C_1 \left(\frac{\gamma - \frac{1}{\psi}}{1 - \frac{1}{\psi}} \right) \text{Var}_t \left(\Delta \xi_{1,t+1} \right)$$
$$\lambda_{\xi_2,t} = C_2 \left(\frac{\gamma - \frac{1}{\psi}}{1 - \frac{1}{\psi}} \right) \text{Var}_t \left(\Delta \xi_{2,t+1} \right) \quad \lambda_{\xi_3,t} = C_3 \left(\frac{\gamma - \frac{1}{\psi}}{1 - \frac{1}{\psi}} \right) \text{Var}_t \left(\Delta \xi_{3,t+1} \right),$$

and $\beta^i_{c3,t}$, $\beta^i_{\xi_1,t}$, $\beta^i_{\xi_2,t}$, $\beta^i_{\xi_3,t}$ denote risk loadings of asset i at date t with respect to consumption growth and changes in beliefs of high mean-low variance, high mean-high variance and low mean-low variance consumption growth states, and $\lambda_{c3,t}$, $\lambda_{\xi_1,t}$, $\lambda_{\xi_2,t}$, $\lambda_{\xi_3,t}$ are market prices of those betas.

Table 7: Risk Loadings for Simple Option Portfolio Returns

This table reports average $\hat{\beta}^i_{c1}$, $\hat{\beta}^i_{\mu}$, $\hat{\beta}^i_{\sigma}$, $\hat{\beta}^i_{c2}$, $\hat{\beta}^i_{\ln\mu}$ and $\hat{\beta}^i_{\ln\sigma}$ for each portfolio formed with simple option returns. $\hat{\beta}^i_{c1}$, $\hat{\beta}^i_{\mu}$ and $\hat{\beta}^i_{\sigma}$ are estimated from regression (18), and $\hat{\beta}^i_{c2}$, $\hat{\beta}^i_{\ln\mu}$ and $\hat{\beta}^i_{\ln\sigma}$ are from regression (19). t-statistics are reported in parentheses. The sample period is 1996.Q1 to 2016.Q1.

Portfolio	$\hat{\beta}^i_{c1}$	$\hat{\beta}^i_{\mu}$	$\hat{\beta}^i_{\sigma}$	$\hat{\beta}^i_{c2}$	$\hat{\beta}^i_{\ln\mu}$	$\hat{\beta}^i_{\ln\sigma}$
1	0.2559	-0.4515	-0.4403	0.3343	-0.5709	-0.1553
	(2.55)	(-3.55)	(-0.68)	(3.47)	(-10.64)	(-0.70)
2	0.3514	0.9996	-1.0515	0.3880	0.1414	-0.4178
	(5.85)	(7.37)	(-1.83)	(6.37)	(3.16)	(-2.14)
3	0.2929	0.8970	-1.6633	0.3336	0.1414	-0.5588
	(8.50)	(13.29)	(-4.43)	(8.82)	(6.36)	(-4.20)
4	0.2989	0.7934	-1.7875	0.3109	0.2119	-0.6061
	(6.24)	(12.92)	(-5.49)	(6.50)	(11.45)	(-5.48)
5	0.3223	0.5193	-0.3490	0.3391	0.1182	-0.1049
	(14.05)	(5.89)	(-1.29)	(12.93)	(2.98)	(-1.07)
6	0.2505	0.4711	-1.4082	0.2613	0.1209	-0.4532
	(9.26)	(6.66)	(-7.85)	(9.39)	(4.32)	(-7.24)
7	0.2518	0.5106	-0.1374	0.2621	0.1296	-0.0376
	(10.57)	(5.45)	(-0.81)	(10.35)	(3.46)	(-0.63)
8	0.1621	0.9540	-0.5188	0.1808	0.2446	-0.1916
	(11.60)	(16.63)	(-3.85)	(10.76)	(9.30)	(-4.00)
9	0.1527	0.4270	-0.4273	0.1575	0.1349	-0.1203
	(17.26)	(7.43)	(-5.75)	(15.54)	(5.38)	(-4.46)
10	0.1560	0.5635	-0.9449	0.1710	0.1450	-0.3145
	(15.54)	(15.89)	(-11.71)	(13.58)	(8.86)	(-9.94)

Table 8: Risk Loadings for Delta-Hedged Option Portfolio Returns

This table reports average $\hat{\beta}^i_{c1}$, $\hat{\beta}^i_{\mu}$, $\hat{\beta}^i_{\sigma}$, $\hat{\beta}^i_{c2}$, $\hat{\beta}^i_{\ln\mu}$ and $\hat{\beta}^i_{\ln\sigma}$ for each portfolio formed with delta-hedged option returns. $\hat{\beta}^i_{c1}$, $\hat{\beta}^i_{\mu}$ and $\hat{\beta}^i_{\sigma}$ are estimated from regression (18), and $\hat{\beta}^i_{c2}$, $\hat{\beta}^i_{\ln\mu}$ and $\hat{\beta}^i_{\ln\sigma}$ are from regression (19). t-statistics are reported in parentheses. The sample period is 1996.Q1 to 2016.Q1.

Portfolio	$\hat{\beta}^i_{c1}$	$\hat{\beta}^i_{\mu}$	$\hat{\beta}^i_{\sigma}$	$\hat{\beta}^i_{c2}$	$\hat{\beta}^i_{\ln\mu}$	$\hat{\beta}^i_{\ln\sigma}$
1	-0.0469	0.0672	-0.1162	-0.0455	0.0172	-0.0488
	(-23.50)	(8.36)	(-4.60)	(-22.74)	(5.18)	(-6.36)
2	-0.0327	-0.0302	-0.0022	-0.0310	-0.0179	-0.0086
	(-22.44)	(-4.68)	(-0.18)	(-21.88)	(-6.32)	(-2.55)
3	-0.0310	-0.0100	0.0146	-0.0305	-0.0056	-0.0036
	(-19.84)	(-1.20)	(1.10)	(-20.37)	(-1.49)	(-0.95)
4	-0.0221	-0.0167	0.0485	-0.0210	-0.0113	0.0086
	(-16.20)	(-2.51)	(4.30)	(-15.74)	(-4.07)	(2.60)
5	-0.0259	0.0002	-0.0064	-0.0253	-0.0036	-0.0083
	(-20.76)	(0.04)	(-0.89)	(-21.64)	(-1.24)	(-3.80)
6	-0.0231	-0.0107	0.0101	-0.0229	-0.0048	-0.0029
	(-20.33)	(-2.02)	(0.82)	(-22.27)	(-1.86)	(-0.78)
7	-0.0161	-0.0172	0.0067	-0.0163	-0.0067	-0.0023
	(-12.40)	(-3.59)	(1.04)	(-14.20)	(-2.92)	(-1.19)
8	-0.0229	-0.0160	-0.0171	-0.0229	-0.0069	-0.0105
	(-14.34)	(-4.04)	(-1.48)	(-15.69)	(-4.02)	(-2.84)
9	-0.0170	-0.0273	-0.0060	-0.0168	-0.0113	-0.0069
	(-11.81)	(-6.89)	(-0.88)	(-12.79)	(-6.91)	(-3.19)
10	-0.0231	-0.0141	-0.0174	-0.0238	-0.0040	-0.0092
	(-24.26)	(-3.83)	(-4.38)	(-29.81)	(-3.88)	(-6.64)

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