Capital Asset Pricing Model and Stochastic Volatility: A Case study of India

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Abstract

Bansal and Yaron (2004) demonstrate, by calibration, that the Consumption-Based Capital Asset Pricing Model (CCAPM) can be rescued by assuming that consumption growth rate follows a stochastic volatility model. They show that the conditional equity premium is a linear function of conditional consumption and market return volatilities, which can be estimated handily by various Generalized Autoregressive Conditonal Heterskedasticity (GARCH) and Stochastic Volatility (SV) models. Using the data from India, we find that conditional consumption and market volatilities are capable of explaining cross-sectional return differences. Also, the model prediction is consistent with observed declining equity premium.

JEL Classification: E21; G1; G12

Keywords: Financial Economics, Macroeconomics and Monetary Economics, Equity Premium Puzzle

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1. Introduction

The development of the famous Consumption Based Capital Asset Pricing Model (CCAPM) is an early attempt of financial economists to explore the links between asset returns and macroeconomic variables that capture the sources of systematic risk. In a two period model with exogenous labor income, the equity premium is proportional to the aggregate consumption growth, in which the multiplicative factor is elasticity of intertemporal substitution of consumption.

Fama and French (1993) advocate a three factor model - market return, the return of small less big stocks (SMB), and the return on a portfolio of high book-market value stocks less low book-market value stocks (HML). Although the Fama and French (1993) model as a resounding success, it is still not clear how these factors relate to underlying macroeconomic risk. Actually, the economic interpretation of SMB and HML remain as a source of controversy.

Lettau and Ludvigson (2002) examine CCAPM in a conditional sense. They express the stochastic discount factor as a conditional or scaled factor model and examine the time-varing coefficients by interacting consumption growth with a cointegrating factor $\widehat{cay}$ - a cointegrating residual between consumption, asset (nonhuman) wealth, and labor income (all in log). The parameters in the stochastic discount factor depend on investor's expectations of future excess return. Lettau and Ludvigson (2001) demonstrate that $\widehat{cay}$ drives time-variation in conditional expected return. Using the assumption that consumption growth rate follows a stochastic volatility model, Bansal and Yaron (2004, hereafter referred to as the BY model) show, by calibration, that the conditional equity premium is a linear function of conditional consumption and market return volatilities.

Fung, Lau, and Chan (2014) proceed to estimate conditional volatities and then test the validity of BY model. Their first step is to estimate conditional consumption and market volatilities by two Stochastic Volatility (SV) models and two Generalized Autoregressive Conditional Heteroskedasticity (GARCH) models, namely Exponential GARCH (EGARCH) and Threshold GARCH (TGARCH). Their second step is to use the predicted volatilities as factors and apply the Fama-MacBeth approach to test the validity of the BY model using U.S. 25 Fama-French portfolio returns sorted by size and book-to-market value. Fung, Lau, and Chan find that the theoretical premium of the BY model outperforms traditional CAPM that is based observed market premium. They can explain 55% variation of cross-section return difference by using GARCH consumption and market volatilities.

In this paper, we apply data from an emrging economy-India-rather than the U.S. data to estimate conditional volatities and then test the validity of BY model. The first step is to estimate conditional consumption and market volatilities by two Stochastic Volatility (SV) models and by varisou Generalized Autoregressive Conditional Heteroskedasticity (GARCH) models including Exponential GARCH (EGARCH), Periodic GARCH (PGARCH), and Threshold GARCH (TGARCH). The second step is to use the predicted volatilities as factors for a testing of the BY model. This paper will address in the following sections a couple of questions. With the ex-post market risk premium being replaced by conditional consumption and market return volatilities, does it improve the predictive power of Captial-based Asset Pricing Modle (CAPM)? Is this study robust to different sepcifications of GARCH models?

We find that the Bansal and Yaron theoretical premium significantly outperforms traditional CAPM using observed market premium. Using GARCH consumption and market volatility alone can explain most of variation of cross-section return difference. It improves the Fama and French model, by replacing the ex-post market risk premium with the Bansal and Yaron (2004) premium.

This paper is structured as follows. Section 2 outlines briefly the derivation of the the Bansal and Yaron market premium. Section 3 models conditional volatilities. Two Stochastic Volatilities and three typical GARCH type volatilities are estimated: Exponential GARCH (EGARCH), Periodic GARCH (PGARCH), and Threshold GARCH (TGARCH). Section 4 delineates the estimation equations. Section 5 provides the results from the India data. Section 6 concludes.

2. Outline of Bansal and Yaron (2004) Model

We now consider the Bansal and Yaron (2004) model. It shows that, if consumption and dividend growth rate contain a small long-run predictable component, consumption volatility is stochastic, and, if the representative household has Epstein and Zin preference, the asset and return premium will be a linear function of conditional consumption and market volatility. The Euler condition is given by

$$E_t[\delta^{\theta} G_{t+1}^{-\frac{\theta}{\psi}} R_{a,t+1}^{-(1-\theta)} R_{i,t+1}] = 1 \tag{1}$$

where δ is the discount factor, G_{t+1} is gross return of consumption, $R_{a,t+1}$ is the gross return on an asset that delivers aggregate consumption as its dividends each period, and $R_{i,t+1}$ is the individual asset return. As well-documented in the literature, this class of preference disentangles the relation between intertemporal elasticity of substitution (IES) and risk aversion. The parameter $\theta = \frac{1-\gamma}{1-\frac{1}{\psi}}$, with $\gamma \geq 0$ as the degree of risk aversion, ψ denotes IES. Campbell and Shiller (1988) show that the log-linearized asset return ($r_{a,t+1}$) can be expressed as

$$r_{a,t+1} = \kappa_0 + \kappa_1 z_{t+1} - z_t + g_{t+1} \tag{2}$$

where κ_0 and κ_1 are constants; $z_t = \log(\frac{P_t}{C_t})$ is the log price-consumption ratio, and g_{t+1} is the log return of consumption. The log-linearized first order euler condition is

$$m_{t+1} = \theta \log \delta - \frac{\theta}{\psi} g_{t+1} + (\theta - 1) r_{a,t+1} \tag{3}$$

where m_{t+1} is the stochastic discount factor. When $\theta = 1$, then $\gamma = \frac{1}{\psi}$, and the above equation is pinned down to the case of Constant Elasticity of Subsitution (CES) utility function. Moreover, if $\theta=1$ and $\gamma=1$, we get the standard case of log utility. In the spirit of neo-classical Real Business Cycle model (RBC), an exogenous i.i.d shock perturbs consumption and output from their steady paths. The system of shocks is

$$x_{t+1}=\rho x_t+\varphi_e\sigma_t e_{t+1}$$
$$g_{t+1}=\mu+x_t+\sigma_t\eta_{t+1}$$
$$g_{d,t+1}=\mu_d+\phi x_t+\varphi_d\sigma_t u_{t+1}$$
$$\sigma_{t+1}^2=\sigma^2+\nu_1(\sigma_t^2-\sigma^2)+\sigma_w w_{t+1}$$
$$e_{t+1},\eta_{t+1},w_{t+1},u_{t+1}\sim N(0,1)$$

This system of equation suggests that consumption (g_{t+1}) and dividend growth rates($g_{d,t+1}$) are driven by an unobservable process x_t, and the volatility of the latter exhibits mean-reversion (ρ) but perturbed by an i.i.d shock (e_{t+1})[1]. Bansal and Yaron (2004) solve the log price-consumption ratio by method of undetermined coefficients, and find that

$$z_t=A_0+A_1x_t+A_2\sigma_t^2 \tag{4}$$
$$A_1=\frac{1-\frac{1}{\psi}}{1-\kappa_1\rho},\quad A_2=\frac{0.5[(\theta-\frac{\theta}{\psi})^2+(\theta A_1\kappa_1\varphi_e)^2]}{\theta(1-\kappa_1\nu_1)}$$

There are two noteworthy features of this model. First, if γ and ψ are larger than 1, then θ is negative, and a rise in volatility lowers the price-consumption ratio, since the intertemporal effect dominates the substitution effect. Second, the risk premium is a positive function of the volatility persistence parameter ρ ; meaning that the representative consumer dislikes a prolonged period of consumption shocks. After some algebra, the market premium in the presence of time-varying economic uncertainty takes the form:

$$E_t(r_{m,t+1}-r_{f,t})=\beta_{m,e}\lambda_{m,e}\sigma_t^2+\beta_{m,w}\lambda_{m,w}\sigma_w^2-0.5var_t(r_{m,t+1}) \tag{5}$$

where σ_t^2 and σ_w^2 are the conditional consumption and wealth volatilities; λ is the price of risk, and β is the quantity of risk. The risk premium of any asset, given by CAPM, can be expressed as

$$E_t(r_{i,t+1}-r_{f,t})=\rho+\beta_{m,e}\lambda_{m,e}\sigma_t^2-0.5var_t(r_{m,t+1})+\varepsilon_t \tag{6}$$

The BY model calls for estimation of two equations. Equation (5) states that long-run market risk premium is determined by conditional consumption and market return volatility. In particular, the cointegrating vector is $(\beta_{m,e}\lambda_{m,e},-0.5)$. This paper focuses on equation (6), which explains cross-sectional return differences by conditional volatilities.

The essence of the BY model is that persistent stochastic volatility can explain risk premium. Here we provide an empirical test, by regressing cross-sectional return against different variants of conditional stochastic volatility. Choosing the best stochastic

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[1] Without w_{t+1}, it will become a GARCH model.

volatility model is not the purpose of this paper. Rather, we want to show that if equation (6) can be explained by some common GARCH and SV models, it should provide indirect support for the BY model. More importantly, it provides an alternative for the Fama-French model. While the independence of Fama-French factors is controversial, aggregate consumption and market return volatilities should be uncorrected. Next section is devoted to the description of various conditional volatility models.

Data and Methodology

The consumption data of India are collected from the Federal Reserve Bank of St. Louis Economic Research Database [2]. We use the quarterly private aggregate consumption data and then calculate the (log) returns. The Fama-French factors, market return risk free rate and sorted portfolio returns are available at Agarwalla, Jacob and Varma (2013) working paper[3]. The sample periold is Q1 of 1993 to Q2 of 2012.

Fung, Lau, and Chan (2014) used the U.S 25 Fama-French portfolio return as the dependent variable. These data are value-weighted returns for the intersection of five size portfolios and five book-to-market equity (BE/ME) portfolios on the New York Stock Exchange, the American Stock Exchange, and NASDAQ stocks in Compustat. We use data from Agarwalla, Jacob and Varma (2013) who computed the portfolio returns using Bombay Stock Exchange (BSE) index data from the CMIE Prowess. This dataset is an improvement over earlier data. More firms are included; illiquid firms are excluded; the size cut-off point is redefined; and surivor bias is correted. However, they only provide six portfolios based on size (measure by market capitalization, small and big) and value (book/market ratio, growth, neutral and value). We convert the original data from monthly to quarterly series.

Due to limited number of cross-sections (in this case, six), we cannot adopt the Fama-McBeth(1973) procdure. The more appropriate method is time series approach. There is excessive missing observations of the big-value portfolio. Therefore, it will not be used for estimation and we have five portfolios. The independent variables are various GARCH models. If the Bansal and Yaron (2014) model holds for a less developed country like India, it should work for different specifications of conditional volatilities. The benchmark model is:

$$E_t(r_{i,t+1} - r_{f,t}) = \gamma_0 + \beta_1 \lambda_c \sigma^2_{c,t+1} + \beta_2 \lambda_m \sigma^2_{m,t+1} + e_t \qquad ()$$

where $\sigma^2_{c,t+1}$ and $\sigma^2_{m,t+1}$ are conditional consumption and market volatilities respectively. These volatilities will be estimated by GARCH and the stochastic volatility models.

The literature on GARCH type models are well-documented, interested readers can refer to Bollerslev et al. (1992), Bollerslev et al. (1994) for a survey. We will also consider the Exponential GARCH (EGARCH), Threshold GARCH (TGARCH) and Power GARCH (PGARCH) to model asymmetry inherent in the series. Stochastic

[2] http://research.stlouisfed.org/fred2/

[3] http://www.iimahd.ernet.in/~jrvarma/Indian-Fama-French-Momentum/

Volatility (SV) models which are reviewed in, for example, Taylor (1999), Ghysels et al. (1996) have been increasingly recognized as a viable alternative to GARCH models, although the latter are still the standard in empirical applications[4].

The stochastic volatility model considered in this section follows Harvey *et al.* (1994) and Mills (1999).

$$r_t = \sigma_t \varepsilon_t \qquad ()$$

$$h_t = \ln \sigma_t^2 = \gamma + \phi h_{t-1} + \eta_t \qquad ()$$

$$\eta_t \sim N(0, \sigma_\eta^2)$$

r_t is the continuously compounded return of an asset; σ_t denotes the volatility. There is no intercept in the mean equation. h_t is always positive and takes on an AR(1) process. An appropriate mean equation can be augmented to equation (). ε_t and η_t are assumed to be two independent errors. This process is nonlinear in nature, which can be transformed into a linear function by appropriate change of variable.

We define $y_t = \ln r_t^2$. It can be shown that $E(\ln \varepsilon_t^2) = -1.27$ and $var(\ln \varepsilon_t^2) = \dfrac{\pi^2}{2}$. An unobserved component state space representation for y_t has the form

$$y_t = -1.27 + h_t + \xi_t, \quad \xi_t \sim N(0, \frac{\pi^2}{2}) \qquad ()$$

$$h_t = \gamma + \phi h_{t-1} + \eta_t, \quad \eta_t \sim N(0, \sigma_\eta^2) \qquad ()$$

$$E[\xi_t \eta_t] = 0 \qquad ()$$

ξ_t and η_t are two independent white noises. Thes two equations will estimated simultaneously. For a detailed estimation procedure, see Théoret and Racicot (2010).

Results

The consumption and BSE market return conditional volatilities are reported in Figure 1-Figure 8. The temporal movements of the three GARCH consumption volatilities are similar, which is consistent with our regression results that the significance of the consumption volatility coefficients do not depend on model specification. One of the possible reason is that asymmetry is not a characteristic of aggregate consumption series. For GARCH, EGARCH and PGARCH, there are four spikes in volatility – 1997, 2001, 2003 and 2008. However, EGARCH has different prediction in the last four quarters in the sampel period (Figure.2). The stochastive volatility is reported in Figure 4. Comparing to the GARCH volatilities, there are two discernible differences. 1. The range of volatility is smaller – 0.04-0.068 only. 2. The temporal movement is more smoothed. That said, the temporal comovement is still similar to those of GARCH volatilities.

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[4] For comparison, discussion of merits and deciding rules of these two models, see Fleming and Kirby (2003), Preminger and Haftner (2006), and Heynen and Kat (1994).

From Figure 5-Figure 8, it is obvious that GARCH, EGARCH and stochastic volatility models are very similar. The range of quarterly volatility is 0.4-4.5%. Most models predict a big drop in the second half of 2008. However, the variation of PGARCH is significantly smaller than other models. The PGARCH predicts no change in some period. The estimated stochastic volatility of BSC market return is a modified version of equation (). We encountered convergence when there is an intercept; therefore, in the final model, the constant is dropped.

Tables 1-4 report the Bansal and Yaron (2004) estimation using various GARCH volatilities. All standard errors are corrected by Newey-West (1987). As a usual practice, we include the intercept term in all equations. To control for serial correlation, we add an auto-regression and moverage average term to the equation if the coefficient is significant. If the Bansal and Yaron (2004) is true for a developing country like India, the conditional market and consumption volatility coefficients should be jointly significant. At the bottom of each table, the Chi-square statistic is reported.

From Table.1, it is shown that the Bansal and Yaron (2004) model fails miserably when using GARCH volatilities in a time series setting. For firms with high market capitalization, the temporal persistence is captured by the moving average coefficient; for small firms, it is captured by autoregressive coefficient. Neither the aggregate consumption growth nor the BSC market return volatility is significant. They are not jointly significant, either. One of the possibility is that market index returns are always characterized by asymmetry. We proceed to test the Bansal and Yaron (2004) with two asymmetric volatilities.

The performance of Bansal and Yaron (2004) model improves significantly when using EGARCH and PGARCH volatilities. As shown in Table. 2, The market volatility coefficent is significant in all five portfolios. For insance, a one percent increase in market volatility, the return of Big-Growth portfolio will increase by 2.62 points. The consumption volatility coefficients are significant for two portfolios -Small-Growth and Small-Value. The null hypothesis of joint significance is rejected in all models. The pattern is similar when using PGARCH volatility (Table. 3). The market return volatility coefficient is significant in the Big-Neutral, Small-Growth and Small-Value portfolios; so is the joint hypothesis. However, the consumption volatility coefficient is only significant in the Small-Value portfolio. In any case, we show that once asymmetry is accounted for, a linear combination of conditional aggregate consumption and market volatility is capable of explaining temporal variation of size-value sorted portfolio returns.

How about using stochastic volatility? As shown in Table. 4, the results are similar to those of PGARCH model. There is no significant change. Concluding from these tables, we found that the Bansal and Yaron (2004) works the best for small-sized firms. For the case of stochastic volatility (Table. 4), for instance, a one percent increase in market volatility would result in a 5.25 percent in Small-Growth portfolio. Our result is consistent with Fung, Lau, and Chan (2014) that the GARCH type model, in general, outperforms the stochastic volalitity model under the Bansal and Yaron (2004) model.

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Appendix

Table 1 Bansal-Yaron Estimation Using GARCH Volatility

	Portfolio Returns				
	Big-Growth	**Big-Neutral**	**Small-Growth**	**Small-Neutral**	**Small-Value**
Constant	5.321455 (0.5925)	4.095748 (0.7251)	9.098820 (0.3187)	8.422526 (0.4085)	11.26048 (0.4007)
Garch Market Volatility	-2.3102 (0.9473)	2.031 (0.1399)	-1.213 (0.7064)	-1.046 (0.7810)	-14.03 (0.7772)
Garch Consumption Volatility	-1.159 (0.5301)	-3.238306 (0.8596)	-1.826 (0.3486)	-1.412 (0.4646)	-16.83274 (0.4449)
AR(1)			0.191349 (0.0214)	0.198456 (0.0374)	0.153622 (0.1567)
MA(1)	0.312646 (0.0089)	0.182025 (0.0443)			
Joint Significance (p-value)	0.085731	0.595791	0.338	0.354	0.742

*indicates 10% significance
**indicates 5% significance
*** indicates 1% significance
Standard error corrected by Newey-West

Table 2 Bansal-Yaron Estimation Using EGARCH Volatility

	Portfolio Returns				
	Big-Growth	**Big-Neutral**	**Small-Growth**	**Small-Neutral**	**Small-Value**
Constant	-8.691701 (0.1381)	-12.21063 (0.1245)	-4.907468 (0.6037)	-4.954727 (0.6319)	-6.500758 (0.5679)
EGarch Market Volatility	2.617 (0.0554)	3.17 (0.0428)	3.69 (0.0151)	3.792 (0.0226)	6.57 (0.0691)
EGarch Consumption Volatility	-2.143 (0.3538)	-1.7148 (0.5286)	-4.03 (0.01367)	-3.935 (0.2102)	-2.862 (0.05355)
AR(1) **MA(1)**	0.5398 (0.0582)				
Joint Significance (p-value)	0.0485	0.0497	0.00437	0.0337	0.00827

*indicates 10% significance
**indicates 5% significance
*** indicates 1% significance
Standard error corrected by Newey-West

Table 3 Bansal-Yaron Estimation Using PGARCH Volatility

	Portfolio Returns				
	Big-Growth	**Big-Neutral**	**Small-Growth**	**Small-Neutral**	**Small-Value**
Constant	11.29073 (0.3473)	-31.33 (0.0285)	-7.635436 (0.6376)	-15.95064 (0.3719)	-23.73830 (0.2490)
PGarch Market Volatility	2.218 (0.6397)	1.461 (0.0043)	2.73 (0.0907)	8.312 (0.1650)	11.93 (0.0862)
PGarch Consumption Volatility	-21.62418 (0.3490)	18.71683 (0.4431)	-19.00919 (0.3755)	2.787404 (0.9362)	-9.894031 (0.07916)
AR(1)					
MA(1)	0.346122 (0.0175)				
Joint Significance (p-value)	0.619	0.0006	0.0143	0.1865	0.0052

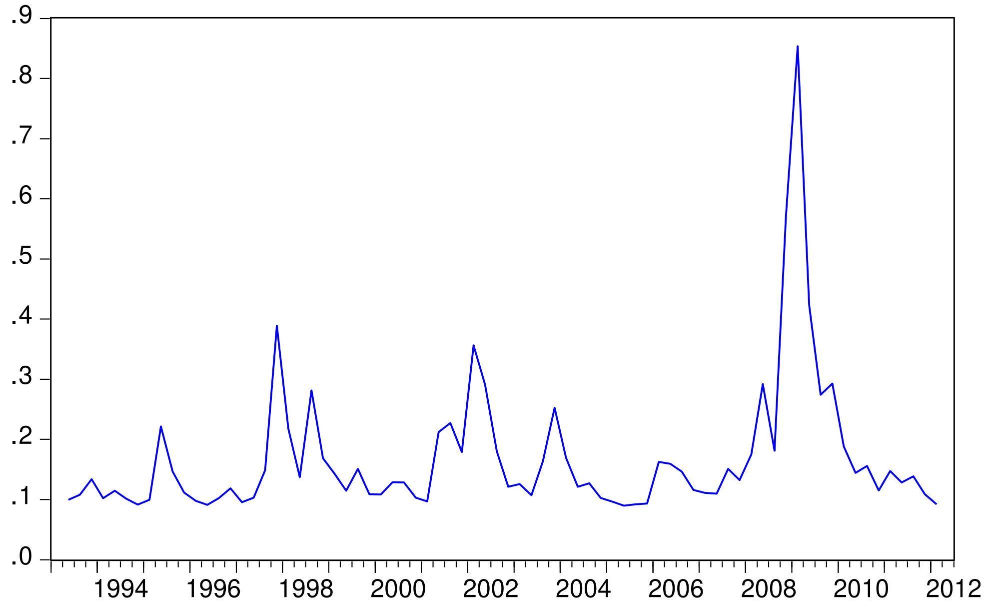
*indicates 10% significance
**indicates 5% significance
*** indicates 1% significance
Standard error corrected by Newey-West

Table 4 Bansal-Yaron Estimation Using Stochastic Volatility

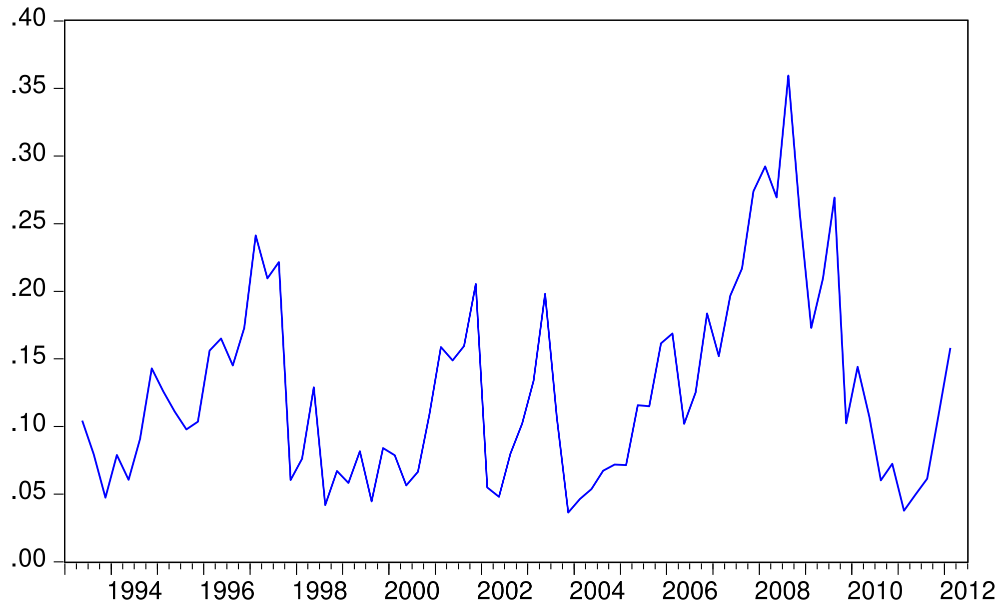
	Portfolio Returns				
	Big-Growth	**Big-Neutral**	**Small-Growth**	**Small-Neutral**	**Small-Value**
Constant	12.50835 (0.5676)	17.99351 (0.4328)	14.50869 (0.5861)	16.15944 (0.5938)	21.08931 (0.5266)
Stochastic Market Volatility	4.677 (0.2541)	1.799 (0.4328)	5.248 (0.03026)	-3.7 (0.3096)	2.946 (0.06178)
Stochastic Consumption Volatility	-5.534 (0.8333)	1.135 (0.7064)	-8.79 (0.7908)	-2.35 (0.6624)	-6.2 (0.2714)
AR(1)	0.258581 (0.0013)		0.185174 (0.0212)	0.181176 (0.1157)	
MA(1)		0.152553 (0.0719)			0.155629 (0.1857)
Joint Significance (p-value)	0.2018	0.71	0.037	0.5464	0.0569

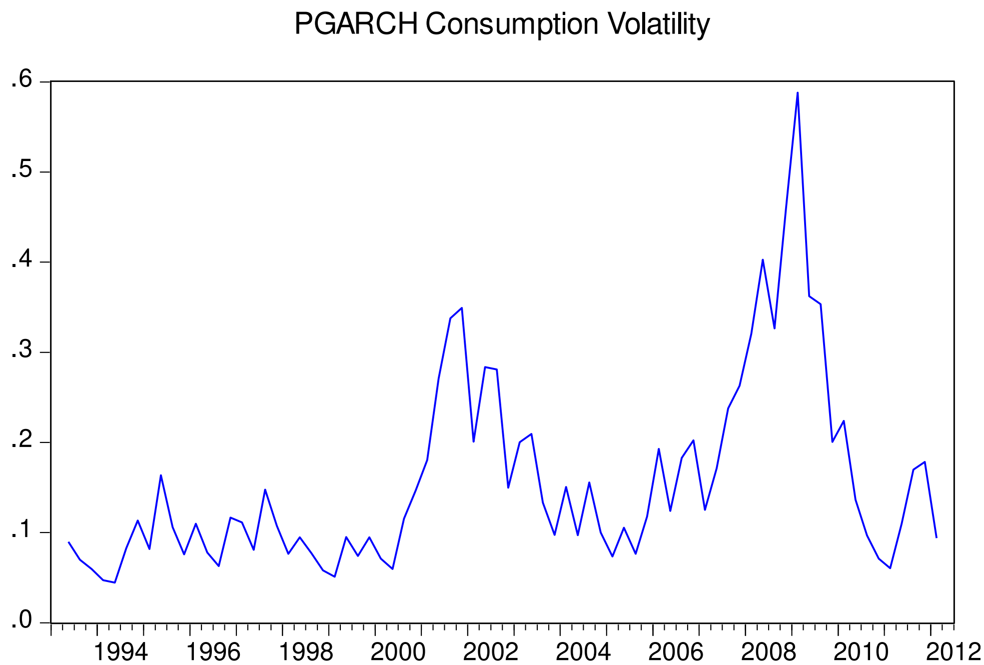
*indicates 10% significance
**indicates 5% significance
*** indicates 1% significance
Standard error corrected by Newey-West

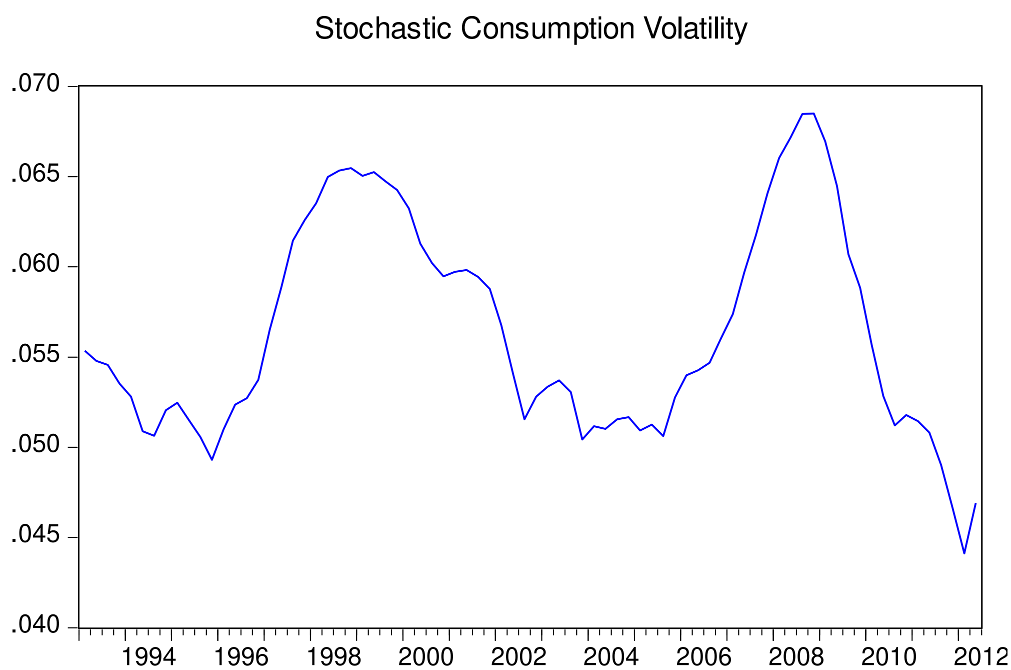
GARCH Consumption Volatility



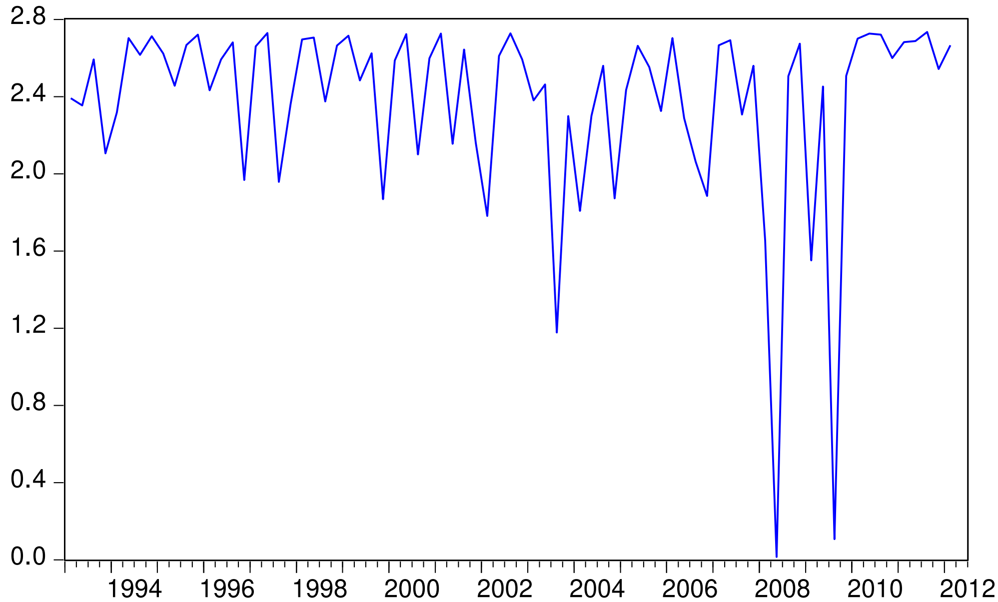
EGARCH Consumption Volatility



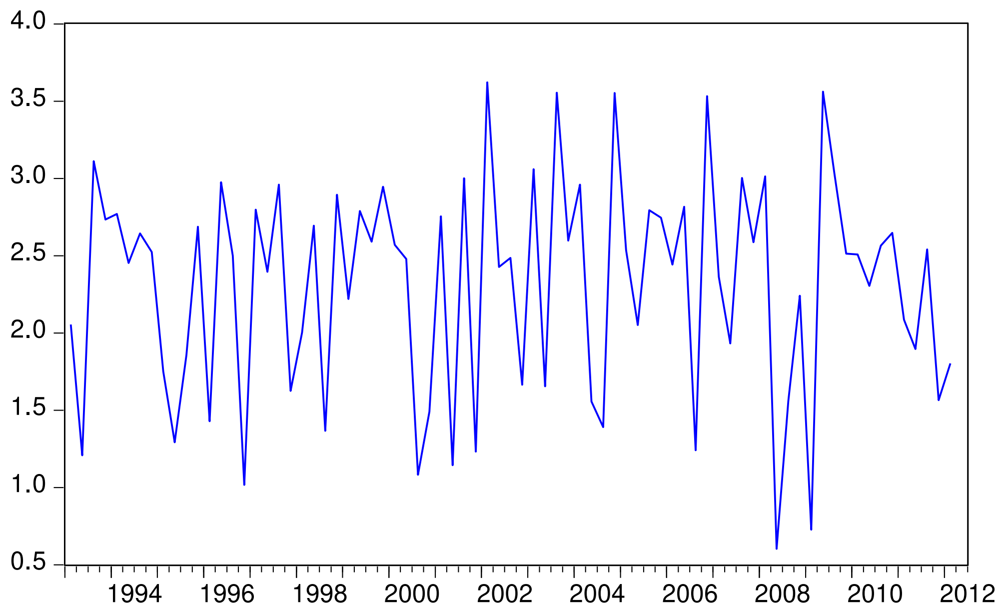

PGARCH Consumption Volatility
.6
.5
.4
.3
.2
.1
.0
1994
1996
1998
2000
2002
2004
2006
2008
2010
2012


Stochastic Consumption Volatility
.070
.065
.060
.055
.050
.045
.040
1994
1996
1998
2000
2002
2004
2006
2008
2010
2012

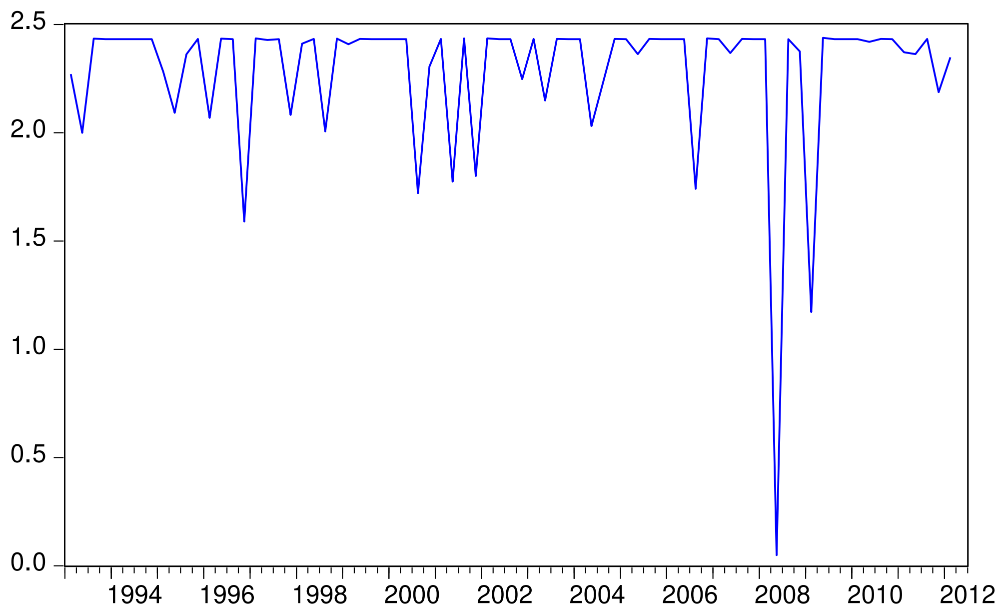
GARCH Market Volatility



EGARCH Market Volatility



PGARCH Market Volatility



Stochastic Market Volatility