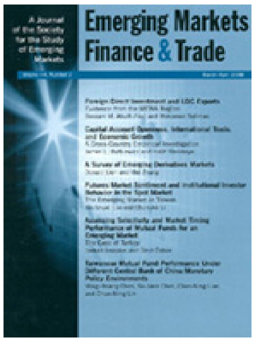


Emerging Markets Finance and Trade

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

**Ender Demir, Ka Wai Terence Fung & Zhou Lu**

**To cite this article:** Ender Demir, Ka Wai Terence Fung & Zhou Lu (2015): Capital Asset Pricing Model and Stochastic Volatility: A Case Study of India, Emerging Markets Finance and Trade, DOI: 10.1080/1540496X.2015.1062302

**To link to this article:** http://dx.doi.org/10.1080/1540496X.2015.1062302

*Emerging Markets Finance & Trade*, 1–14, 2015

ISSN: 1540-496X print/1558-0938 online
DOI: 10.1080/1540496X.2015.1062302



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

Ender Demir[1], Ka Wai Terence Fung[2], and Zhou Lu[3]

[1]*Faculty of Tourism, Istanbul Medeniyet University, Istanbul, Turkey;* [2]*Division of Business and Management, Beijing Normal University and Hong Kong Baptist University - United International College, Zhuhai, China;* [3]*Department of Economics and Business, City College of New York, New York, USA*



*ABSTRACT:* The existing literature demonstrates that under a general equilibrium model, the performance of the Capital Asset Pricing Model (CAPM) can be improved significantly by using conditional consumption and market return volatilities as factors. This article tests the validity of these factors explaining stock return differences using a less developed country (India) as a case study. While the earlier studies used panel data to test CAPM, we use portfolios sorted by size and book-to-market equity (BE/ME) ratio. We found that conditional volatility has a limited effect on firms with large capitalization but a significant impact on small-growth and small-value firms.

*KEY WORDS:* asset pricing model, equity premium puzzle, stochastic volatility

## Introduction

The development of the famous consumption-based capital asset pricing model (CCAPM) is financial economists' early attempt to explore the links between asset returns and macroeconomic variables that capture the sources of systematic risk.[1] 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 the elasticity of the intertemporal substitution of consumption. However, when facing empirical evidence, the CCAPM fails miserably. Jagannathan and Wang (1996) attribute the failure of general class of CAPM to two reasons. First, the CAPM holds in a conditional sense only. The stochastic discount factor is linear, as stated in the CAPM, but the coefficients are time varying. The static specification of market premium fails to take into account the effect of time-varying investment opportunities in the calculation of asset risk. For example, the betas of firms with relatively higher leverage rise during recessions; firms with different types of assets will be affected by the business cycle in a different way and to a different extent. Second, the return on the value-weighted portfolio of all stocks is a bad proxy-to-wealth return.

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

Lettau and Ludvigson (2001) examine the CCAPM in a conditional sense. They express the stochastic discount factor as a conditional or scaled factor model and examine the time-varying coefficients by interacting consumption growth with a cointegrating factor $\widehat{cay}$—a cointegrating residual between consumption, asset (nonhuman) wealth, and labor income. The parameters in the stochastic discount factor depend on investors' expectations of future excess return. Lettau and Ludvigson (2001) demonstrate that

Address correspondence to Ender Demir, Istanbul Medeniyet University, Ünalan St. Ünalan Sok., D-100 Highway sideway, 34700 Üsküdar, Istanbul, Turkey. E-mail: ender.demir@medeniyet.edu.tr

Color versions of one or more of the figures in the article can be found online at www.tandfonline.com/mree.

$\widehat{cay}$ drives time variation in conditional expected return. Using the assumption that the consumption growth rate follows a stochastic volatility model, Bansal and Yaron (2004) 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 volatilities and then test the validity of Bansal and Yaron's (2004) 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: 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 Bansal and Yaron (2004) model using U.S. 25 Fama-French portfolio returns sorted by size and book-to-market value. Fung, Lau, and Chan (2014) find that the theoretical premium of the Bansal and Yaron (2004) model outperforms the traditional CAPM that is based on observed market premium. They can explain a 55 percent variation of cross-section return difference by using GARCH consumption and market volatilities.

In this article, we apply data from an emerging economy, India, rather than the United States (a developed country) to estimate conditional volatilities and then test the validity of the Bansal and Yaron (2004) model. The first step is to estimate conditional consumption and market volatilities by stochastic volatility and by various GARCH models, including EGARCH, Power GARCH (PGARCH), and TGARCH.[2] The second step is to use the predicted volatilities as factors for a testing of the Bansal and Yaron (2004) model. In the following sections, we will address the following questions. When the ex post market risk premium is replaced by conditional consumption and market return volatilities, is the predictive power of the CAPM improved? Is this study robust regarding the different specifications of GARCH models?

This article contributes to the literature by providing an alternative to the Fama and French model (Fama and French 1993) for evaluating portfolio investment and hedging purposes. The early literature attempted to explain systematic differences in returns with macroeconomic factors (Chen et al. 1986). However, the statistical evidence was very weak. This study shows that the conditional volatilities of certain macroeconomic variables, indeed, can explain return differences. We find that, using portfolios sorted by size and book-to-market equity (BE/ME) ratio, the combined effect of conditional consumption growth and market return volatilities is limited for firms with large capitalization but significant for small-growth and small-value firms in a time-series setting.

This article is structured as follows. The next section is literature review. Then we proceed to briefly outline the derivation of the Bansal and Yaron market premium, delineate the data collection and estimation methods; and discuss the results from the India data.

## Literature Review

There is no lack of research documenting the CAPM and factor-pricing model regarding evidence from the Indian stock market. Sharma and Mahendru (2009) examine the validity of the efficient market hypothesis on the Indian securities market using company data from the Bombay Stock Exchange (BSE), Asia's oldest stock exchange. They find limited evidence that investors can reap profit by using the effect of stock prices on futures prices. Eleswarapu (1993) examines the seasonal pattern of the liquidity premium in asset pricing. He finds that, during the 1961–90 period, the liquidity premium is reliably positive only during the month of January but disappears the rest of the year. He also shows that size effect is significant, even after controlling for relative bid-ask spreads, which provide evidence of potential arbitrage profit.

Sehgal and Jain (2011) investigate whether there are any momentum patterns in stock and sectoral returns and whether they can be explained by risk factors. It is found that companies with higher short-term prior returns (six to twelve months) tend to record higher momentum profits under the 6–6 trading strategy. Risk models like the CAPM and Fama-French model fail to capture momentum profits; for example, firms with larger market capitalization reported higher momentum profits, thus defying the risk story. Gupta and Kumar (2014) use a large pool of sample data from a wide range of companies to test the relevance of the Fama-French three-factor model in explaining the cross-sectional differences in Indian stock market returns. The same size and value effect Fama and French (1993) document is also documented for U.S. portfolios.

Sehgal and Tripathi (2005) test the size effect in the Indian stock market using data from 482 top companies from the period 1990–2003. They find a strong size premium using six alternative measures of company size, market capitalization, enterprise value, net fixed assets, net annual sales, total assets, and net working capital. More importantly, the seasonal and cyclical components have been modeled. Thus, the presence of a strong size premium also raises doubts about the informational efficiency of the Indian equity market. Ansari and Khan (2012) explore the sources of momentum profit employing both risk-based and behavioral models of the Indian stock market during 1995–2006. While risk-based models such as the CAPM and Fama-French could not account for the variation of momentum profit, idiosyncratic risk was positively related to momentum profit—evidence of behavioral factors and investors' sentiment as sources of momentum.

We aim to apply the Fung, Lau, and Chan (2014) estimation method on the BSE index. We deviate from Fung, Lau, and Chan (2014) in two aspects. First, the sample object is a less-developed country—India. Second, the estimation is a pure time-series approach, instead of Fama-MacBeth (1973).[3]

## Theoretical Framework

The Bansal and Yaron (2004) model is a general equilibrium model with the following assumptions: (1) The representative household has the Epstein and Zin (1989) preference; (2) the consumption and dividend growth rate contain a small long-run predictable component; and (3) the volatility of aggregate consumption growth follows a stochastic path. Therefore, the asset and return premium will be a linear function of conditional consumption and market volatilities. The first-order condition is

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

where $\delta$ 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. The Epstein and Zin (1989) preference separates the relation between intertemporal elasticity of substitution (IES) and risk aversion. The parameter $\theta = \frac{1-\gamma}{1-\frac{1}{\psi}}$ ($\psi$ denotes IES; $\gamma \geq 0$) is the risk-aversion coefficient. 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 $\kappa_0$ and $\kappa_1$ are constants and $z_t = log(\frac{P_t}{C_t})$ is the log price-consumption ratio. In addition, $g_{t+1}$ is the log return of consumption. The log-linearized Equation (1) 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.

Note that when $\theta = 1$, then $\gamma = \frac{1}{\psi}$, and Equation (3) is pinned down to the case of the constant elasticity of substitution (CES) utility function. When $\theta = 1$ and $\gamma = 1$, it is equivalent to log utility.

Bansal and Yaron (2004) proceed to introduce exogenous shocks to perturb consumption and output from their steady states. The system of shocks is given by the following:

$$x_{t+1} = \rho x_t + \varphi_e \sigma_t e_{t+1}$$

$$g_{t+1} = \mu + x_t + \sigma_t \eta_{t+1}$$

$$g_{d,t+1} = \mu_d + \phi x_t + \varphi_d \sigma_t u_{t+1}$$

$$\sigma_{t+1}^2 = \sigma^2 + v_1(\sigma_t^2 - \sigma^2) + \sigma_w w_{t+1}$$

$$e_{t+1}, \eta_{t+1}, w_{t+1}, u_{t+1} \sim N(0,1)$$

This system of equations 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 $(\rho)$ but is perturbed by an independent and identically distributed (i.i.d) shock $(e_{t+1})$. Using undetermined coefficients, they find that

$$z_t = A_0 + A_1 x_t + A_2 \sigma_t^2 \tag{4}$$

$$A_1 = \frac{1 - \frac{1}{\psi}}{1 - \kappa_1 \rho}, \quad A_2 = \frac{0.5[(\theta - \frac{\theta}{\psi})^2 + (\theta A_1 \kappa_1 \varphi_e)^2]}{\theta(1 - \kappa_1 v_1)}.$$

There are two noteworthy features of this model: (1) If $\gamma$ and $\psi$ are larger than one, then $\theta$ is negative, and a rise in volatility lowers the price-consumption ratio since the intertemporal effect dominates the substitution effect; (2) the risk premium is a positive function of the volatility persistence parameter $\rho$, meaning that the representative consumer dislikes a prolonged period of consumption shocks. It can be shown that the market premium in the presence of time-varying economic uncertainty is

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

where $\sigma_t^2$ and $\sigma_w^2$ are the conditional consumption and wealth volatilities; $\lambda$ is the price of risk; and $\beta$ is the quantity of risk. The risk premium of any asset, given by the 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 Bansal and Yaron (2004) model calls for the estimation of two equations. Equation (5) states that the long-run market risk premium is determined by conditional consumption and market return volatility. In particular, the cointegrating vector is $(\beta_{m,e}\lambda_{m,e}, -0.5)$. We focus on Equation (6), which explains cross-sectional return differences by conditional volatilities. We intend to demonstrate that if Equation (6) can be explained by some common GARCH and stochastic volatility models, it constitutes indirect support for Bansal and Yaron (2004). Moreover, it would provide an alternative estimation to the Fama-French model.

## Data and Methodology

The consumption data of India are collected from the Federal Reserve Bank of St. Louis's Economic Research Database (http://research.stlouisfed.org/fred2/). 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 from the working paper of Agarwalla, Jacob, and Varma (2013) (http://www.iimahd.ernet.in/~jrvarma/Indian-Fama-French-Momentum/). The sample period is from the first quarter of 1993 to the second quarter of 2012.

Fung, Lau, and Chan (2014) use 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 compute the portfolio returns using Bombay Stock Exchange (BSE) index data from the CMIE Prowess. This data set is an improvement over earlier data. More firms are included; illiquid firms are excluded. The size cutoff point is redefined, and survivor bias is corrected. However, they only provide six portfolios based on size (measured 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 a limited number of cross sections (in this case, six), we cannot adopt the Fama and MacBeth (1973) procedure. The more appropriate method is the time-series approach. There are excessive missing observations of the big-value portfolio. Therefore, it will not be used for estimation; we have five portfolios. The independent variables are various GARCH models. If the Bansal and Yaron (2004) model holds for a less-developed country like India, it should work for different specifications of conditional volatilities. The benchmark model is

$$E_t(r_{i,t+1} - r_{f,t}) = \gamma_0 + \beta_1\lambda_c\sigma^2_{c,t+1} + \beta_2\lambda_m\sigma^2_{m,t+1} + e_t, \tag{7}$$

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 research on GARCH-type models is well documented (Bollerslev, Chou, and Kroner 1992; Bollerslev, Engle, and Nelson 1994; Fleming and Kirby 2003). We will also consider the EGARCH, TGARCH and PGARCH to model the asymmetry inherent in the series. Stochastic volatility models, which are reviewed in, for example, Ghysels, Harvey, and Renault (1996) and Taylor (1994), 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).

$$r_t = \sigma_t\varepsilon_t \tag{8}$$

$$h_t = \ln\,\sigma_t^2 = \gamma + \phi h_{t-1} + \eta_t \tag{9}$$

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

where $r_t$ is the continuously compounded return of an asset; $\sigma_t$ 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 (8). $\varepsilon_t$ and $\eta_t$ are assumed to be two independent errors. This process is nonlinear in nature and can be transformed into a linear function by an 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 $var(\ln\,\varepsilon_t^2) = \frac{\pi^2}{2}$. An unobserved component state space representation for $y_t$ has the form

$$y_t = -1.27 + h_t + \xi_t, \quad \xi_t \sim N\left(0, \frac{\pi^2}{2}\right) \tag{10}$$

$$h_t = \gamma + \phi h_{t-1} + \eta_t, \qquad \eta_t \sim N(0, \sigma^2_\eta) \tag{11}$$

$$E[\xi_t\eta_t] = 0, \tag{12}$$

where $\xi_t$ and $\eta_t$ are two independent white noises. Equations (10) and (11) will be estimated simultaneously. For a detailed estimation procedure, see Théoret and Racicot (2010).[5]

## Results

The consumption and BSE market return conditional volatilities are reported from 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 reasons is that asymmetry is not a characteristic of an aggregate consumption series. For GARCH, EGARCH, and PGARCH, there are four spikes in volatility—1997, 2001, 2003, and 2008. However, EGARCH has a different prediction in the last four quarters in the sample period (Figure 2). The stochastic volatility is reported in Figure 4. Comparing to the GARCH volatilities, there are two discernible differences. First, the range of volatility is smaller (only 0.04–0.06), and second, the temporal movement is smoother (characterized by fewer spikes)



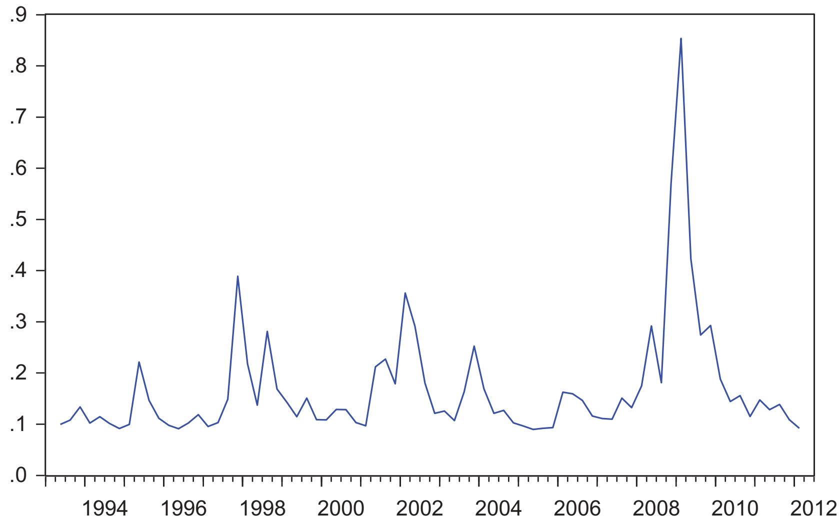


**Figure 1. GARCH consumption volatility (quarterly).**

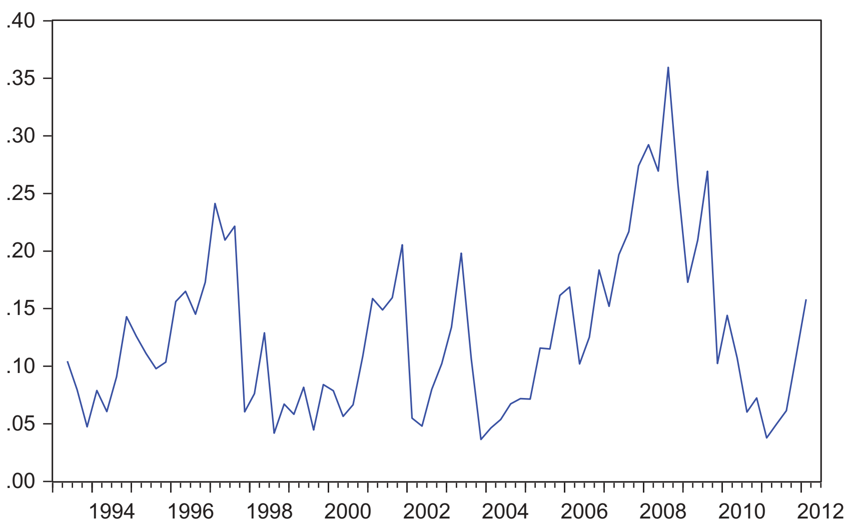


**Figure 2. EGARCH consumption volatility (quarterly).**

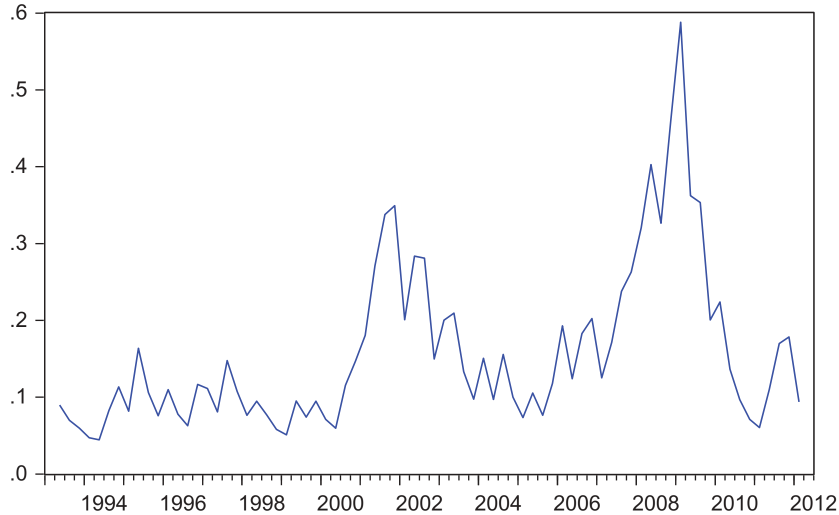


**Figure 3. PGARCH consumption volatility (quarterly).**

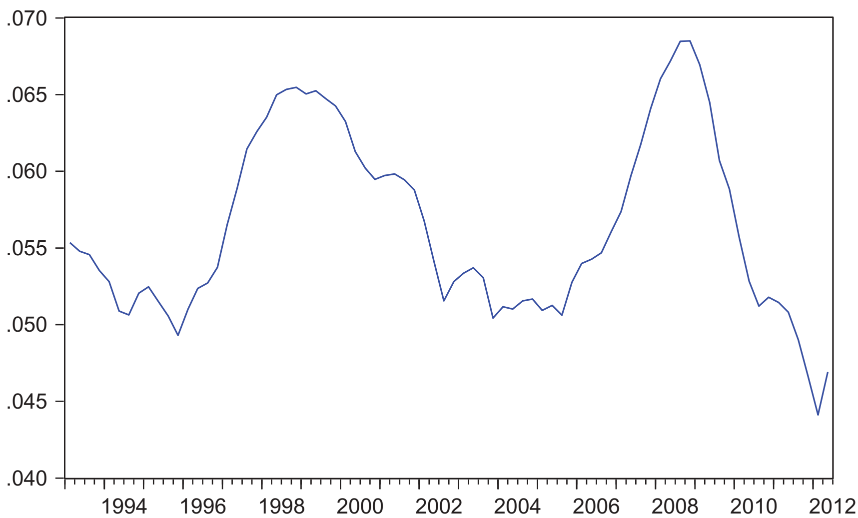


**Figure 4. Stochastic consumption volatility (quarterly).**

over the whole sample period. That said, the temporal comovement is still similar to those of GARCH volatilities.

From Figures 5–8, it is obvious that the GARCH, EGARCH, and stochastic volatility models are very similar. The range of quarterly volatility is 0.4–4.5 percent. Most models predict a big drop in the second half of 2008. However, the variation of the PGARCH is significantly smaller than other models. The PGARCH predicts no change in some periods. The estimated stochastic volatility of the market return is a modified version of Equation (11). We encounter 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 and West (1987). As a usual practice, we include the intercept term in all equations. To control for serial correlation, we add an autoregressive and moving average (ARMA) term to the equation if the coefficient is significant. If the Bansal and Yaron (2004)

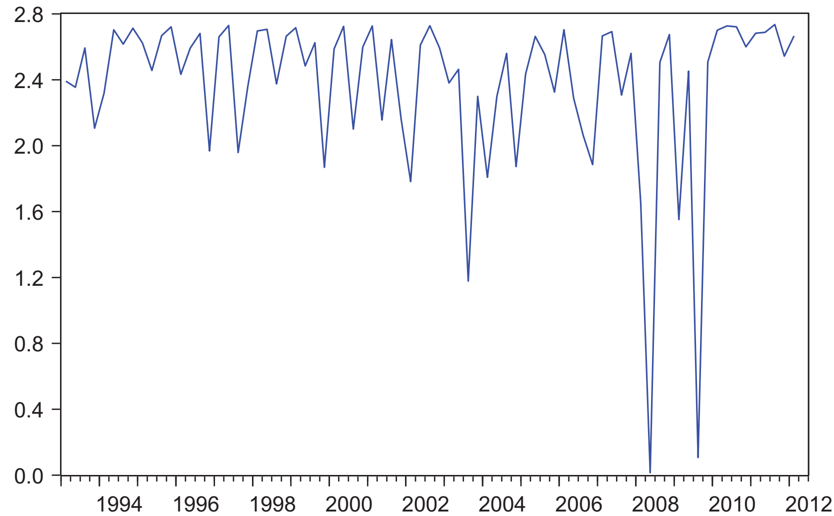


**Figure 5. GARCH market volatility (quarterly).**

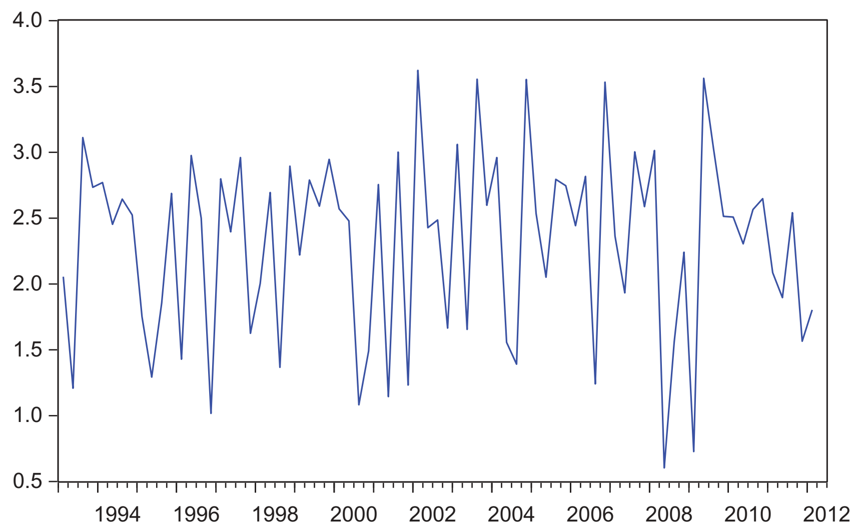


**Figure 6. EGARCH market volatility (quarterly).**



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

The performance of the Bansal and Yaron (2004) model improves significantly when using EGARCH and PGARCH volatilities. As shown in Table 2, the market volatility coefficient is significant in all five portfolios. For instance, with a 1 percent increase in market volatility, the return

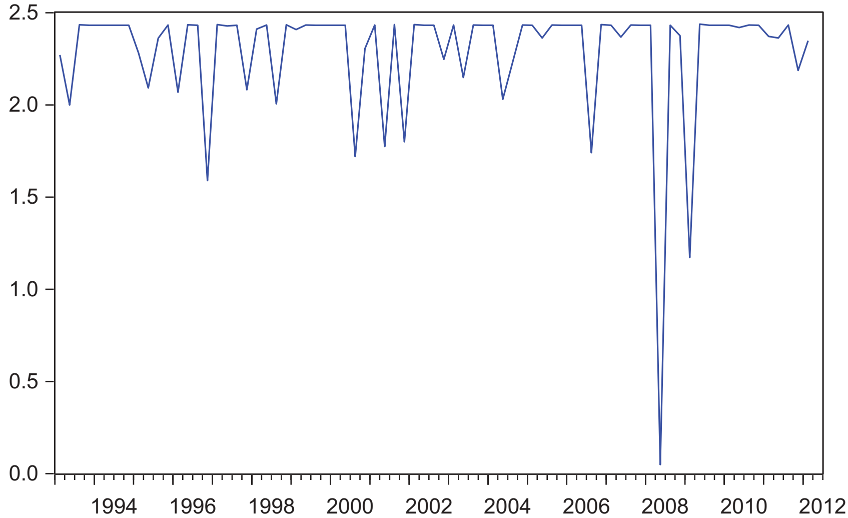


**Figure 7. PARCH market volatility (quarterly).**

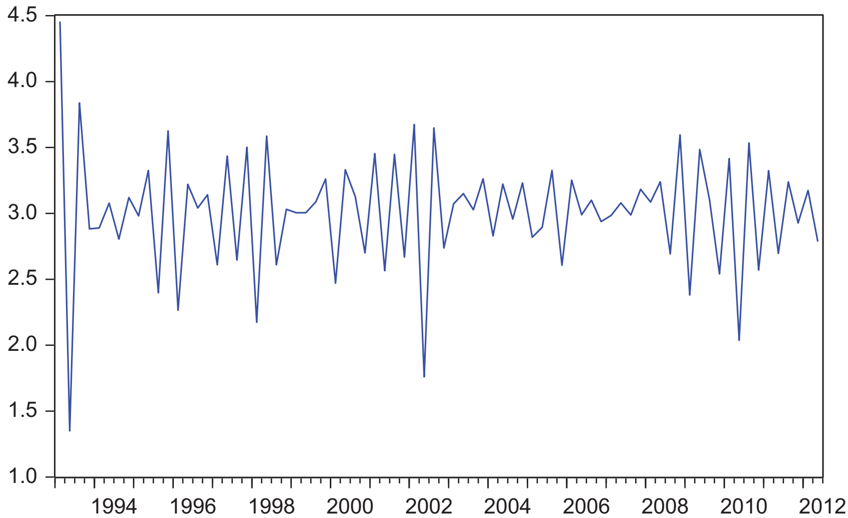


**Figure 8. Stochastic market volatility (quarterly).**

of a 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 the temporal variation of size/value-sorted portfolio returns.

As shown in Table 4, when stochastic volatility is used, the results are similar to those of the PGARCH model. There is no significant change. From these tables, we conclude that the Bansal and Yaron model (2004) works the best for small-sized firms. For the case of stochastic volatility (Table 4),

**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 |

*Notes*: Standard error corrected by Newey-West. *10 percent significance; **5 percent significance; ***1 percent significance.

**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) | 0.5398* | | | | |
| MA(1) | (0.0582) | | | | |
| Joint significance (*p*-value) | 0.0485** | 0.0497** | 0.00437*** | 0.0337** | 0.00827*** |

*Notes*: Standard error corrected by Newey-West. *10 percent significance; **5 percent significance; ***1 percent significance.

**Table 3. Bansal-Yaron estimation using PGARCH volatility**

| | Portfolio returns | | | | |
|---|---|---|---|---|---|
| | **Big-growth** | **Big-neutral** | **Small-growth** | **Small-neutral** | **Small-value** |
| **Constant** | 11.29073 | −31.33** | −7.635436 | −15.95064 | −23.73830 |
| | (0.3473) | (0.0285) | (0.6376) | (0.3719) | (0.2490) |
| **PGARCH market volatility** | 2.218 | 1.461*** | 2.73* | 8.312 | 11.93* |
| | (0.6397) | (0.0043) | (0.0907) | (0.1650) | (0.0862) |
| **PGARCH consumption volatility** | −21.62418 | 18.71683 | −19.00919 | 2.787404 | −9.894031* |
| | (0.3490) | (0.4431) | (0.3755) | (0.9362) | (0.07916) |
| **AR(1)** | | | | | |
| **MA(1)** | 0.346122 | | | | |
| | (0.0175) | | | | |
| Joint significance (*p*-value) | 0.619 | 0.0006*** | 0.0143** | 0.1865 | 0.0052*** |

*Notes*: Standard error corrected by Newey-West. *10 percent significance; **5 percent significance; ***1 percent significance.

**Table 4. Bansal-Yaron estimation using stochastic volatility**

| | Portfolio returns | | | | |
|---|---|---|---|---|---|
| | **Big-growth** | **Big-neutral** | **Small-growth** | **Small-neutral** | **Small-value** |
| **Constant** | 12.50835 | 17.99351 | 14.50869 | 16.15944 | 21.08931 |
| | (0.5676) | (0.4328) | (0.5861) | (0.5938) | (0.5266) |
| **Stochastic market volatility** | 4.677 | 1.799 | 5.248** | −3.7 | 2.946* |
| | (0.2541) | (0.4328) | (0.03026) | (0.3096) | (0.06178) |
| **Stochastic consumption volatility** | −5.534 | 1.135 | −8.79 | −2.35 | −6.2 |
| | (0.8333) | (0.7064) | (0.7908) | (0.6624) | (0.2714) |
| **AR(1)** | 0.258581*** | | 0.185174** | 0.181176 | |
| | (0.0013) | | (0.0212) | (0.1157) | |
| **MA(1)** | | 0.152553* | | | 0.155629 |
| | | (0.0719) | | | (0.1857) |
| Joint significance (*p*-value) | 0.2018 | 0.71 | 0.037** | 0.5464 | 0.0569* |

*Notes*: *10 percent significance; **5 percent significance; ***1 percent significance.

for example, a 1 percent increase in market volatility would result in a 5.25 percent increase in the small-growth portfolio. This finding is consistent with the stylized fact that small firms tend to have higher abnormal returns (Fama and French 1993; Roll 1977). Our result is consistent with Fung, Lau, and Chan (2014), that the GARCH-type model, in general, outperforms the stochastic volatility model under the Bansal and Yaron (2004) model.

## Conclusion

Fung, Lau, and Chan (2014), using the Bansal and Yaron (2004) general equilibrium model, demonstrate that the performance of the capital asset pricing model (CAPM) can be improved significantly by using conditional consumption and market return volatilities as factors. We estimate conditional volatilities and then test the validity of the Bansal and Yaron (2004) model by using Indian stock market data. As a first step, conditional consumption and market volatilities are estimated by stochastic volatility and by various generalized autoregressive conditional heteroskedasticity (GARCH) models, including exponential GARCH (EGARCH), power GARCH (PGARCH), and threshold GARCH

(TGARCH). The second step is to use the predicted volatilities as factors for a testing of the Bansal and Yaron (2004) model.

We find that asymmetric GARCH consumption and market return volatility coefficients are significant in sorted portfolios, especially small-growth and small-value portfolios. Hence, this case study provides empirical support for the Bansal and Yaron (2004) theoretical model. The finding that the GARCH model outperforms stochastic volatility in predicting emerging market returns is consistent with Carvalhal and de Melo Mendes (2008). Despite the positive evidence, there is one limitation of this study—relatively small sample size. The original data frequency is monthly. However, aggregate consumption, as part of GDP, is always reported quarterly, which limits the sample size. For a less-developed country like India, those macroeconomic data have only recently become available.



## Notes

1. Another strand of literature explores the linkage between stock returns and the microfinance structure of companies (Inci 2011).
2. Carvalhal and de Melo Mendes (2008) demonstrate that ARCH models are appropriate for forecasting the stock returns of emerging markets.
3. An alternative approach is using macroeconomic factors as explanatory variables (see Inci 2011). There is no need for the Shanken (1992) correction.
4. For comparison, a discussion of merits, and the deciding rules of these two models, see Fleming and Kirby (2003), Heynen and Kat (1994), and Preminger and Haftner (2006).
5. Heynen and Kat (1994) as well as Preminger and Haftner (2006) survey the literature comparing GARCH to the stochastic volatility model.

## References

Agarwalla, S. K., J. Jacob, and J. R. Varma. 2013. Four factor model in Indian equities market, Working Paper. No. 2013-09-05, Indian Institute of Management, Ahmedabad, India.

Ansari, V. A., and S. Khan. 2012. Momentum anomaly: Evidence from India. *Managerial Finance* 38, no. 2: 206–23. doi:10.1108/03074351211193730.

Bansal, R., and A. Yaron. 2004. Risks for the long-run: A potential resolution of asset pricing puzzles. *The Journal of Finance* 59, no. 4: 1481–509. doi:10.1111/jofi.2004.59.issue-4.

Bollerslev, T., R. Chou, and K. Kroner. 1992. ARCH modeling in finance: A review of the theory and empirical evidence. *Journal of Econometrics* 52, no. 1–2: 5–59. doi:10.1016/0304-4076(92)90064-X.

Bollerslev, T., R. Engle, and D. Nelson. 1994. Arch models. In *Handbook of econometrics*, eds. R. Engle, and D. McFadden, Vol. 4, 2959–3038. Amsterdam, The Netherlands: Elsevier Science.

Campbell, J., and R. Shiller. 1988. The dividend-price ratio and expectations of future dividends and discount factors. *Review of Financial Studies* 1: 195–227.

Carvalhal, A., and B. V. de Melo Mendes. 2008. Evaluating the forecast accuracy of emerging market stock returns. *Emerging Markets Finance and Trade* 44, no. 1: 21–40. doi:10.2753/REE1540-496X440102.

Chen, N., R. Roll, and S. Ross. 1986. Economic forces and the stock market. *The Journal of Business* 59: 383–404.

Eleswarapu, V. R. 1993. The seasonal behavior of the liquidity premium in asset pricing. *Journal of Financial Economics* 34, no. 3: 373–86. doi:10.1016/0304-405X(93)90032-7.

Epstein, L. G., and S. E. Zin. 1989. Substitution, risk aversion, and the temporal behavior of consumption and asset returns: A theoretical framework. *Econometrica* 57, no. 4: 937–69.

Fama, E., and K. French. 1993. Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics* 33, no. 1: 3–56. doi:10.1016/0304-405X(93)90023-5.

Fama, E., and J. MacBeth. 1973. Risk, return and equilibrium: Empirical tests. *Journal of Political Economy* 81, no. 3: 607–36.

Fleming, J., and C. Kirby. 2003. A closer look at the relation between GARCH and stochastic autoregressive volatility. *Journal of Financial Econometrics* 1, no. 3: 365–419. doi:10.1093/jjfinec/nbg016.

Fung, K. W. T., C. K. M. Lau, and K. H. Chan. 2014. The conditional CAPM, cross-section returns and stochastic volatility. *Economic Modelling* 38: 316–27. doi:10.1016/j.econmod.2014.01.009.

Ghysels, E., A. Harvey, and E. Renault. 1996. Stochastic volatility. In *Handbook of statistics*, eds. G. Maddala, and C. Rao, Vol. 14, 119–91. North-Holland, Amsterdam: Statistical Methods in Finance.

Gupta, C. P., and R. Kumar. 2014. A re-examination of factors affecting returns in Indian stock market. *Journal of Emerging Market Finance*. Forthcoming.

Harvey, A., E. Ruiz, and N. Shephard. 1994. Multivariate stochastic variance models. *Review of Economic Studies* 61: 247–64.

Heynen, R., and H. Kat. 1994. Volatility prediction: A comparison of the stochastic volatility, GARCH (1,1) and GARCH (1,1) models. *The Journal of Derivatives* 2, no. 2: 50–65. doi:10.3905/jod.1994.407912.

Inci, A. C. 2011. Capital investment, earnings, and annual stock returns: Causality relationships in China. *Eurasian Economic Review* 1, no. 2: 95–125.
Jagannathan, R., and Z. Wang. 1996. The conditional CAPM and the cross-section of expected returns. *The Journal of Finance* 51, no. 1: 3–53. doi:10.1111/j.1540-6261.1996.tb05201.x.
Lettau, M., and S. Ludvigson. 2001. Resurrecting the (C)CAPM: A cross-sectional test when risk premia are time-varying. *Journal of Political Economy* 109, no. 6: 1238–87. doi:10.1086/323282.
Mills, T. C. 1999. *The econometric modelling of financial time series*. 2nd ed. Cambridge, UK: Cambridge University Press.
Newey, W. K., and K. D. West. 1987. Hypothesis testing with efficient method of moments estimation. *International Economic Review* 28, no. 3: 777–87.
Preminger, A., and C. Haftner. 2006. Deciding between GARCH and stochastic volatility via strong decision rules. Working paper no. 06–03, Monaster Center of Economic Research, Ben Gurion University of the Negev.
Roll, R. 1977. A critique of the asset pricing theory's tests Part I: On past and potential testability of the theory. *Journal of Financial Economics* 4, no. 2: 129–76. doi:10.1016/0304-405X(77)90009-5.
Sehgal, S., and S. Jain. 2011. Short-term momentum patterns in stock and sectoral returns: Evidence from India. *Journal of Advances in Management Research* 8, no. 1: 99–122. doi:10.1108/09727981111129327.
Sehgal, S., and V. Tripathi. 2005. Size effect in indian stock market: Some empirical evidence. *Vision: The Journal of Business Perspective* 9, no. 4: 27–42. doi:10.1177/097226290500900403.
Shanken, J. 1992. On the estimation of beta-pricing models. *Review of Financial Studies* 5, no. 1: 1–33. doi:10.1093/rfs/5.1.1.
Sharma, G. D., and M. Mahendru. 2009. Efficiency hypothesis of the stock markets: A case of Indian securities. *International Journal of Business and Management* 4, no. 3: 136–44. doi:10.5539/ijbm.v4n3p136.
Taylor, S. 1994. Modeling stochastic volatility: A review and comparative study. *Mathematical Finance* 4, no. 2: 183–204. doi:10.1111/mafi.1994.4.issue-2.
Théoret, R., and F.-É. Racicot. 2010. Forecasting stochastic volatility using the kalman filter: An application to canadian interest rates and price-earnings ratio, MPRA Paper 35911, University Library of Munich, Germany.