

# Option Valuation with Long-run and Short-run Volatility Components

Peter Christoffersen  
McGill University and CIRANO

Kris Jacobs  
McGill University and CIRANO

Yintian Wang\*  
McGill University

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## Abstract

This paper presents a new model for the valuation of European options. In our model, the volatility of returns consists of two components. One of these components is a long-run component, and it can be modeled as fully persistent. The other component is short-run and has a zero mean. Our model can be viewed as an affine version of Engle and Lee (1999), allowing for easy valuation of European options. We investigate the model through an integrated analysis of returns and options data. The performance of the model is spectacular when compared to a benchmark single-component volatility model that is well-established in the literature. The improvement in the model's performance is due to its richer dynamics which enable it to jointly model long-maturity and short-maturity options.

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# 1 Introduction

There is a consensus in the literature that combining time-variation in the conditional variance of asset returns (Engle (1982), Bollerslev (1986)) with a leverage effect (Black (1976)) constitutes a potential solution to well-known biases associated with the Black-Scholes (1973) model, such as the smile and the smirk. To model the smirk, these models generate higher prices for out-of-the-money put options as compared to the Black-Scholes formula. Equivalently, the models generate negative skewness in the distribution of asset returns. In the continuous-time option valuation literature, the Heston (1993) model addresses some of these biases. This model contains a leverage effect as well as stochastic volatility.<sup>1</sup> In the discrete-time literature, the NGARCH(1,1) option valuation model proposed by Duan (1995) contains time-variation in conditional variance as well as a leverage effect. The model by Heston and Nandi (2000) is closely related to Duan's model.

Many existing empirical studies have confirmed the importance of time-varying volatility, the leverage effect and negative skewness in continuous-time and discrete-time setups, using parametric as well as non-parametric techniques.<sup>2</sup> However, it has become clear that while these models help explain the biases of the Black-Scholes model in a qualitative sense, they come up short in a quantitative sense. Using parameters estimated from returns or options data, these models reduce the biases of the Black-Scholes model, but the magnitude of the effects is insufficient to completely resolve the biases. The resulting pricing errors have the same sign as the Black-Scholes pricing errors, but are smaller in magnitude. We therefore need models that possess the same qualitative features as the models in Heston (1993) and Duan (1995), but that contain stronger quantitative effects. These models need to generate more flexible skewness and volatility of volatility dynamics in order to fit observed option prices.

One interesting approach in this respect is the inclusion of jump processes. In most existing studies, jumps are added to models that already contain time-variation in the conditional variance as well as a leverage effect. The empirical findings in this literature have been mixed. In general, for Poisson processes, jumps in returns and volatility improve option valuation when parameters are estimated using historical time series of returns, but usually not when parameters are estimated using the cross-section of option prices.<sup>3</sup> Huang and Wu (2004) find that other types of jump processes may provide a better fit.

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<sup>1</sup>The importance of stochastic volatility is also studied in Hull and White (1987), Melino and Turnbull (1990), Scott (1987) and Wiggins (1987).

<sup>2</sup>See for example Ait-Sahalia and Lo (1998), Amin and Ng (1993), Bakshi, Cao and Chen (1997), Bates (1996, 2000), Benzoni (1998), Bollerslev and Mikkelsen (1999), Chernov and Ghysels (2000), Duan, Ritchken and Sun (2004), Engle and Mustafa (1992), Eraker (2004), Heston and Nandi (2000), Jones (2003), Nandi (1998) and Pan (2003).

<sup>3</sup>See for example Bakshi, Cao and Chen (1997), Eraker, Johannes and Polson (2003), Eraker (2004) and Pan (2002).

This paper takes a different approach. We attempt to remedy the remaining option biases by modeling richer volatility dynamics.<sup>4</sup> It has been observed using a variety of diagnostics that it is difficult to fit the autocorrelation function of return volatility using a benchmark model such as a GARCH(1,1). Similar remarks apply to stochastic volatility models such as Heston (1993). The main problem is that volatility autocorrelations are too high at longer lags to be explained by a GARCH(1,1), unless the process is extremely persistent. This extreme persistence may impact negatively on other aspects of option valuation, such as the valuation of short-maturity options.

In fact, it has been observed in the literature that volatility may be better modeled using a fractionally integrated process, rather than a stationary GARCH process.<sup>5</sup> Andersen, Bollerslev, Diebold and Labys (2003) confirm this finding using realized volatility. Bollerslev and Mikkelsen (1996, 1999) and Comte, Coutin and Renault (2001) investigate and discuss some of the implications of long memory for option valuation. Using fractional integration models for option valuation is cumbersome. Optimization is very time-intensive and a number of ad-hoc choices have to be made regarding implementation. This paper addresses the same issues using a different type of model that is easier to implement and captures the stylized facts addressed by long-memory models at horizons relevant for option valuation. The model builds on Heston and Nandi (2000) and Engle and Lee (1999). In our model, the volatility of returns consists of two components. One of these components is a long-run component, and it can be modeled as (fully) persistent. The other component is short-run and mean zero. The model is able to generate autocorrelation functions that are richer than those of a GARCH(1,1) model while using just a few additional parameters. We illustrate how this impacts on option valuation by studying the term structure of volatility.

Unobserved component or factor models are very popular in the finance literature. See Fama and French (1988), Poterba and Summers (1988) and Summers (1986) for applications to stock prices. In the option pricing literature, Bates (2000) and Taylor and Xu (1994) investigate two-factor stochastic volatility models. Duffie, Pan and Singleton (2000) provide a general continuous-time framework for the valuation of contingent claims using multifactor affine models. Eraker (2004) suggests the usefulness of a multifactor approach based on his empirical results. Alizadeh, Brandt and Diebold (2002) uncover two factors in stochastic volatility models of exchange rates using range-based estimation. Unobserved component models are also very popular in the term structure literature, although in this literature the models are more commonly referred to as multifactor models.<sup>6</sup> There are very interesting parallels between our approach and results and stylized facts in the term structure literature. In the term structure literature it is customary to model short-run fluctuations around a time-varying long-run mean of the short rate. In our framework we model short-run fluctuations

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<sup>4</sup>Adding jumps to the new volatility specification may of course improve the model further.

<sup>5</sup>See Baillie, Bollerslev and Mikkelsen (1996).

<sup>6</sup>See for example Dai and Singleton (2000), Duffee (1999), Duffie and Singleton (1999) and Pearson and Sun (1994).

around a time-varying long-run volatility.

Dynamic factor and component models can be implemented in continuous or discrete time.<sup>7</sup> We choose a discrete-time approach because of the ease of implementation. In particular, our model is related to the GARCH class of processes and volatility filtering and forecasting are relatively straightforward, which is critically important for option valuation. An additional advantage of our model is parsimony: the most general model we investigate has seven parameters. The models with jumps in returns and volatility discussed above are much more heavily parameterized. We speculate that parsimony may help our model's out-of-sample performance.

We investigate the model through an integrated analysis of returns and options data. We study two models: one where the long-run component is constrained to be fully persistent and one where it is not. We refer to these models as the persistent component model and the component model respectively. When persistence of the long-run component is freely estimated, it is very close to one. The performance of the component model is spectacular when compared with a benchmark GARCH(1,1) model. When using all available option data, the RMSE of the component model is on average 16.5% lower than that of the benchmark GARCH model in-sample and 22.1% out-of-sample. When using long-maturity options only, the RMSE improvement is on average 17.8% in-sample and 33.7% out-of-sample. The improvement in the model's performance is due to its richer dynamics, which enable it to jointly model long-maturity and short-maturity options. Our out-of-sample results strongly suggest that these richer dynamics are not simply due to spurious in-sample overfitting. The persistent component model performs better than the benchmark GARCH(1,1) model, but it is inferior to the component model both in- and out-of-sample. We also provide a detailed study of the term structure of volatilities for our proposed models and the benchmark model.

We use the GARCH(1,1) as a benchmark model for three reasons: First, the component model is a natural generalization of the GARCH(1,1) model. Second, Heston and Nandi (2000) find that the GARCH(1,1) slightly outperforms the ad-hoc implied volatility benchmark model in Dumas, Fleming and Whaley (1998). We have confirmed this result with our data. Third, in separate work we find that the GARCH(1,1) performs very similarly to the benchmark stochastic volatility model in Heston (1993) which can be viewed as the continuous time limit of the GARCH(1,1) model.

The paper proceeds as follows. Section 2 introduces the model. Section 3 discusses the volatility term structure and Section 4 discusses option valuation. Section 5 discusses the empirical results, and Section 6 concludes.

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<sup>7</sup>Duffie, Pan and Singleton (2000) suggest a multifactor continuous-time model that captures the spirit of our approach, but do not investigate the model empirically.

## 2 Return Dynamics with Volatility Components

In this section we first present the Heston-Nandi GARCH(1,1) model which will serve as the benchmark model throughout the paper. We then construct the component model as a natural extension of a rearranged version of the GARCH(1,1) model. Finally the persistent component model is presented as a special case of the component model.

### 2.1 The Heston and Nandi GARCH(1,1) Model

Heston and Nandi (2000) propose a class of GARCH models that allow for a closed-form solution for the price of a European call option. They present an empirical analysis of the GARCH(1,1) version of this model, which is given by

$$\begin{aligned}\ln(S_{t+1}) &= \ln(S_t) + r + \lambda h_{t+1} + \sqrt{h_{t+1}} z_{t+1} \\ h_{t+1} &= w + b_1 h_t + a_1 (z_t - c_1 \sqrt{h_t})^2\end{aligned}\tag{1}$$

where  $S_{t+1}$  denotes the underlying asset price,  $r$  the risk free rate,  $\lambda$  the price of risk and  $h_{t+1}$  the daily variance on day  $t + 1$  which is known at the end of day  $t$ . The  $z_{t+1}$  shock is assumed to be i.i.d.  $N(0, 1)$ . The Heston-Nandi model captures time variation in the conditional variance as in Engle (1982) and Bollerslev (1986),<sup>8</sup> and the parameter  $c_1$  captures the leverage effect. The leverage effect captures the negative relationship between shocks to returns and volatility (Black (1976)), which results in a negatively skewed distribution of returns.<sup>9</sup> Note that the GARCH(1,1) dynamic in (1) is slightly different from the more conventional NGARCH model used by Engle and Ng (1993) and Hentschel (1995), which is used for option valuation in Duan (1995). The reason is that the dynamic in (1) is engineered to yield a closed-form solution for option valuation, whereas a closed-form solution does not obtain for the more conventional GARCH dynamic. Hsieh and Ritchken (2000) provide evidence that the more traditional GARCH model may actually slightly dominate the fit of (1). Our main point can be demonstrated using either dynamic. Because of the convenience of the closed-form solution provided by dynamics such as (1), we use this as a benchmark in our empirical analysis and we model the richer component structure within the Heston-Nandi framework.

To better appreciate the workings of the component models presented below, note that by using the expression for the unconditional variance

$$E[h_{t+1}] \equiv \sigma^2 = \frac{w + a_1}{1 - b_1 - a_1 c_1^2}$$

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<sup>8</sup>For an early application of GARCH to stock returns, see French, Schwert and Stambaugh (1987).

<sup>9</sup>Its importance for option valuation has been emphasized among others by Benzoni (1998), Chernov and Ghysels (2000), Christoffersen and Jacobs (2004), Eraker (2004), Eraker, Johannes and Polson (2003), Heston (1993), Heston and Nandi (2000) and Nandi (1998).

the variance process can now be rewritten as

$$h_{t+1} = \sigma^2 + b_1 (h_t - \sigma^2) + a_1 \left( (z_t - c_1 \sqrt{h_t})^2 - (1 + c_1^2 \sigma^2) \right) \quad (2)$$

## 2.2 Building a Component Volatility Model

The expression for the GARCH(1,1) variance process in (2) highlights the role of the parameter  $\sigma^2$  as the constant unconditional mean of the conditional variance process. A natural generalization is then to specify  $\sigma^2$  as time-varying. Denoting this time-varying component by  $q_{t+1}$ , the expression for the variance in (2) can be generalized to

$$h_{t+1} = q_{t+1} + \beta (h_t - q_t) + \alpha \left( (z_t - \gamma_1 \sqrt{h_t})^2 - (1 + \gamma_1^2 q_t) \right) \quad (3)$$

This model is similar in spirit to the component model of Engle and Lee (1999). The difference between our model and Engle and Lee (1999) is that the functional form of the GARCH dynamic (3) allows for a closed-form solution for European option prices. This is similar to the difference between the Heston-Nandi (2000) GARCH(1,1) dynamic and the more traditional NGARCH(1,1) dynamic discussed in the previous subsection. In specification (3), the conditional volatility  $h_{t+1}$  can most usefully be thought of as having two components. Following Engle and Lee (1999), we refer to the component  $q_{t+1}$  as the long-run component, and to  $h_{t+1} - q_{t+1}$  as the short-run component. We will discuss this terminology in some more detail below. Note that by construction the unconditional mean of the short-run component  $h_{t+1} - q_{t+1}$  is zero.

The model can also be written as

$$\begin{aligned} h_{t+1} &= q_{t+1} + (\alpha \gamma_1^2 + \beta) (h_t - q_t) + \alpha \left( (z_t - \gamma_1 \sqrt{h_t})^2 - (1 + \gamma_1^2 h_t) \right) \\ &= q_{t+1} + \tilde{\beta} (h_t - q_t) + \alpha \left( (z_t - \gamma_1 \sqrt{h_t})^2 - (1 + \gamma_1^2 h_t) \right) \end{aligned} \quad (4)$$

where  $\tilde{\beta} = \alpha \gamma_1^2 + \beta$ . This representation is useful because we can think of

$$\begin{aligned} v_{1,t} &\equiv \left( z_t - \gamma_1 \sqrt{h_t} \right)^2 - (1 + \gamma_1^2 h_t) \\ &= (z_t^2 - 1) - 2\gamma_1 \sqrt{h_t} z_t \end{aligned} \quad (5)$$

as a mean-zero innovation.

The model is completed by specifying the functional form of the long-run volatility component. In a first step, we assume that  $q_{t+1}$  follows the process

$$q_{t+1} = \omega + \rho q_t + \varphi \left( (z_t^2 - 1) - 2\gamma_2 \sqrt{h_t} z_t \right) \quad (6)$$

Note that we can therefore write the component volatility model as

$$\begin{aligned} h_{t+1} &= q_{t+1} + \tilde{\beta}(h_t - q_t) + \alpha v_{1,t} \\ q_{t+1} &= \omega + \rho q_t + \varphi v_{2,t} \end{aligned} \tag{7}$$

with

$$v_{i,t} = (z_t^2 - 1) - 2\gamma_i \sqrt{h_t} z_t, \text{ for } i = 1, 2. \tag{8}$$

and  $E_{t-1}[v_{i,t}] = 0$ ,  $i = 1, 2$ . Also note that the model contains seven parameters:  $\alpha$ ,  $\tilde{\beta}$ ,  $\gamma_1$ ,  $\gamma_2$ ,  $\omega$ ,  $\rho$  and  $\varphi$  in addition to the price of risk,  $\lambda$ .

### 2.3 A Fully Persistent Special Case

In our empirical work, we also investigate a special case of the model in (7). Notice that in (7) the long-run component of volatility will be a mean reverting process for  $\rho < 1$ . We also estimate a version of the model which imposes  $\rho = 1$ . The resulting process is

$$\begin{aligned} h_{t+1} &= q_{t+1} + \tilde{\beta}(h_t - q_t) + \alpha v_{1,t} \\ q_{t+1} &= \omega + q_t + \varphi v_{2,t} \end{aligned} \tag{9}$$

and  $v_{i,t}$ ,  $i = 1, 2$  are as in (8). The model now contains six parameters:  $\alpha$ ,  $\tilde{\beta}$ ,  $\gamma_1$ ,  $\gamma_2$ ,  $\omega$  and  $\varphi$  in addition to the price of risk,  $\lambda$ .

In this case the process for long-run volatility contains a unit root and shocks to the long-run volatility never die out: they have a “permanent” effect. Recall that following Engle and Lee (1999) in (7) we refer to  $q_{t+1}$  as the long-run component and to  $h_{t+1} - q_{t+1}$  as the short-run component. In the special case (9) we can also refer to  $q_{t+1}$  as the “permanent” component, because innovations to  $q_{t+1}$  are truly “permanent” and do not die out. It is then customary to refer to  $h_{t+1} - q_{t+1}$  as the “transitory” component, which reverts to zero. It is in fact this permanent-effects version of the model that is most closely related to models which have been studied more extensively in the finance and economics literature, rather than the more general model in (7).<sup>10</sup> We will refer to this model as the persistent component model.

It is clear that (9) is nested by (7). It is therefore to be expected that the in-sample fit of (7) is superior. However, out-of-sample this may not necessarily be the case. It is often the case that more parsimonious models perform better out-of-sample if the restriction imposed by the model is a sufficiently adequate representation of reality. The persistent component model may also be better able to capture structural breaks in volatility out-of-sample, because a unit root in the process allows it to adjust to a structural break, which not possible for a mean-reverting process. It will therefore be of interest to verify how close  $\rho$  is to one when estimating the more general model (7).

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<sup>10</sup>See Fama and French (1988), Poterba and Summers (1988) and Summers (1986) for applications to stock prices. See Beveridge and Nelson (1981) for an application to macroeconomics.

### 3 Variance Term Structures

To intuitively understand the shortcomings of existing models such as the GARCH(1,1) model in (1) and the improvements provided by our model (7), it is instructive to graphically illustrate the workings of both models in a dimension that critically affects their performance. In this section we graphically illustrate the variance term structures and some other related properties of the models that are key for option valuation.

#### 3.1 The Variance Term Structure for the GARCH(1,1) Model

Following the logic used for the component model in (7), we can rewrite the GARCH(1,1) variance dynamic in (2). We have

$$h_{t+1} = \sigma^2 + \tilde{b}_1 (h_t - \sigma^2) + a_1 \left( (z_t^2 - 1) - 2c_1 \sqrt{h_t} z_t \right) \quad (10)$$

where  $\tilde{b}_1 = b_1 + a_1 c_1^2$  and where the innovation term has a zero conditional mean. From (10) the multi-step forecast of the conditional variance is

$$E_t [h_{t+k}] = \sigma^2 + \tilde{b}_1^{k-1} (h_{t+1} - \sigma^2)$$

where the conditional expectation is taken at the end of day  $t$ . Notice that  $\tilde{b}_1$  is directly interpretable as the variance persistence in this representation of the model.

We can now define a convenient measure of the variance term structure for maturity  $K$  as

$$h_{t+1:t+K} \equiv \frac{1}{K} \sum_{k=1}^K E_t [h_{t+k}] = \frac{1}{K} \sum_{k=1}^K \sigma^2 + \tilde{b}_1^{k-1} (h_{t+1} - \sigma^2) = \sigma^2 + \frac{1 - \tilde{b}_1^K}{1 - \tilde{b}_1} \frac{(h_{t+1} - \sigma^2)}{K}$$

This variance term structure measure succinctly captures important information about the model's potential for explaining the variation of option values across maturities.<sup>11</sup> To compare different models, it is convenient to set the current variance,  $h_{t+1}$ , to a simple  $m$  multiple of the long run variance. In this case the variance term structure relative to the unconditional variance is given by

$$h_{t+1:t+K}/\sigma^2 \equiv 1 + \frac{1 - \tilde{b}_1^K}{1 - \tilde{b}_1} \frac{(m - 1)}{K}$$

The dash-dot lines in the top panels of Figures 1 and 2 show the term structure of variance for the GARCH(1,1) model for a low and high initial conditional variance respectively. We

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<sup>11</sup>Notice that due to the price of risk term in the conditional mean of returns, the term structure of variance as defined here is not exactly equal to the conditional variance of cumulative returns over  $K$  days.



use parameter values estimated via MLE on daily S&P500 returns (the estimation details are in Table 2 and will be discussed further below). We set  $m = \frac{1}{2}$  in Figure 1 and  $m = 2$  in Figure 2. The figures present the variance term structure for up to 250 days, which corresponds approximately to the number of trading days in a year and therefore captures the empirically relevant term structure for option valuation. It can be clearly seen from Figures 1 and 2 that for the GARCH(1,1) model, the conditional variance converges to the long-run variance rather fast.

We can also learn about the dynamics of the variance term structure through impulse response functions. For the GARCH(1,1) model, the effect of a shock at time  $t$ ,  $z_t$ , on the expected  $k$ -day ahead variance is

$$\partial(E_t[h_{t+k}])/\partial z_t^2 = \tilde{b}_1^{k-1} a_1 \left(1 - c_1 \sqrt{h_t/z_t}\right)$$

and thus the effect on the variance term structure is

$$\partial E_t[h_{t:t+K}]/\partial z_t^2 = \frac{1 - \tilde{b}_1^K}{1 - \tilde{b}_1} \frac{a_1}{K} \left(1 - c_1 \sqrt{h_t/z_t}\right)$$

The bottom-left panels of Figures 3 and 4 plot the impulse responses to the term structure of variance for  $h_t = \sigma^2$  and  $z_t = 2$  and  $z_t = -2$  respectively, again using the parameter estimates from Table 2. The impulse responses are normalized by the unconditional variance. Notice that the effect of a shock dies out rather quickly for the GARCH(1,1) model. Comparing across Figures 3 and 4 we see the asymmetric response of the variance term structure from a positive versus negative shock to returns. This can be thought of as the term structure of the leverage effect. Due to the presence of a positive  $c_1$ , a positive shock has less impact than a negative shock along the entire term structure of variance.

### 3.2 The Variance Term Structure for the Component Model

In the component model we have

$$\begin{aligned} h_{t+1} &= q_{t+1} + \tilde{\beta}(h_t - q_t) + \alpha v_{1,t} \\ q_{t+1} &= \omega + \rho q_t + \varphi v_{2,t} \end{aligned}$$

The multi-day forecast of the two components are

$$\begin{aligned} E_t[h_{t+k} - q_{t+k}] &= \tilde{\beta}^{k-1} (h_{t+1} - q_{t+1}) \\ E_t[q_{t+k}] &= \frac{\omega}{1-\rho} + \rho^{k-1} \left(q_{t+1} - \frac{\omega}{1-\rho}\right) \\ &\equiv \sigma^2 + \rho^{k-1} (q_{t+1} - \sigma^2) \end{aligned}$$

The simplicity of these multi-day forecasts is a key advantage of the component model. The multi-day variance forecast is a simple sum of two exponential components. Notice that  $\tilde{\beta}$  and  $\rho$  correspond directly to the persistence of the short-run and long-run components respectively.

We can now calculate the variance term structure in the component model for maturity  $K$  as

$$\begin{aligned} h_{t+1:t+K} &\equiv \frac{1}{K} \sum_{k=1}^K E_t [q_{t+k}] + E_t [h_{t+k} - q_{t+k}] \\ &= \frac{1}{K} \sum_{k=1}^K \sigma^2 + \rho^{k-1} (q_{t+1} - \sigma^2) + \tilde{\beta}^{k-1} (h_{t+1} - q_{t+1}) \\ &= \sigma^2 + \frac{1 - \rho^K}{1 - \rho} \frac{q_{t+1} - \sigma^2}{K} + \frac{1 - \tilde{\beta}^K}{1 - \tilde{\beta}} \frac{h_{t+1} - q_{t+1}}{K} \end{aligned}$$

If we set  $q_{t+1}$  and  $h_{t+1}$  equal to  $m_1$  and  $m_2$  multiples of the long run variance respectively, then we get the variance term structure relative to the unconditional variance simply as

$$h_{t+1:t+K}/\sigma^2 = 1 + \frac{1 - \rho^K}{1 - \rho} \frac{m_1 - 1}{K} + \frac{1 - \tilde{\beta}^K}{1 - \tilde{\beta}} \frac{m_2 - m_1}{K} \quad (11)$$

The solid lines in the top panels in Figures 1 and 2 show the term structure of variance for the component model using parameters estimated via MLE on daily S&P500 returns from Table 2. We set  $m_1 = \frac{3}{4}$ ,  $m_2 = \frac{1}{2}$  in Figure 1 and  $m_1 = \frac{7}{4}$ ,  $m_2 = 2$  in Figure 2. By picking  $m_2$  equal to the  $m$  used for the GARCH(1,1) model, we ensure comparability across models within each figure because the spot variances relative to their long-run variances are identical.<sup>12</sup> The main conclusion from Figures 1 and 2 is that compared to the dash-dot GARCH(1,1), the conditional variance converges more slowly to the unconditional variance in the component model. This is particularly so on days with a high spot variance. The middle and bottom panels show the contribution to the total variance from each component. Notice the strong persistence in the long-run component.

We can also calculate impulse response functions in the component model. The effects of a shock at time  $t$ ,  $z_t$  on the expected  $k$ -day ahead variance components are

$$\begin{aligned} \partial E_t [q_{t+k}] / \partial z_t^2 &= \rho^{k-1} \varphi \left( 1 - \gamma_2 \sqrt{h_t} / z_t \right) \\ \partial E_t [h_{t+k} - q_{t+k}] / \partial z_t^2 &= \tilde{\beta}^{k-1} \alpha \left( 1 - \gamma_1 \sqrt{h_t} / z_t \right) \\ \partial E_t [h_{t+k}] / \partial z_t^2 &= \tilde{\beta}^{k-1} \alpha \left( 1 - \gamma_1 \sqrt{h_t} / z_t \right) + \rho^{k-1} \varphi \left( 1 - \gamma_2 \sqrt{h_t} / z_t \right) \end{aligned}$$

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<sup>12</sup>Note that we need  $m_1 \neq m_2$  in this numerical experiment to generate a “short-term” effect in (11). Changing  $m_1$  will change the picture but the main conclusions stay the same.

Notice again the simplicity due to the component structure. The impulse response on the term structure of variance is then

$$\partial E_t [h_{t:t+K}] / \partial z_t^2 = \frac{1 - \tilde{\beta}^K}{1 - \tilde{\beta}} \frac{\alpha}{K} \left( 1 - \gamma_1 \sqrt{h_t/z_t} \right) + \frac{1 - \rho^K}{1 - \rho} \frac{\varphi}{K} \left( 1 - \gamma_2 \sqrt{h_t/z_t} \right)$$

The top-left panels of Figures 3 and 4 plot the impulse responses to the term structure of variance for  $h_t = \sigma^2$  and  $z_t = 2$  and  $z_t = -2$  respectively. The figures reinforce the message from Figures 1 and 2 that using parameterizations estimated from the data, the component model is quite different from the GARCH(1,1) model. The effects of shocks are much longer lasting in the component model using estimated parameter values because of the parameterization of the long-run component. Comparing across Figures 3 and 4 it is also clear that the term structure of the leverage effect is more flexible. As a result current shocks and the current state of the economy potentially have a much more profound impact on the pricing of options across maturities in the component model.

It has been argued in the literature that the hyperbolic rate of decay displayed by long memory processes may be a more adequate representation for the conditional variance of returns.<sup>13</sup> We do not disagree with these findings. Instead, we argue that Figures 1 through 4 demonstrate that in the component model the combination of two variance components with exponential decay gives rise to a slower decay pattern that sufficiently adequately captures the hyperbolic decay pattern of long memory processes for the horizons relevant for option valuation. This is of interest because although the long memory representation may be a more adequate representation of the data, it is harder to implement.

Figure 5 presents a final piece of evidence that helps to intuitively understand the differences between the GARCH(1,1) and component models. It shows the autocorrelation function of the squared return innovations,  $\varepsilon_{t+1}^2 = z_{t+1}^2 h_{t+1}$  for the GARCH(1,1) and the component model. The expressions used to compute the autocorrelation functions for the models are available upon request. The component model generates larger autocorrelations at shorter and longer lags. The autocorrelation for the GARCH (1,1) starts low and decays to zero rather quickly. Finally, notice again that the shape of the autocorrelation function for the component model mimics the autocorrelation function of long memory models much more closely than the GARCH (1,1) model (see Bollerslev and Mikkelsen (1996) for evidence on long memory in volatility). Maheu (2002) presents Monte-Carlo evidence that a component model similar to the one in this paper can capture these long-range dependencies. The component model can therefore be thought of as a viable intermediary between short-memory GARCH(1,1) models and true long-memory models.

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<sup>13</sup>See Bollerslev and Mikkelsen (1996,1999), Baillie, Bollerslev and Mikkelsen (1996) and Ding, Granger and Engle (1993).

## 4 Option Valuation

We now turn to the ultimate purpose of this paper, namely the valuation of derivatives on an underlying asset with dynamic variance components. For the purpose of option valuation we need the risk-neutral return dynamics rather than the physical dynamics in (1), (7) and (9).

### 4.1 The Risk-Neutral GARCH(1,1) Dynamic

The risk-neutral dynamics for the GARCH(1,1) model are given in Heston and Nandi (2000)<sup>14</sup> as

$$\begin{aligned}\ln(S_{t+1}) &= \ln(S_t) + r - \frac{1}{2}h_{t+1} + \sqrt{h_{t+1}}z_{t+1}^* \\ h_{t+1} &= w + b_1h_t + a_1(z_t^* - c_1^*\sqrt{h_t})^2\end{aligned}\tag{12}$$

with  $c_1^* = c_1 + \lambda + 0.5$  and  $z_t^* \sim N(0, 1)$ . For the component volatility models, the most convenient way to express the risk-neutral dynamics is to use the following mapping with the GARCH(2,2) model.

### 4.2 The GARCH(2,2) Mapping

In order to construct the mapping from a component model to a GARCH(2,2) model note that  $q_{t+1}$  in (6) can be written as

$$q_{t+1} = \frac{\omega + \varphi((z_t^2 - 1) - 2\gamma_2\sqrt{h_t}z_t)}{1 - \rho L}$$

where  $L$  denotes the lag operator. Substituting this expression and its lagged version into the expression for  $h_{t+1}$  in (4), it becomes clear that we can write the conditional variance in the component model as a GARCH (2, 2) process.

$$\begin{aligned}\ln(S_{t+1}) &= \ln(S_t) + r + \lambda h_{t+1} + \sqrt{h_{t+1}}z_{t+1} \\ h_{t+1} &= w + b_1h_t + b_2h_{t-1} + a_1(z_t - c_1\sqrt{h_t})^2 + a_2(z_{t-1} - c_2\sqrt{h_{t-1}})^2\end{aligned}\tag{13}$$

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<sup>14</sup>For the underlying theory on risk neutral distributions in discrete time option valuation see Rubinstein (1976), Brennan (1979), Amin and Ng (1993), Duan (1995), Camara (2003), and Schroeder (2004).

where

$$\begin{aligned}
a_1 &= \alpha + \varphi \\
a_2 &= -(\rho\alpha + \tilde{\beta}\varphi) \\
b_1 &= \left(\rho + \tilde{\beta}\right) - \frac{(\alpha\gamma_1 + \varphi\gamma_2)^2}{a_1} \\
b_2 &= -\frac{(\rho\alpha\gamma_1 + \tilde{\beta}\varphi\gamma_2)^2}{a_2} - \rho\tilde{\beta} \\
c_1 &= \frac{\gamma_1\alpha + \gamma_2\varphi}{a_1} \\
c_2 &= -\frac{\rho\gamma_1\alpha + \varphi\gamma_2\tilde{\beta}}{a_2} \\
w &= (\omega - \varphi)(1 - \tilde{\beta}) - \alpha(1 - \rho)
\end{aligned} \tag{14}$$

The relationship between the model in (13) and the model in (7) deserves more comment. Equation (14) shows that the component model can be viewed as a GARCH(2,2) model with nonlinear parameter restrictions. These restrictions yield the component structure which enables interpretation of the model as having a potentially persistent long-run component and a rapidly mean-reverting short-run component. We implement the model and present the empirical results in terms of the component parameters rather than the GARCH(2,2) parameters. This interpretation of the results is very helpful when thinking about the variance term structure implications of the model, as Figures 1-4 above illustrate. The component structure allows for simple term structure formulas which in the general GARCH(2,2) model are much more cumbersome and harder to interpret. Due to its natural extension of the GARCH(1,1) model, the component model is also useful for implementation when sensible parameter starting values must be chosen for estimation. In contrast, it is quite difficult to come up with sensible starting values for estimating a GARCH(2,2) process.

The restrictions in (14) allow us to obtain the GARCH(2,2) parameters given the components estimates. A natural question is if we can obtain the component parameters given GARCH(2,2) estimates. In Appendix A we invert the mapping in (14) to get the component model parameters as functions of the GARCH(2,2) parameters. The mapping illustrates more advantages from implementing the component model as opposed to a GARCH(2,2) model: It turns out that the roots in the characteristic equation for the GARCH(2,2) model are exactly the persistence parameters  $\tilde{\beta}$  and  $\rho$  in the component model. Thus estimating the component model forces the characteristic roots in the GARCH(2,2) model to be real. Furthermore, the stationarity requirement in the component model is simply that  $\tilde{\beta} < 1$  and  $\rho < 1$  whereas it is much more complicated in the GARCH(2,2) model. The upshot is that the component model is much easier to implement from the point of view of finding reasonable starting values and enforcing stationarity in estimation.

The mapping between the component model and the GARCH(2,2) model is useful for the purpose of option valuation. For option valuation, we need the risk-neutral dynamic. For the GARCH(2,2) model in (13), the risk-neutral representation is

$$\begin{aligned}\ln(S_{t+1}) &= \ln(S_t) + r - \frac{1}{2}h_{t+1} + \sqrt{h_{t+1}}z_{t+1}^* \\ h_{t+1} &= w + b_1h_t + b_2h_{t-1} + a_1 \left( z_t^* - c_1^* \sqrt{h_t} \right)^2 + a_2 \left( z_{t-1}^* - c_2^* \sqrt{h_{t-1}} \right)^2\end{aligned}\quad (15)$$

where  $c_i^* = c_i + \lambda + 0.5, i = 1, 2$  and  $z_t^* \sim N(0, 1)$ .

### 4.3 The Option Valuation Formula

Given the risk-neutral dynamics, option valuation is relatively straightforward. We use the result of Heston and Nandi (2000) that at time  $t$ , a European call option with strike price  $K$  that expires at time  $T$  is worth

$$\begin{aligned}\text{Call Price} &= e^{-r(T-t)} E_t^*[Max(S_T - K, 0)] \\ &= \frac{1}{2}S_t + \frac{e^{-r(T-t)}}{\pi} \int_0^\infty \text{Re} \left[ \frac{K^{-i\phi} f^*(t, T; i\phi + 1)}{i\phi} \right] d\phi \\ &\quad - K e^{-r(T-t)} \left( \frac{1}{2} + \frac{1}{\pi} \int_0^\infty \text{Re} \left[ \frac{K^{-i\phi} f^*(t, T; i\phi)}{i\phi} \right] d\phi \right)\end{aligned}\quad (16)$$

where  $f^*(t, T; i\phi)$  is the conditional characteristic function of the logarithm of the spot price under the risk neutral measure. For the return dynamics in this paper, we can characterize the generating function of the stock price with a set of difference equations. We apply the techniques in Heston and Nandi (2000) to get for the GARCH(2,2) representation of the model in (15):

$$f(t, T; \phi) = S_t^\phi \exp \left( A_t + B_{1t}h_{t+1} + B_{2t}h_t + C_t(z_t - c_2\sqrt{h_t})^2 \right)$$

with coefficients

$$\begin{aligned}A_t &= A_{t+1} + \phi r + B_{1t+1}w - \frac{1}{2} \ln(1 - 2a_1B_{1t+1} - 2C_{t+1}) \\ B_{1t} &= \phi(-0.5) + \frac{1/2\phi^2 + 2(B_{1t+1}a_1c_1 + C_{t+1}c_2)(B_{1t+1}a_1c_1 + C_{t+1}c_2 - \phi)}{1 - 2B_{1t+1}a_1 - 2C_{t+1}} \\ &\quad + (B_{1t+1}a_1c_1^2 + C_{t+1}c_2^2) + b_1B_{1t+1} + B_{2t+1} \\ B_{2t} &= b_2B_{1t+1} \\ C_t &= a_2B_{1t+1}\end{aligned}$$

where  $A_t, B_{1t}, B_{2t}$ , and  $C_t$  implicitly are functions of  $T$  and  $\phi$ . This system of difference equations can be solved backwards using the terminal condition

$$A_T = B_{1T} = B_{2T} = C_T = 0.$$

Note that this result for the GARCH(2,2) model is different from the one listed in Appendix A of Heston and Nandi (2000), which contains some typos. We present the derivation for the GARCH(2,2) model in Appendix B. The correction of the general GARCH(p,q) case is available upon request.<sup>15</sup>

## 5 Empirical Results

This section presents the empirical results. We first discuss the data, followed by an empirical evaluation of the model estimated under the physical measure using a historical series of stock returns. Subsequently we present estimation results obtained by estimating the risk-neutral version of the model using options data.

### 5.1 Data

We conduct our empirical analysis using six years of data on S&P 500 call options, for the period 1990-1995. We apply standard filters to the data following Bakshi, Cao and Chen (1997). We only use Wednesday options data. Wednesday is the day of the week least likely to be a holiday. It is also less likely than other days such as Monday and Friday to be affected by day-of-the-week effects. For those weeks where Wednesday is a holiday, we use the next trading day. The decision to pick one day every week is to some extent motivated by computational constraints. The optimization problems are fairly time-intensive, and limiting the number of options reduces the computational burden. Using only Wednesday data allows us to study a fairly long time-series, which is useful considering the highly persistent volatility processes. An additional motivation for only using Wednesday data is that following the work of Dumas, Fleming and Whaley (1998), several studies have used this setup (see for instance Heston and Nandi (2000)).

We perform a number of in-sample and out-of-sample experiments using the options data. We first estimate the model parameters using the 1990-1992 data and subsequently test the model out-of-sample using the 1993 data. We also estimate the model parameters using the 1992-1994 data and subsequently test the model out-of-sample using the 1995 data. For

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<sup>15</sup>We verified the accuracy of our results by comparing closed-form prices with Monte Carlo prices. The empirical results in Heston and Nandi (2000) are for the GARCH(1,1) case and are not affected by this discrepancy for higher-order models. Our implementation of the pricing for the GARCH(1,1) case thus uses the expressions in Heston and Nandi (2000). The moment generating function can also be derived explicitly in terms of the component model. This result is available upon request.

both estimation exercises we use a volatility updating rule for the 500 days predating the Wednesday used in the estimation exercise. This volatility updating rule is initialized at the model's unconditional variance. We also perform an extensive empirical analysis using return data. Ideally we would like to use the same sample periods for these estimation exercises, but it is well-known that it is difficult to estimate GARCH parameters precisely using relatively short samples on returns. We therefore use a long sample of returns (1963-1995) on the S&P 500.

Table 1 presents descriptive statistics for the options data for 1990-1995 by moneyness and maturity. Panels A and B indicate that the data are standard. We can clearly observe the volatility smirk from Panel C and it is clear that the slope of the smirk differs across maturities. Descriptive statistics for different sub-periods (not reported here) demonstrate that the slope also changes across time, but that the smirk is present throughout the sample. The top panel of Figure 6 gives some indication of the pattern of implied volatility over time. For the 312 days of options data used in the empirical analysis, we present the average implied volatility of the options on that day. It is evident from Figure 6 that there is substantial clustering in implied volatilities. It can also be seen that volatility is higher in the early part of the sample. The bottom panel of Figure 6 presents a time series for the 30-day at-the-money volatility (VIX) index from the CBOE for our sample period. A comparison with the top panel clearly indicates that the options data in our sample are representative of market conditions, although the time series based on our sample is of course a bit more noisy due to the presence of options with different moneyness and maturities.

## 5.2 Empirical Results using Returns Data

Table 2 presents estimation results obtained using returns data for 1963-1995 for the physical model dynamics. We present results for three models: the GARCH(1,1) model (1), the component model (7) and the persistent component model (9). Almost all parameters are estimated significantly different from zero at conventional significance levels.<sup>16</sup> In terms of fit, the log likelihood values indicate that the fit of the component model is much better than that of the persistent component model, which in turn fits much better than the GARCH(1,1) model.

The improvement in fit for the component GARCH model over the persistent component GARCH model is perhaps somewhat surprising when inspecting the persistence of the component GARCH model. The persistence is equal to 0.996. It therefore would appear that equating this persistence to 1, as is done in the persistent component model, is an interesting hypothesis, but apparently modeling these small differences from one is important. It must of course be noted that the picture is more complex: while the persistence

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<sup>16</sup>The standard errors are computed using the outer product of the gradient at the optimal parameter values.



of the long-run component ( $\rho$ ) is 0.990 for the component model as opposed to 1 for the persistent component model, the persistence of the short-run component ( $\tilde{\beta}$ ) is 0.644 versus 0.764 and this may account for the differences in performance. Note that the persistence of the GARCH(1,1) model is estimated at 0.955, which is consistent with earlier literature. It is slightly lower than the estimate in Christoffersen, Heston and Jacobs (2004) and a bit higher than the average of the estimates in Heston and Nandi (2000).

The ability of the models to generate richer patterns for the conditional versions of leverage and volatility of volatility is critical. For option valuation, the conditional versions of these quantities and their variation through time are just as important as the unconditional versions. The conditional versions of leverage and volatility of volatility are computed as follows. For the GARCH(1,1) model the conditional variance of variance is

$$\begin{aligned} Var_t(h_{t+2}) &= E_t [h_{t+2} - E_t [h_{t+2}]]^2 \\ &= 2a_1^2 + 4a_1^2 c_1^2 h_{t+1} \end{aligned} \quad (17)$$

and the leverage effect can be defined as

$$\begin{aligned} Cov_t(\ln(S_{t+1}), h_{t+2}) &= E_t [(\ln(S_{t+1}) - E_t[\ln(S_{t+1})]) (h_{t+2} - E_t[h_{t+2}])] \\ &= E_t \left[ \sqrt{h_{t+1}} z_{t+1} \left( a_1 z_{t+1}^2 - 2a_1 c_1 z_{t+1} \sqrt{h_{t+1}} - a_1 \right) \right] \\ &= -2a_1 c_1 h_{t+1} \end{aligned} \quad (18)$$

The conditional variance of variance in the component model is

$$Var_t(h_{t+2}) = 2(\alpha + \varphi)^2 + 4(\gamma_1 \alpha + \gamma_2 \varphi)^2 h_{t+1} \quad (19)$$

and the leverage effect in the component model is

$$Cov_t(\ln(S_{t+1}), h_{t+2}) = -2(\gamma_1 \alpha + \gamma_2 \varphi) h_{t+1} \quad (20)$$

Figures 7 and 8 present the conditional leverage and conditional variance of variance for the GARCH(1,1) model and the component model over the option sample 1990-1995 using the MLE parameter values in Table 2. It can be clearly seen that the level as well as the time-series variation in these critical quantities are fundamentally different between the two models. In Figure 7 the leverage effect is much more volatile in the component model and it takes on much more extreme values on certain days. In Figure 8 the variance of variance in the component model is in general much higher than in the GARCH(1,1) model and it also more volatile. Thus the more flexible component model is capable of generating not only more flexible term structures of variance, it is also able to generate more skewness and kurtosis dynamics which are key for explaining the variation in index options prices.

Table 2 also presents some unconditional summary statistics for the different models. The computation of these statistics deserves some comment. For the GARCH(1,1) model

and the component model, the unconditional versions of the volatility of volatility are computed using the estimate for the unconditional variance in the expressions for the conditional moments (17) and (19). For the persistent component model, the unconditional volatility and the unconditional variance of variance are not defined. To allow a comparison of the unconditional leverage for all three models, we report the moments in (17) and (19) divided by  $h_{t+1}$ . While the unconditional volatility of the GARCH(1,1) model (0.137) is very similar to that of the component GARCH model (0.141), the leverage and the variance of variance of the component GARCH model are larger in absolute value than those of the GARCH(1,1) model. The leverage for the persistent component model is of the same order of magnitude as that of the component model.

We previously discussed Figures 1-4, which emphasize other critical differences between the models. These figures are generated using the parameter estimates in Table 2. Figures 1 and 2 indicate that for the GARCH(1,1) model, forecasted model volatility reverts much more quickly towards the unconditional volatility over long-maturity options' lifetimes than is the case for the component model. Figures 3 and 4 demonstrate that the effects of shocks are much longer lasting in the component model because of the parameterization of the long-run component. As a result current shocks and the current state of the economy have a much more profound impact on the pricing of maturity options across maturities.

Figures 9 and 10 give another perspective on the component models' improvement in performance over the benchmark GARCH(1,1) model. These figures present the sample path for volatility in all three models, as well as the sample path for volatility components for the component model and persistent component model. In each figure, the sample path is obtained by iterating on the variance dynamic starting from the unconditional volatility 500 days before the first volatility included in the figure, as is done in estimation. Initial conditions are therefore unlikely to affect comparisons between the models in these figures. Figure 9 contains the results for the component model. The overall conclusion seems to be that the mean zero short run component in the top-right panel adds short-horizon noise around the long-run component in the bottom-right panel. This results in a volatility dynamic for the component model in the top-left panel that is more noisy than the volatility dynamic for the GARCH(1,1) model in the bottom-left panel. The more noisy sample path in the top-left panel is of course confirmed by the higher value for the variance of variance in Table 2. This increased flexibility results in a better fit. The results for the permanent component model in Figure 10 confirm this conclusion, even though the sample paths for the components in Figure 10 look different from those in Figure 9.<sup>17</sup>

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<sup>17</sup>The figures presented so far have been constructed from the return-based MLE estimates in Table 2. Below we will present four new sets of (risk-neutral) estimates derived from observed option prices. In order to preserve space we will not present new versions of the above figures from these estimates. The option-based estimates imply figures which are qualitatively similar to the return-based figures presented above.

### 5.3 Empirical Results using Options Data

Tables 3-10 present the empirical results for the option-based estimates of the risk-neutral parameters. We present four sets of results. Table 3 presents results for parameters estimated using options data for 1990-1992 using all option contracts in the sample. Note that the shortest maturity is seven days because options with very short maturities were filtered out. Table 4 contains results for 1990-1992 obtained using options with more than 80 days to maturity, because we expect the component models to be particularly useful to model options with long maturities. Tables 5 and 6 present results obtained using options data for 1992-1994, using all contracts and contracts with more than 80 days to maturity respectively. When using the 1990-1992 sample in estimation, we test the model out-of-sample using data for 1993. When using the 1992-1994 sample in estimation, we test the model out-of-sample using 1995 data. Tables 7-10 present results for the two in-sample and two out-of-sample periods by moneyness and maturity. In all cases we obtain parameters by minimizing the dollar mean squared error

$$\$MSE = \frac{1}{N_T} \sum_{t,i} (C_{i,t}^D - C_{i,t}^M)^2 \quad (21)$$

where  $C_{i,t}^D$  is the market price of option  $i$  at time  $t$ ,  $C_{i,t}^M$  is the model price, and  $N_T = \sum_{t=1}^T N_t$ .  $T$  is the total number of days included in the sample and  $N_t$  the number of options included in the sample at date  $t$ .

The parameters in Tables 3-6 are found by applying the nonlinear least squares (NLS) estimation techniques on the  $\$MSE$  expression in (21). In the GARCH(1,1) case the implementation is simple: the NLS routine is called with a set of parameter starting values. The variance dynamic in (1) is then used to update the variance from one Wednesday to the next and the GARCH(1,1) option valuation formula from Heston and Nandi (2000) is used to compute the model prices on each Wednesday. In the component models an extra step is needed. Here the NLS routine is called with starting values for the component model, but the component model is converted to a GARCH(2,2) structure inside the optimization routine using (14). The implied GARCH(2,2) model is now used to update variance from Wednesday to Wednesday using (13) and to price options on each Wednesday using the option valuation formula in (16). Note that the NLS routine is thus optimizing the  $\$MSE$  over the component parameters and not over the implied GARCH(2,2) parameters, which enforces the component structure throughout the optimization. The component structure is again useful both for the interpretation of the model and in implementation where reasonable starting values must be found and stationarity imposed.<sup>18</sup>

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<sup>18</sup>Recall that the risk neutral GARCH process used in option valuation uses the parameterization  $c_i^* = c_i + \lambda + 0.5$  so that  $c_i$  and  $\lambda$  are not separately identified. We therefore simply set  $\lambda$  equal to the MLE

In Table 3 we present results for the 1990-1992 period (in-sample) and the 1993 period (out-of-sample). The standard errors indicate that almost all parameters are estimated significantly different from zero.<sup>19</sup> There are some interesting differences with the parameters estimated from returns in Table 2, but the parameters are mostly of the same order of magnitude. This is also true for critical determinants of the models' performance, such as unconditional volatility, leverage and volatility of volatility. It is interesting to note that in both tables the persistence of the GARCH(1,1) model and the component GARCH model is close to one. This of course motivates the use of the persistent component model, where the persistence is restricted to be one. Note also that the persistence of the short-run components and the long-run components is not dramatically different from Table 2. In the in-sample period, the RMSE of the component model is 89.7% of that of the benchmark GARCH(1,1) model. For the out-of-sample period, it is 76.5%. For the persistent component model, this is 95.5% and 97.1% respectively. Table 4 confirms that the same results obtain when estimating the models using only long-maturity options.

Tables 5 and 6 present the results for the 1992-1994 period (in-sample) and the 1995 period (out-of-sample). The results largely confirm those obtained in Tables 3 and 4. The most important difference is that the in-sample and out-of-sample performance of the component model is even better relative to the benchmark, as compared with the results in Tables 3 and 4. For the 1992-1994 in-sample period, the component model's RMSE is 77.3% of that of the GARCH(1,1) model in Table 5 and 74.8% in Table 6. For the 1995 out-of-sample period, this is 79.2% and 60.4% respectively. The performance of the persistent component model in some cases does not improve much over the performance of the GARCH(1,1) model, and in other cases its performance is actually worse than that of the benchmark. Another interesting difference with Tables 3 and 4 is that in Tables 5 and 6, the persistence of the short-run component is much higher. Finally note that the persistence of the GARCH(1,1) process in Table 5 is lower than in Table 3 but in line with the MLE estimate in Table 2.

We conclude from Tables 3-6 that the performance of the component GARCH model is very impressive. Its RMSE is between 60.4% and 89.7% of the RMSE of the benchmark GARCH(1,1) model. The performance of the persistent component model is less impressive, both in-sample and out-of-sample.

## 5.4 Discussion

It must be emphasized that this improvement in performance is remarkable and to some extent surprising. The GARCH(1,1) model is a good benchmark which itself has a very solid empirical performance (see Heston and Nandi (2000)). The model captures important

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estimate from Table 2 for the respective models and do not report on it in Tables 3-6. This procedure identifies  $c_i$  which in turn identifies the component model parameters.

<sup>19</sup>The standard errors are again computed using the outer product of the gradient at the optimum.

stylized facts about option prices such as volatility clustering and the leverage effect (or equivalently negative skewness). When estimating models from option prices, Christoffersen and Jacobs (2004) find that GARCH models with richer news impact parameterizations do not improve the model fit out-of-sample. Christoffersen, Heston and Jacobs (2004) find that a GARCH model with non-normal innovations improves the model's fit in-sample and for short out-of-sample horizons, but not for long out-of-sample horizons.<sup>20</sup>

One may wonder how the GARCH(1,1) performs compared with the popular continuous-time stochastic volatility model in Heston (1993). Heston and Nandi (2000) demonstrate that the Heston (1993) model is the limit of the GARCH(1,1) model we use in this paper, but the interpretation of limit results is somewhat tenuous (see for example Corradi (2000)). In work not reported here, we therefore compared the empirical performance of the Heston (1993) and GARCH(1,1) models and found that their empirical performance is very similar in-sample as well as out-of-sample. This is not necessarily surprising because both models contain time-variation in conditional variance as well as a leverage effect. We also compared the performance of the GARCH(1,1) model with the implied Black-Scholes model in Dumas, Fleming and Whaley (1998) and confirm the finding of Heston and Nandi (2000) that the GARCH model slightly outperforms the implied Black-Scholes model out-of-sample.

Most of the continuous-time literature has attempted to improve the performance of the Heston (1993) model by adding to it (potentially correlated) jumps in returns and volatility. The empirical findings in this literature have been mixed. In general, Poisson jumps in returns and volatility improve option valuation when parameters are estimated using historical time series of returns, but usually not when parameters are estimated using the cross-section of option prices (see for example Andersen, Benzoni and Lund (2002), Bakshi, Cao and Chen (1997), Bates (1996, 2000), Chernov, Gallant, Ghysels and Tauchen (2003), Eraker, Johannes and Polson (2003), Eraker (2004) and Pan (2002)). In a recent paper, Broadie, Chernov and Johannes (2004) use a long data set on options and an estimation technique that uses returns data and options data and find evidence of the importance of some jumps for pricing. Carr and Wu (2004) and Huang and Wu (2004) model a different type of jump process and find that they are better able to fit options out-of-sample. Finally, Duan, Ritchken and Sun (2002) find that adding jumps to discrete-time models leads to a significant improvement in fit. We therefore conclude that adding jumps or fat-tailed shocks to our model may further improve the fit.

In summary, the option valuation literature is developing rapidly and it is not possible to convincingly judge the importance of some recent developments at this point. We merely want to emphasize that although some available models may achieve a similar performance to the GARCH(1,1) or slightly outperform it in some dimension, there are no models available that spectacularly outperform it in- and out-of-sample. Given its parsimony, the

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<sup>20</sup>Hsieh and Ritchken (2000) contains a discussion on the empirical performance of the HN GARCH(1,1) model vis-a-vis the performance of the more traditional GARCH model of Duan (1995).

GARCH(1,1) is therefore an excellent benchmark for our empirical study. It models a number of important issues such as volatility clustering and negative skewness that are deemed critical for option valuation, and there is not yet consensus regarding the empirical relevance of more richly parameterized models. By choosing GARCH(1,1) as a reference point we set a high standard in terms of empirical performance and parsimony. Because of the performance of this model in other studies, in our opinion the improvement of our model over GARCH(1,1) is spectacular.

Tables 7-10 present results by moneyness and maturity. To save space we only report for the samples that include all options. Note that the tables contain information on MSEs, not RMSEs. In each table, Panel A contains the MSE for the GARCH(1,1) model. To facilitate the interpretation of the table, panels B and C contain MSEs that are normalized by the corresponding MSE for the GARCH(1,1) model. It is clear that an overall MSE which is not too different across the three models as in Table 3 can mask large differences in the models' performance for a given moneyness/maturity cell. Inspection of the out-of-sample results in Tables 8 and 10 is very instructive. The overwhelming conclusion is that the improved out-of-sample performance of the component models is due to the improved valuation of long-maturity options. This is perhaps not surprising given the differences in the impulse response functions discussed above.

Figure 11 graphically represents some related information. For different moneyness bins, we first compute the average Black-Scholes implied volatility for all the options in our sample. Subsequently we compute implied volatilities based on model prices and also average this for all options in the sample. Note that while the implied volatility fit is not perfect, the component model matches the volatility smirk better than the two other models.

Figures 12 and 13 evaluate the performance of the three models along a different dimension, by presenting average weekly bias (average observed market price less average observed model price) over the 1990-1993 and 1992-1995 sample periods respectively. The bias seems to be more highly correlated across models in the 1990-1993 sample. In the 1993-1995 sample, the persistent component model in particular has a markedly different fit from the two other models. The most important conclusion is that the improved performance of the component model does not derive from any particular sample sub-period: the bias of the component GARCH model is smaller than that of the GARCH(1,1) model in most weeks.

## 6 Conclusion and Directions for Future Work

This paper presents a new option valuation model based on the work by Engle and Lee (1999) and Heston and Nandi (2000). The empirical performance of the new variance component model is significantly better than that of the benchmark GARCH (1,1) model, in-sample as well as out-of-sample. This is an important finding because the literature has demonstrated that it is difficult to find empirical models that improve on the GARCH(1,1) model or its

continuous-time limit. The improved performance of the model is due to a richer parameterization which allows for improved joint modeling of long-maturity and short-maturity options. This parameterization can capture the stylized fact that shocks to current conditional volatility impact on the forecast of the conditional variance up to a year in the future. Given that the estimated persistence of the model is close to one, we also investigate a special case of our model in which shocks to the variance never die out. The performance of the persistent component model is satisfactory in some dimensions, but it is strictly dominated by the component model. Note that this is not a trivial finding: even though the persistent component model is nested by the component model, a more parsimonious model can easily outperform a more general one out-of-sample. This is not the case here.

Given the success of the proposed model, a number of further extensions to this work are warranted. First, the empirical performance of the model should of course be validated using other datasets. In particular, it would be interesting to test the model using LEAPS data, because the model may excel at modeling long-maturity LEAPS options. In this regard a direct comparison between component and fractionally integrated volatility models may be interesting. It could also be useful to combine the stylized features of the model with other modeling components that improve option valuation. One interesting experiment could be to replace the Gaussian innovations in this paper by a non-Gaussian distribution in order to create more negative skewness in the distribution of equity returns. Combining the model in this paper with the inverse Gaussian shock model in Christoffersen, Heston and Jacobs (2004) may be a viable approach. Finally, in this paper we have proposed a component model that gives a closed form solution using results from Heston and Nandi (2000) who rely on an affine GARCH model. We believe that this is a logical first step, but the affine structure of the model may be restrictive in ways that are not immediately apparent. It may therefore prove worthwhile to investigate non-affine variance component models.

## 6.1 Appendix A

The mapping between the GARCH(2,2) and the component model given in (14) can be inverted to solve for the component parameters implied by a given GARCH(2,2) specification.

We get the following solution

$$\begin{aligned}
\alpha &= a_1 - \frac{a_1 b_1^2 + 4a_1 b_2 + 2a_1^2 b_1 c_1^2 + a_1^3 c_1^4 + 4a_1 a_2 c_2^2}{2A} - \frac{2a_2 + a_1 b_1 + a_1^2 c_1^2}{2\sqrt{A}} \\
\varphi &= \frac{a_1 b_1^2 + 4a_1 b_2 + 2a_1^2 b_1 c_1^2 + a_1^3 c_1^4 + 4a_1 a_2 c_2^2}{2A} + \frac{2a_2 + a_1 b_1 + a_1^2 c_1^2}{2\sqrt{A}} \\
\tilde{\beta} &= \frac{1}{2} \left( b_1 + a_1 c_1^2 - \sqrt{A} \right) \\
\rho &= \frac{1}{2} \left( b_1 + a_1 c_1^2 + \sqrt{A} \right) \\
\gamma_1 &= \frac{\tilde{\beta} \varphi c_2 + \alpha \rho c_2 - \alpha \tilde{\beta} c_1 - \tilde{\beta} \varphi c_1}{\alpha(\rho - \tilde{\beta})} \\
\gamma_2 &= \frac{\alpha \rho c_1 + \rho \varphi c_1 - \tilde{\beta} \varphi c_2 - \alpha \rho c_2}{\varphi(\rho - \tilde{\beta})}
\end{aligned}$$

where

$$A = (b_1 + a_1 c_1^2)^2 + 4(b_2 + a_2 c_2^2)$$

Notice that  $\alpha, \tilde{\beta}, \varphi$ , and  $\rho$  are real and finite as long as  $A > 0$ .

Notice that the solutions for  $\tilde{\beta}$  and  $\rho$  above are the roots of the polynomial

$$Y^2 - (b_1 + c_1^2 a_1)Y - (b_2 + c_2^2 a_2) \quad (\text{A1})$$

Recall now the GARCH(2,2) process

$$h_{t+1} = w + b_1 h_t + b_2 h_{t-1} + a_1 \left( z_t - c_1 \sqrt{h_t} \right)^2 + a_2 \left( z_{t-1} - c_2 \sqrt{h_{t-1}} \right)^2$$

which can be written

$$h_{t+1} \left( 1 - (b_1 + a_1 c_1^2) L - (b_2 + a_2 c_2^2) L^2 \right) = w + a_1 z_t^2 + a_1 c_1 \sqrt{h_t} z_t + a_2 z_{t-1}^2 + a_2 c_2 \sqrt{h_{t-1}} z_{t-1}$$

where  $L$  is the lag operator.

Nelson and Cao (1992) and Bougerol and Picard (1992) show that the roots of

$$1 - (b_1 + a_1 c_1^2) L - (b_2 + a_2 c_2^2) L^2 \quad (\text{A2})$$

need to be real and lie outside the unit circle in order for the variance to be stationary.

Notice that  $\tilde{\beta}$  and  $\rho$  which are the roots of (A1) are the inverse of the roots of (A2). Therefore,  $\tilde{\beta} < 1$  and  $\rho < 1$  are required for the variance to be stationary in the GARCH(2,2) and the implied component model. Note that the component models forces the roots of the GARCH(2,2) to be real and it makes the stationarity requirements much easier to implement and monitor.



## 6.2 Appendix B

This appendix presents the moment generating function (MGF) for the GARCH(p,q) process used in this paper and in Heston and Nandi (2000). We first derive the MGF of a GARCH(2,2)

$$h_{t+1} = w + b_1 h_t + b_2 h_{t-1} + a_1 \left( z_t - c_1 \sqrt{h_t} \right)^2 + a_2 \left( z_{t-1} - c_2 \sqrt{h_{t-1}} \right)^2$$

as an example and then generalize it to the case of the GARCH(p,q). Let  $x_t = \log(S_t)$ . For convenience we will denote the conditional generating function of  $S_t$  (or equivalently the conditional moment generating function (MGF) of  $x_T$ ) by  $f_t$  instead of the more cumbersome  $f(t; T, \phi)$

$$f_t = E_t[\exp(\phi x_T)] \quad (\text{B1})$$

We shall guess that the MGF takes the log-linear form. We again use the more parsimonious notation  $A_t$  to indicate  $A(t; T, \phi)$ .

$$f_t = \exp \left( \phi x_t + A_t + B_{1t} h_{t+1} + B_{2t} h_t + C_t (z_t - c_2 \sqrt{h_t})^2 \right) \quad (\text{B2})$$

We have

$$f_t = E_t [f_{t+1}] = E_t \left[ \exp \left( \phi x_{t+1} + A_{t+1} + B_{1t+1} h_{t+2} + B_{2t+1} h_{t+1} + C_{t+1} (z_{t+1} - c_2 \sqrt{h_{t+1}})^2 \right) \right] \quad (\text{B3})$$

Since  $x_T$  is known at time  $T$ , equations (A1) and (A2) require the terminal condition

$$A_T = B_{iT} = C_T = 0$$

Substituting the dynamics of  $x_t$  into (B3) and rewriting we get

$$f_t = E_t \exp \left( \begin{array}{l} \phi(x_t + r) + (B_{1t+1} a_1 + C_{t+1}) \left( z_{t+1} - \left( \bar{c}_{t+1} - \frac{\phi}{2(B_{1t+1} a_1 + C_{t+1})} \right) \sqrt{h_{t+1}} \right)^2 + \\ A_{t+1} + B_{1t+1} w + B_{1t+1} b_2 h_t + B_{1t+1} a_2 (z_t - c_2 \sqrt{h_t})^2 + \\ \left( \phi \lambda + B_{1t+1} b_1 + B_{2t+1} + \left( \phi \bar{c}_{t+1} - \frac{\phi^2}{4(B_{1t+1} a_1 + C_{t+1})} \right) + \right) \\ (B_{1t+1} a_1 c_1^2 + C_{t+1} c_2^2) - \bar{c}_{t+1} (B_{1t+1} a_1 c_1 + C_{t+1} c_2) \end{array} \right) h_{t+1} \quad (\text{B4})$$

where

$$\bar{c}_{t+1} = \frac{B_{1t+1} a_1 c_1 + C_{t+1} c_2}{B_{1t+1} a_1 + C_{t+1}}$$

and we have used

$$\begin{aligned}
& (B_{1t+1}a_1 + C_{t+1}) \left( z_{t+1} - \left( \bar{c}_{t+1} - \frac{\phi}{2(B_{1t+1}a_1 + C_{t+1})} \right) \sqrt{h_{t+1}} \right)^2 \\
&= B_{1t+1}a_1(z_{t+1} - c_1\sqrt{h_{t+1}})^2 + C_{t+1}(z_{t+1} - c_2\sqrt{h_{t+1}})^2 \\
&+ z_{t+1}\phi\sqrt{h_{t+1}} + \left( -\phi\bar{c}_{t+1} + \frac{\phi^2}{4(B_{1t+1}a_1 + C_{t+1})} \right) h_{t+1} \\
&- (B_{1t+1}a_1c_1^2 + C_{t+1}c_2^2 - \bar{c}_{t+1}(B_{1t+1}a_1c_1 + C_{t+1}c_2)) h_{t+1}
\end{aligned}$$

Using the result

$$E [\exp(x(z + y)^2)] = \exp\left(-\frac{1}{2} \ln(1 - 2x) + ay^2/(1 - 2x)\right) \quad (\text{B5})$$

in (B4) we get

$$f_t = \exp \left( \begin{array}{l} \phi(x_t + r) + A_{t+1} + B_{1t+1}w - \frac{1}{2} \ln(1 - 2B_{1t+1}a_1 - 2C_{t+1}) + \\ B_{1t+1}b_2h_t + B_{1t+1}a_2(z_t - c_2\sqrt{h_t})^2 + \frac{(B_{1t+1}a_1 + C_{t+1})(\bar{c}_{t+1} - \frac{\phi}{2(B_{1t+1}a_1 + C_{t+1})})^2}{1 - 2B_{1t+1}a_1 - 2C_{t+1}} h_{t+1} + \\ \left( \begin{array}{l} \phi\lambda + B_{1t+1}b_1 + B_{2t+1} + \left( \phi\bar{c}_{t+1} - \frac{\phi^2}{4(B_{1t+1}a_1 + C_{t+1})} \right) + \dots \\ (B_{1t+1}a_1c_1^2 + C_{t+1}c_2^2) - \bar{c}_{t+1}(B_{1t+1}a_1c_1 + C_{t+1}c_2) \end{array} \right) h_{t+1} \end{array} \right) \quad (\text{B6})$$

Matching terms on both sides of (B6) and (B2) gives

$$A_t = A_{t+1} + \phi r + B_{1t+1}w - \frac{1}{2} \ln(1 - 2B_{1t+1}a_1 - 2C_{t+1})$$

$$\begin{aligned}
B_{1t} &= \phi\lambda + B_{1t+1}b_1 + B_{2t+1} + (B_{1t+1}a_1c_1^2 + C_{t+1}c_2^2) \\
&+ \frac{1/2\phi^2 + 2(B_{1t+1}a_1c_1 + C_{t+1}c_2)(B_{1t+1}a_1c_1 + C_{t+1}c_2 - \phi)}{1 - 2B_{1t+1}a_1 - 2C_{t+1}}
\end{aligned}$$

$$B_{2t} = B_{1t+1}b_2, \quad C_t = B_{1t+1}a_2$$

where we have used the fact that

$$\begin{aligned}
& \phi\bar{c}_{t+1} - \frac{\phi^2}{4(B_{1t+1}a_1 + C_{t+1})} - \bar{c}_{t+1}(B_{1t+1}a_1c_1 + C_{t+1}c_2) \\
&+ \frac{(B_{1t+1}a_1 + C_{t+1})(\bar{c}_{t+1} - \frac{\phi}{2(B_{1t+1}a_1 + C_{t+1})})^2}{1 - 2B_{1t+1}a_1 - 2C_{t+1}} \\
&= \frac{1/2\phi^2 + 2(B_{1t+1}a_1c_1 + C_{t+1}c_2)(B_{1t+1}a_1c_1 + C_{t+1}c_2 - \phi)}{1 - 2B_{1t+1}a_1 - 2C_{t+1}}
\end{aligned}$$

The case of GARCH(p,q) follows the same logic but is more notation-intensive. This result is available upon request.

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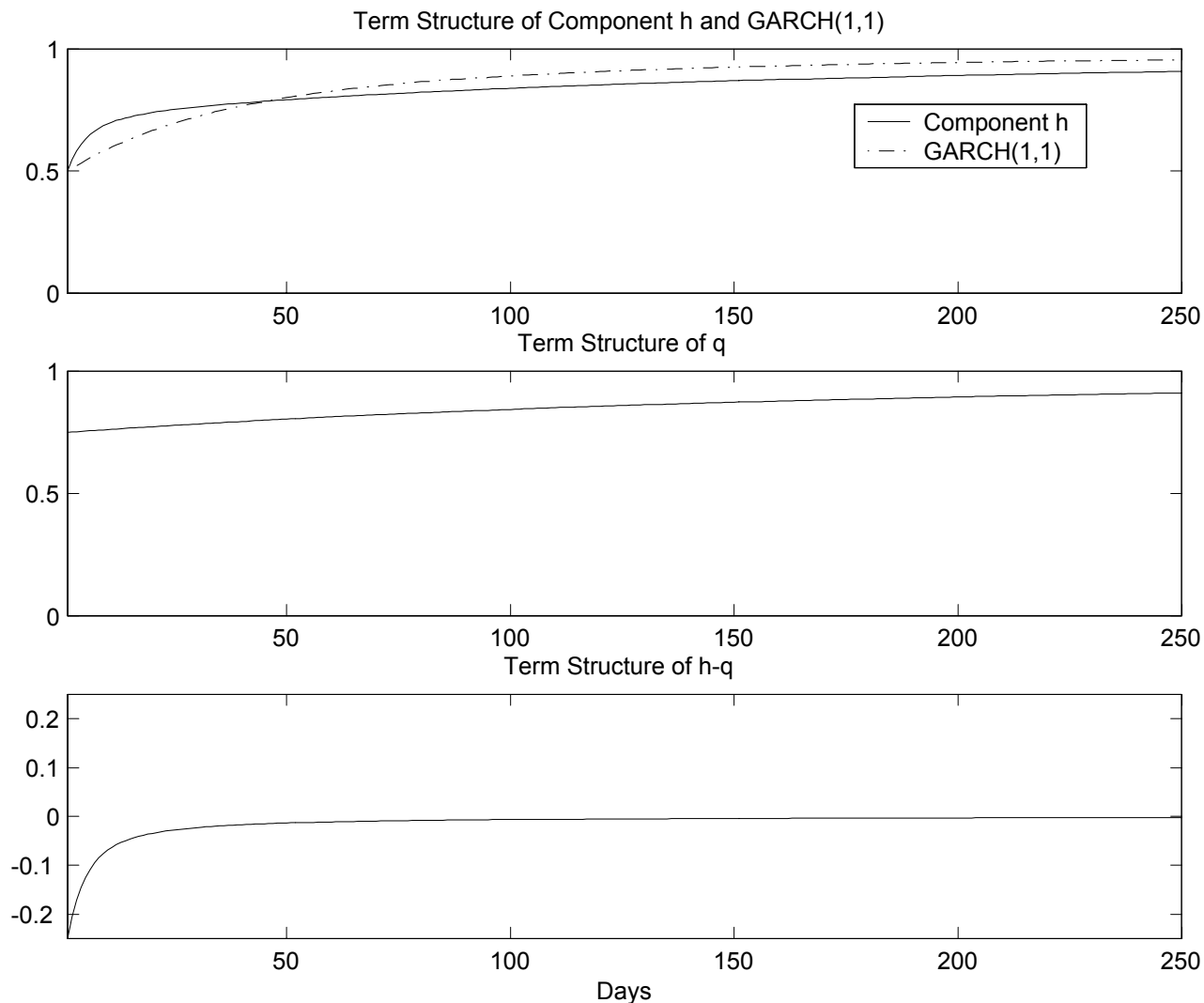
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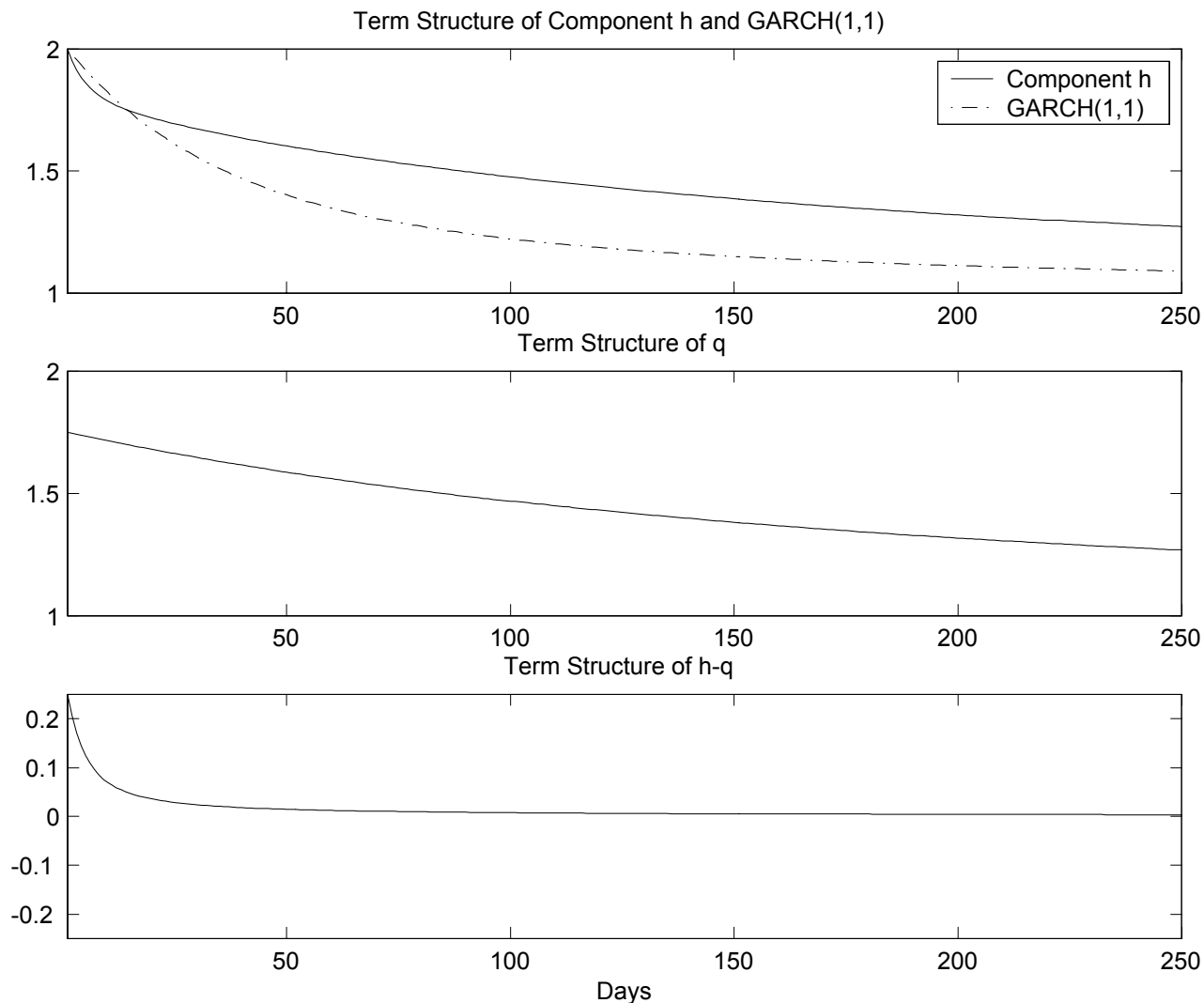
Figure 1. Term Structure of Variance with Low Initial Variance.  
 Component Model Versus GARCH(1,1).  
 Normalized by Unconditional Variance. Estimates Obtained from MLE.



Notes to Figure: In the top panel we plot the variance term structure implied by the component GARCH and GARCH(1,1) models for 1 through 250 days. In the second and third panel we plot the term structure of the individual components for the component model. The parameter values are obtained from MLE estimation on returns in Table 2. The initial value of  $q_{t+1}$  is set to  $0.75\sigma^2$  and the initial value of  $h_{t+1}$  is set to  $0.5\sigma^2$ . The initial value for  $h_{t+1}$  in the GARCH(1,1) is set to  $0.5\sigma^2$  as well. All values are normalized by the unconditional variance  $\sigma^2$ .

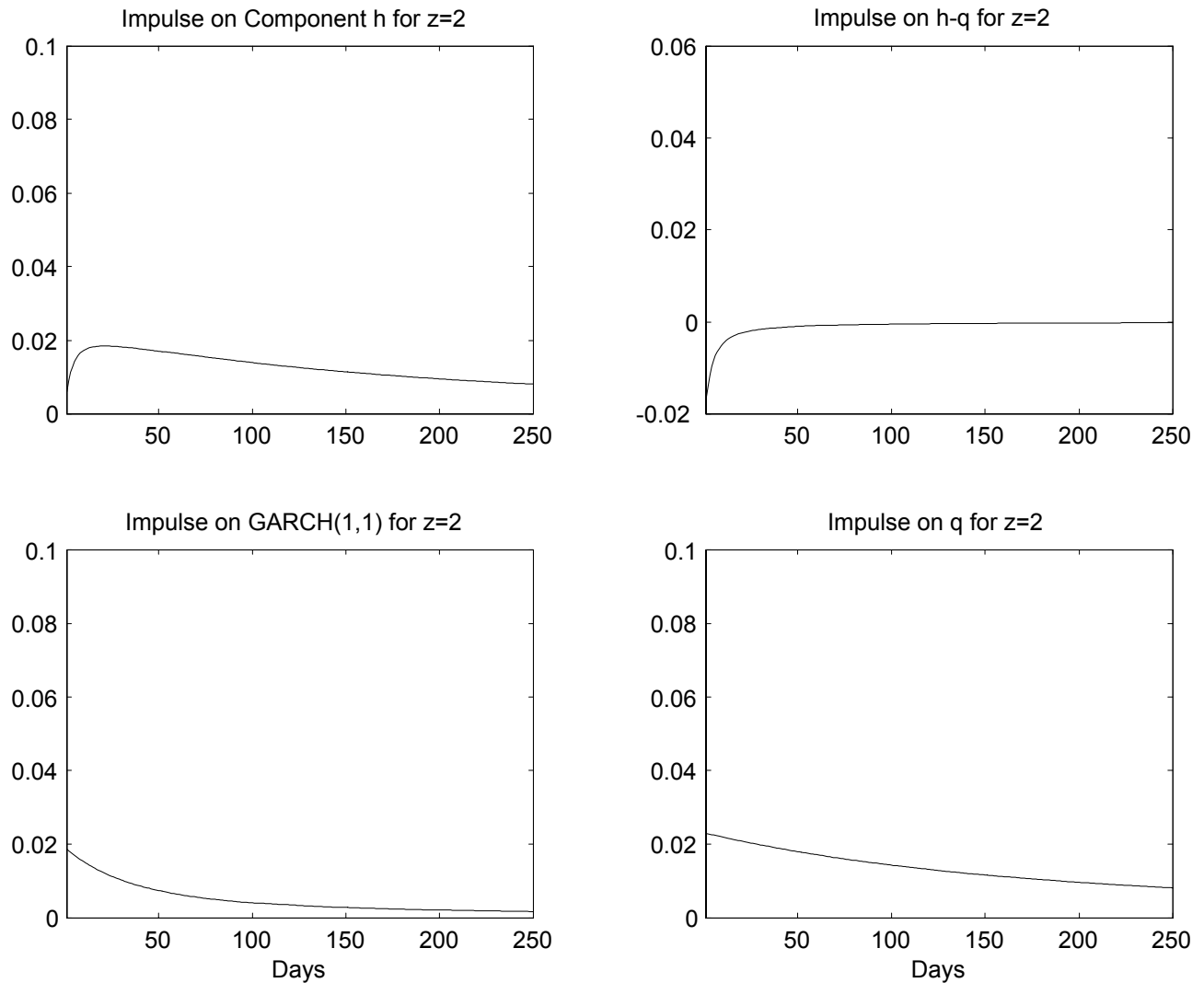


Figure 2. Term Structure of Variance with High Initial Variance.  
 Component Model Versus GARCH(1,1).  
 Normalized by Unconditional Variance. Estimates Obtained from MLE.



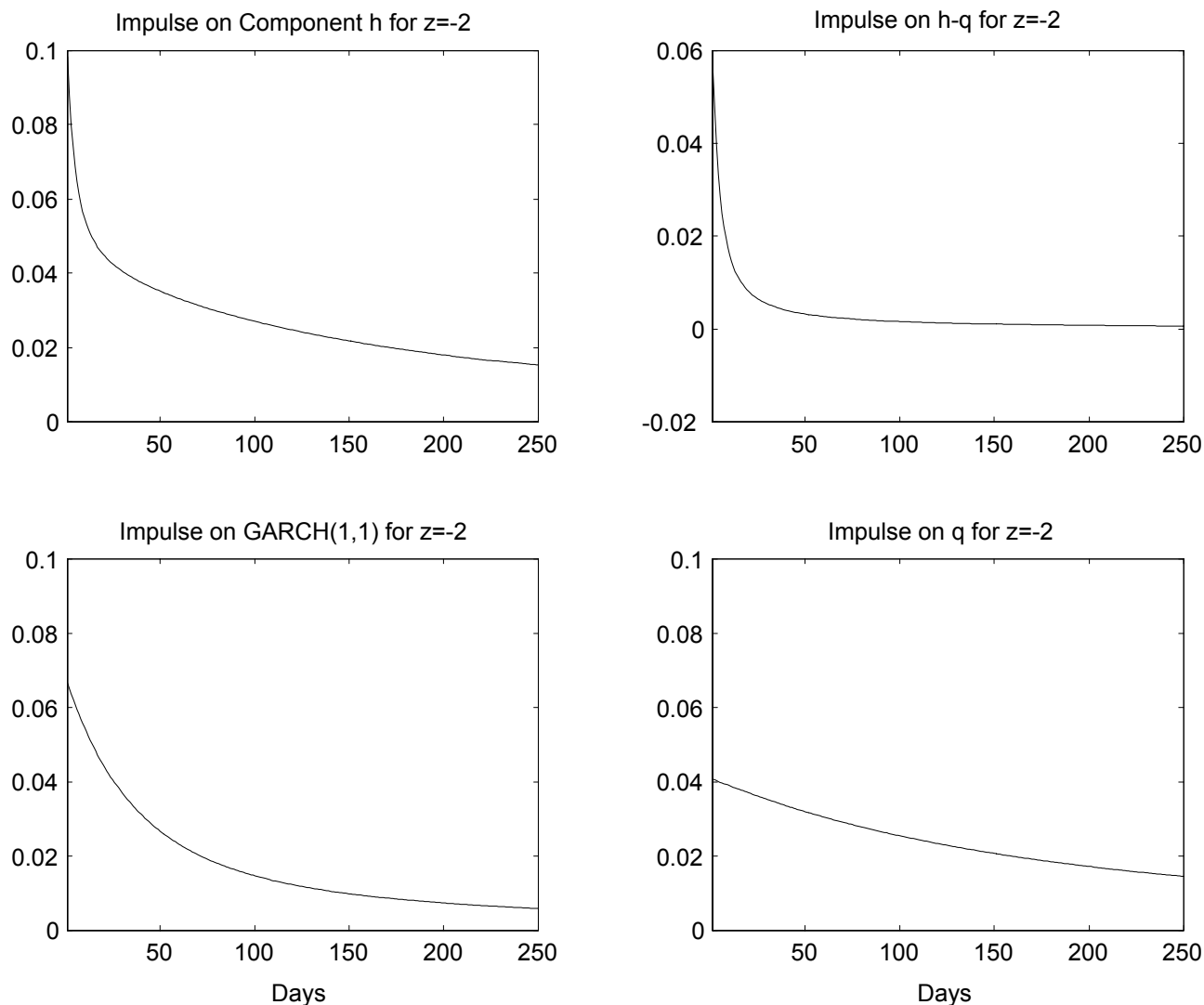
Notes to Figure: In the top panel we plot the variance term structure implied by the component GARCH and GARCH(1,1) models for 1 through 250 days. In the second and third panel we plot the term structure of the individual components for the component model. The parameter values are obtained from MLE estimation on returns in Table 2. The initial value of  $q_{t+1}$  is set to  $1.75\sigma^2$  and the initial value of  $h_{t+1}$  is set to  $2\sigma^2$ . The initial value for  $h_{t+1}$  in the GARCH(1,1) is set to  $2\sigma^2$  as well. All values are normalized by the unconditional variance  $\sigma^2$ .

Figure 3. Term Structure Impulse Response to Positive Return Shock ( $z_t = 2$ ).  
 Component Model Versus GARCH(1,1).  
 Normalized by Unconditional Variance. Estimates Obtained from MLE.



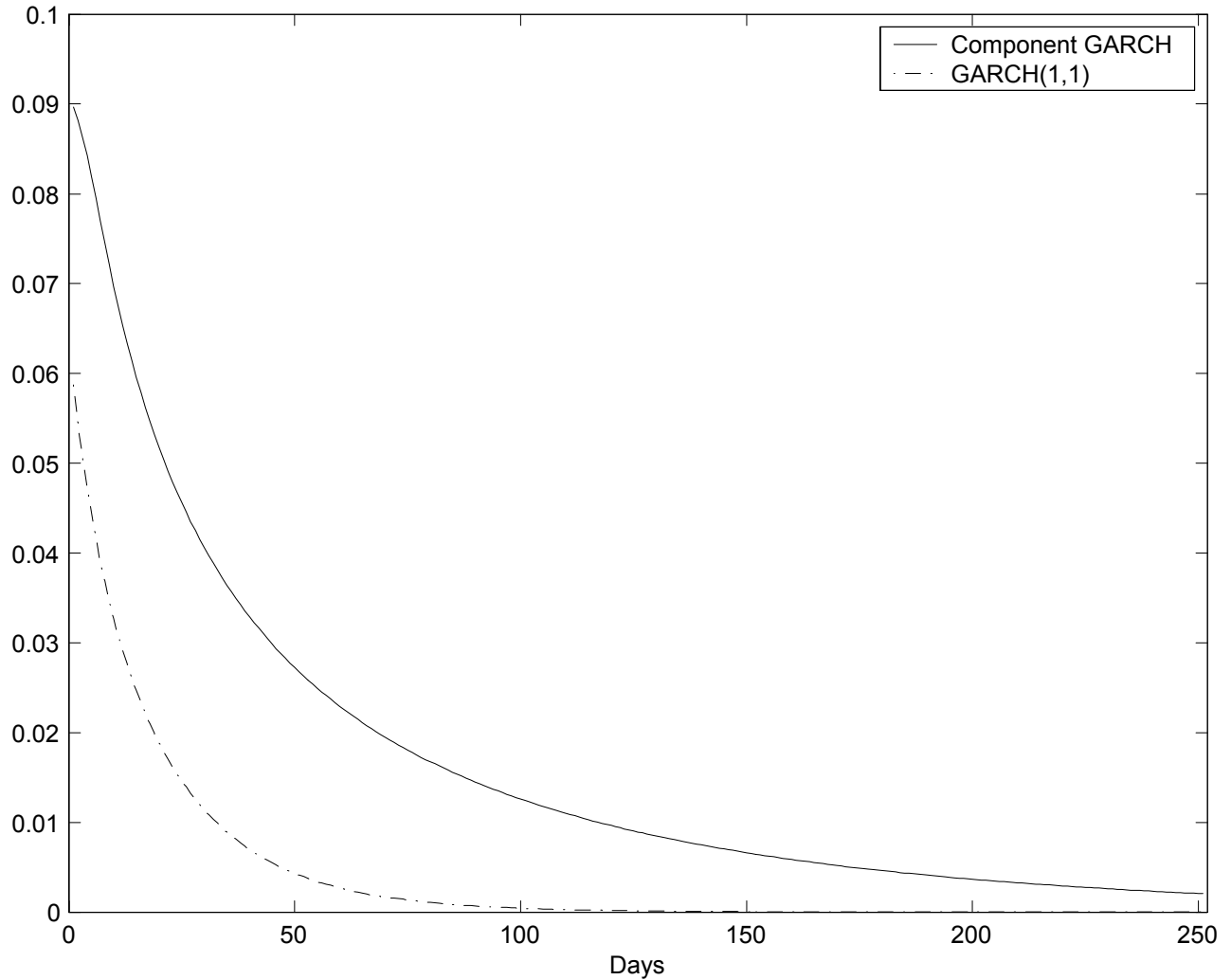
Notes to Figure: In the left-hand panels we plot the variance term structure response to a  $z_t = 2$  shock to the return in the component and GARCH(1,1) models. For the component model, the right-hand panels show the response of the individual components. The parameter values are obtained from the MLE estimation on returns in Table 2. The current variance is set equal to the unconditional value. All values are normalized by the unconditional variance.

Figure 4. Term Structure Impulse Response to Negative Return Shock, ( $z_t = -2$ ).  
 Component Model Versus GARCH(1,1).  
 Normalized by Unconditional Variance. Estimates Obtained from MLE.



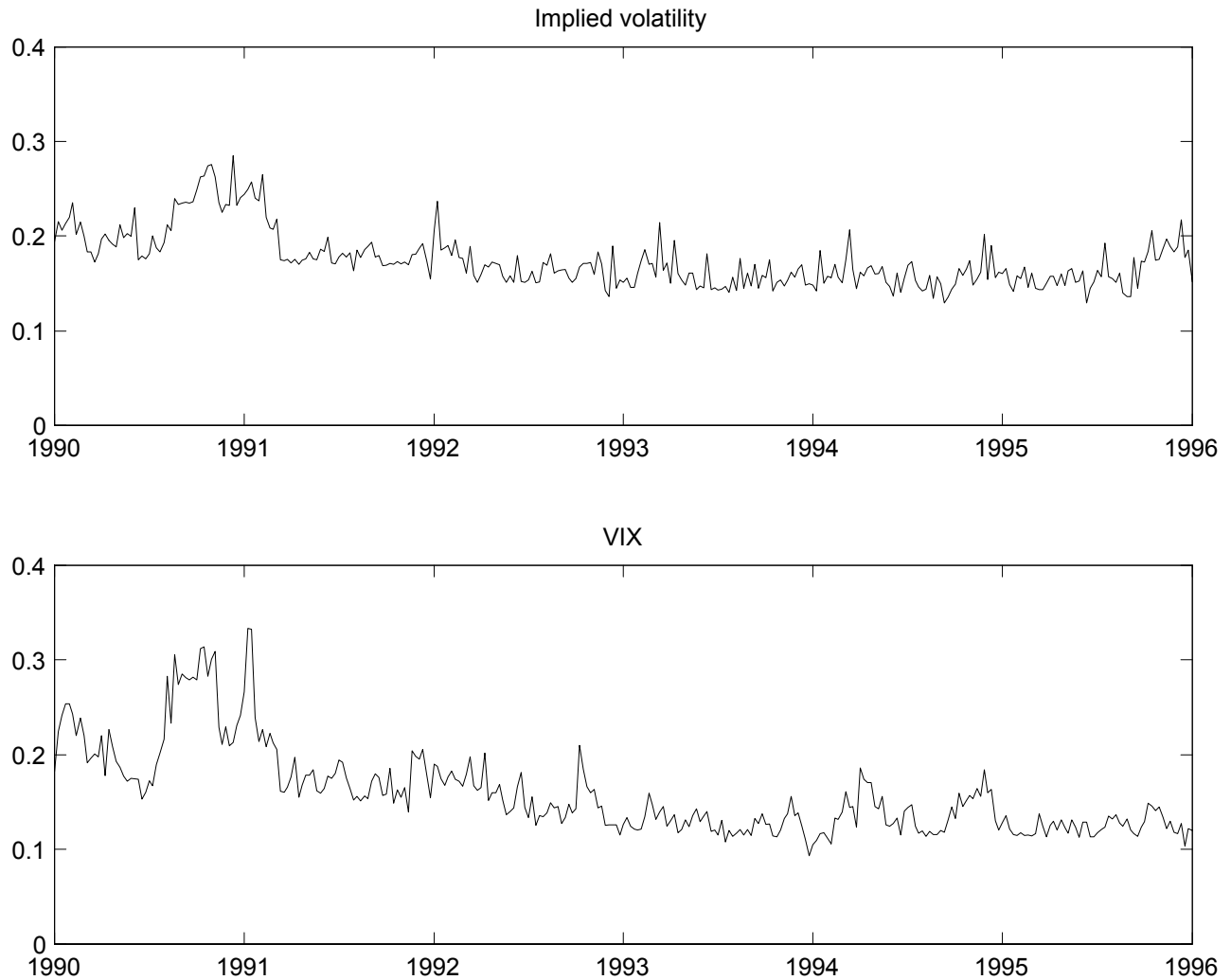
Notes to Figure: In the left-hand panels we plot the variance term structure response to a  $z_t = -2$  shock to the return in the component and GARCH(1,1) models. For the component model, the right-hand panels show the response of the individual components. The parameter values are obtained from the MLE estimation on returns in Table 2. The current variance is set equal to the unconditional value. All values are normalized by the unconditional variance.

Figure 5. Autocorrelation Function of Component GARCH and GARCH(1,1).  
Estimates Obtained from MLE.



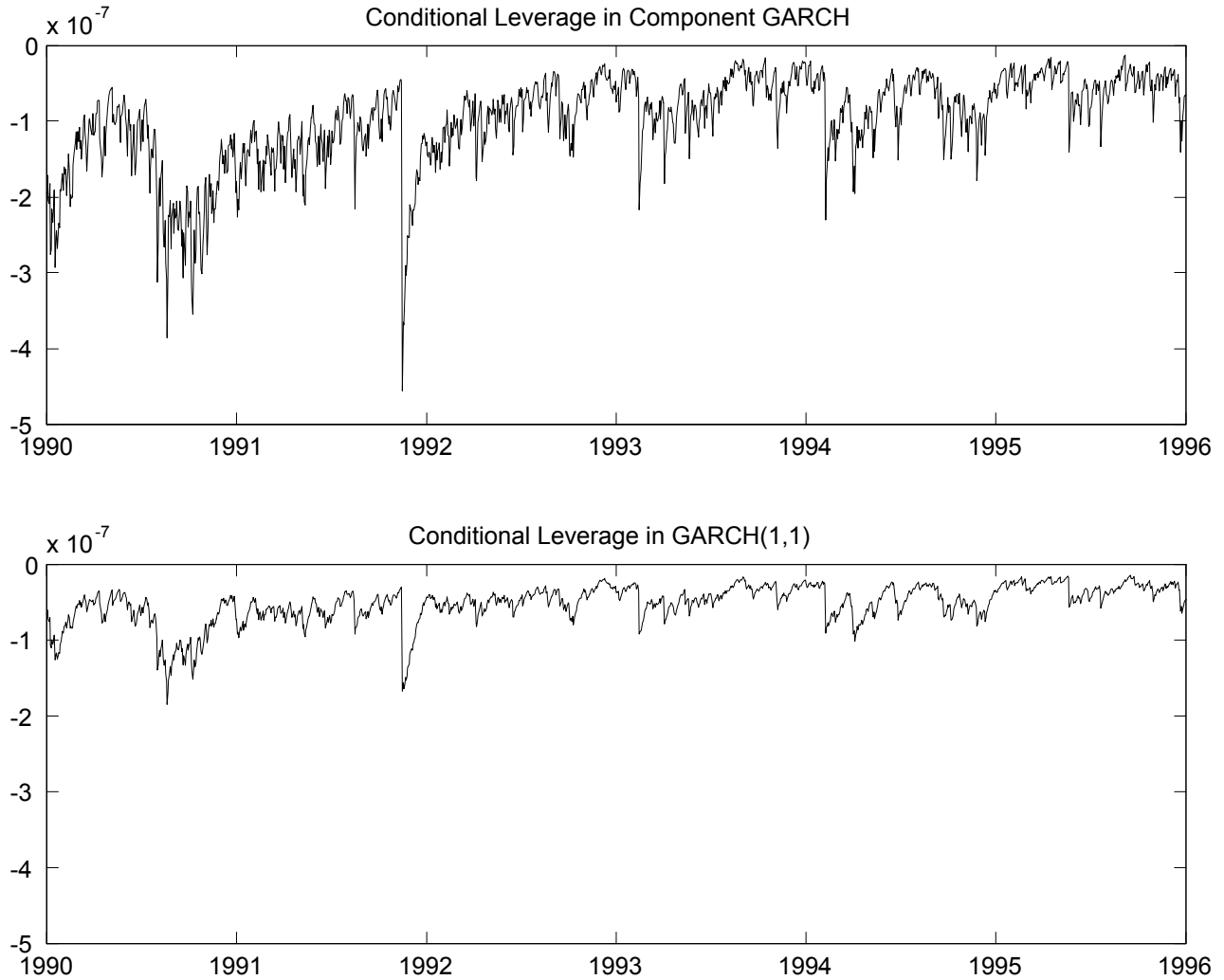
Notes to Figure: We plot the autocorrelation function of the squared GARCH innovations  $\varepsilon_{t+1}^2 = z_{t+1}^2 h_{t+1}$  for lag 1 through 250 lags. The solid line denotes the component GARCH model and the dash-dot line the GARCH(1,1). The parameter values are taken from the MLE estimation on returns in Table 2.

Figure 6. Sample Average Weekly Implied Volatility and VIX.



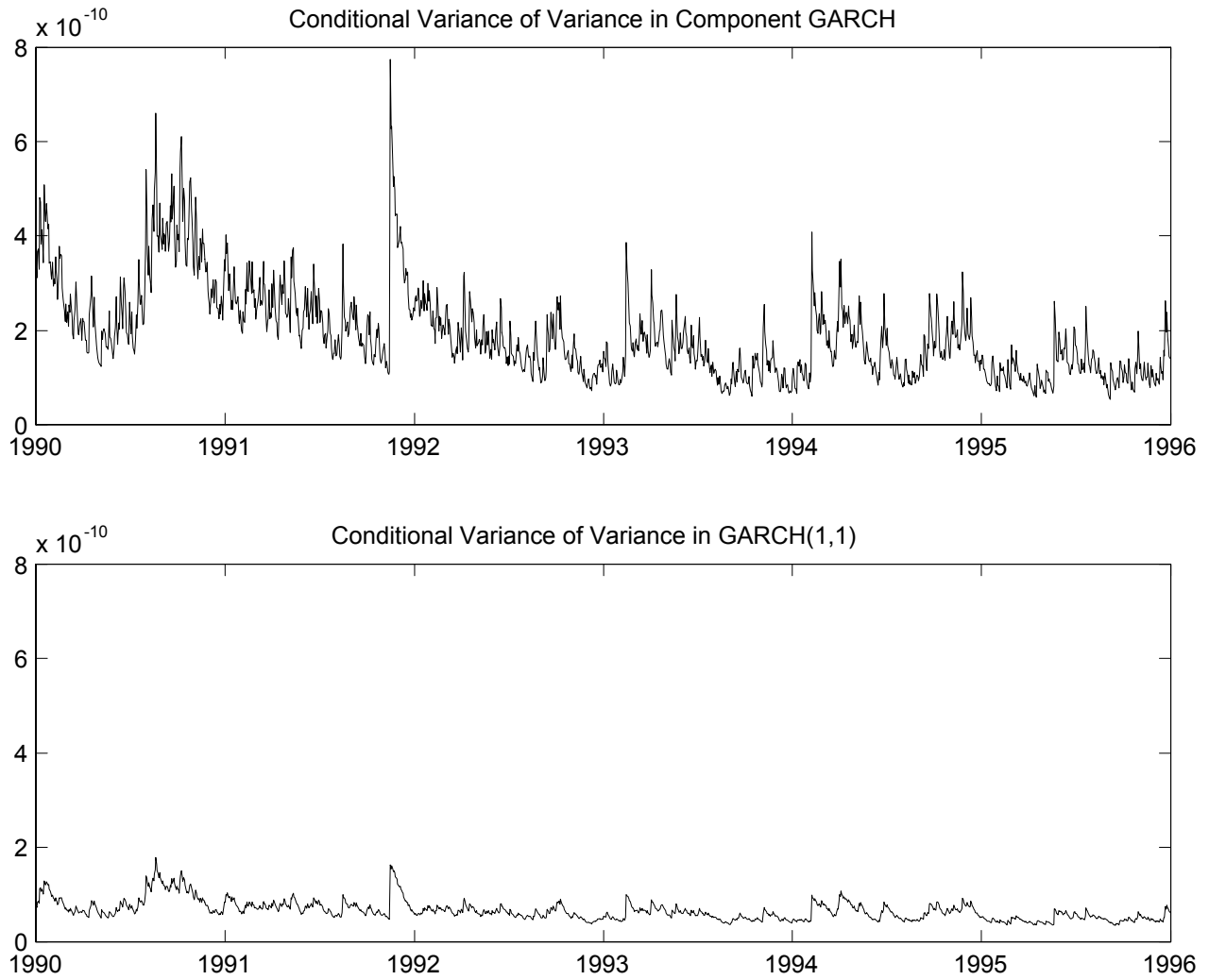
Notes to Figure: The top panel plots the average weekly implied Black-Scholes volatility for the S&P500 call options in our sample. The bottom panel plots the VIX index from the CBOE for comparison.

Figure 7. Conditional Leverage Paths.  
Estimates Obtained from MLE.



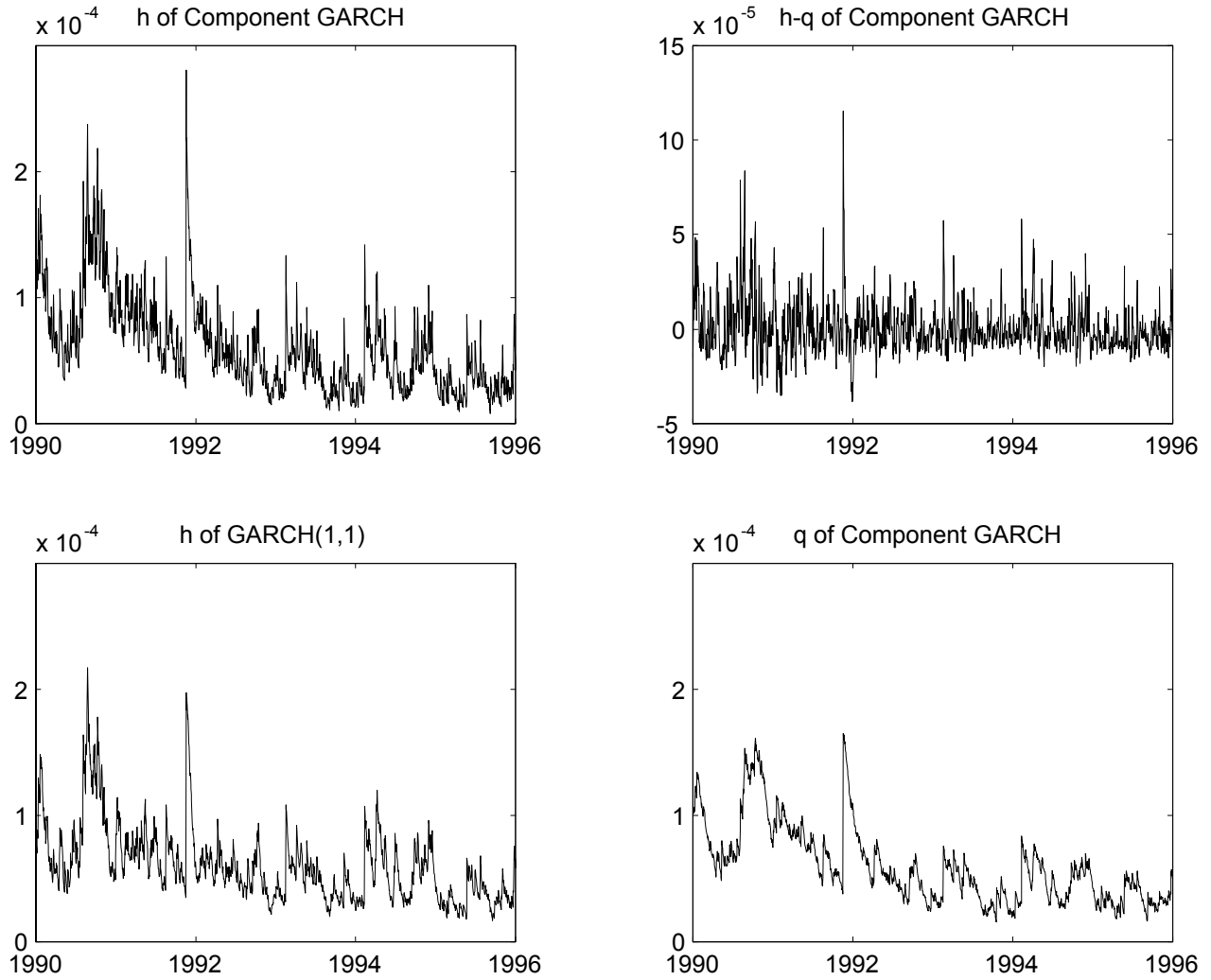
Notes to Figure: We plot the conditional covariance between return and next-day variance as implied by the GARCH models and refer to it as conditional leverage. The top panel shows the component model and the bottom panel shows the GARCH(1,1) model. The scales are identical across panels to facilitate comparison across models. The parameter values are obtained from the MLE estimates on returns in Table 2.

Figure 8: Conditional Variance of Variance Paths.  
Estimates Obtained from MLE.



Notes to Figure: We plot the conditional variance of next day's variance as implied by the GARCH models. The top panel shows the component model and the bottom panel shows the GARCH(1,1) model. The scales are identical across panels to facilitate comparison across models. The parameter values are obtained from the MLE estimates on returns in Table 2.

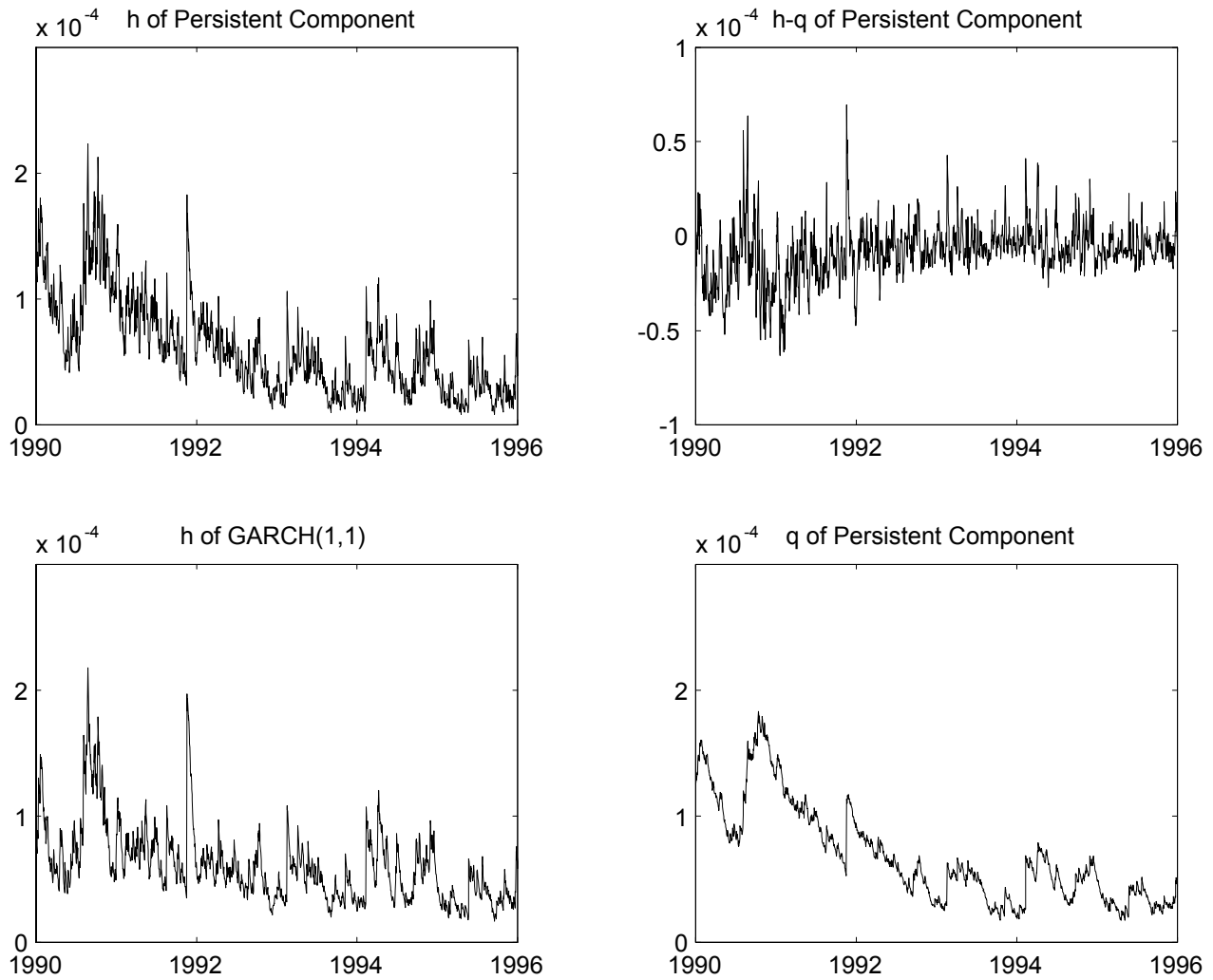
Figure 9. Spot Variance of Component GARCH versus GARCH(1,1).  
Estimates Obtained from MLE.



Notes to Figure: The left-hand panels plot the variance paths from the component and GARCH(1,1) models. The right-hand panels plot the individual components. The parameter values are obtained from MLE estimation on returns in Table 2.

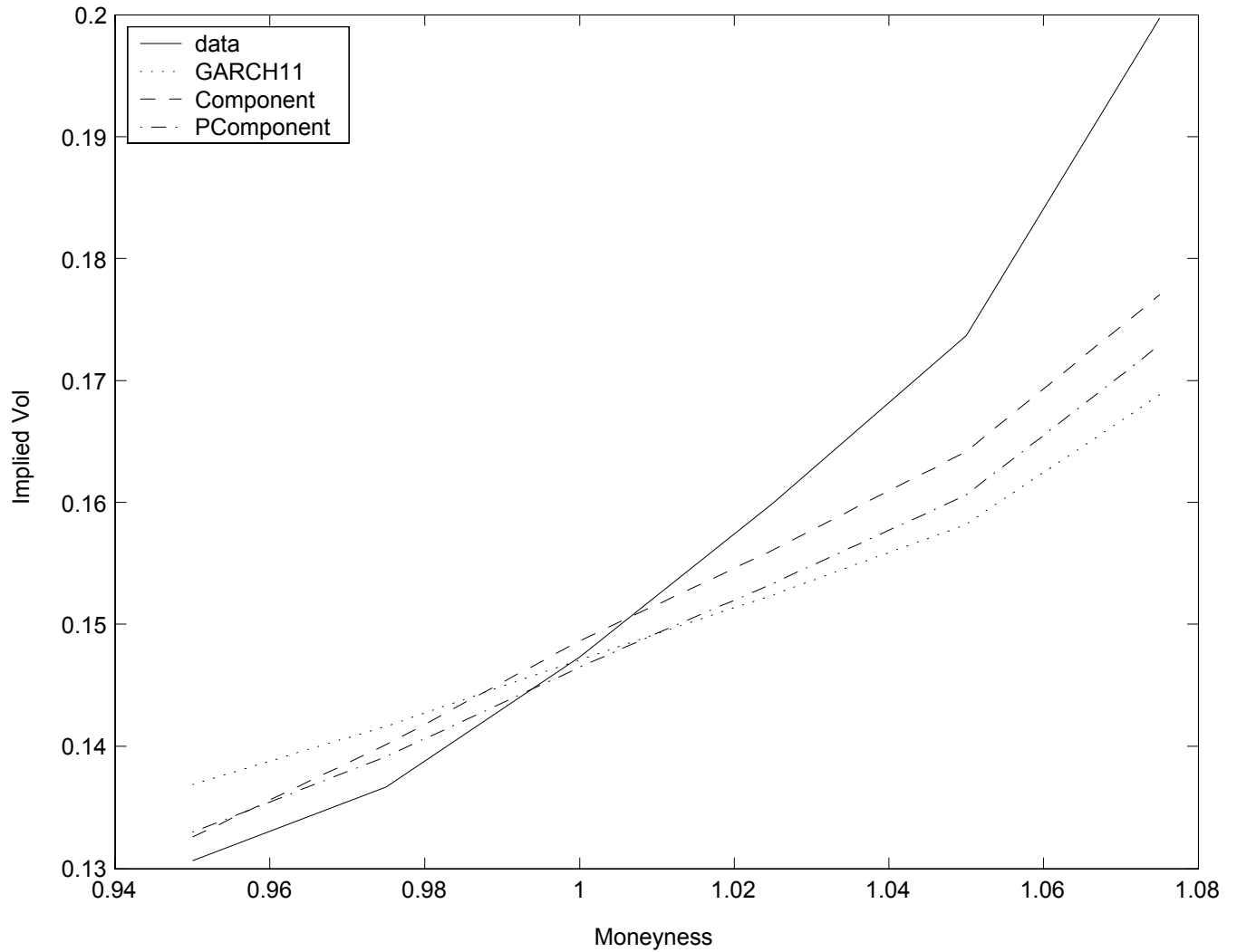


Figure 10. Spot Variance of Persistent Component Model versus GARCH(1,1).  
Estimates Obtained from MLE.



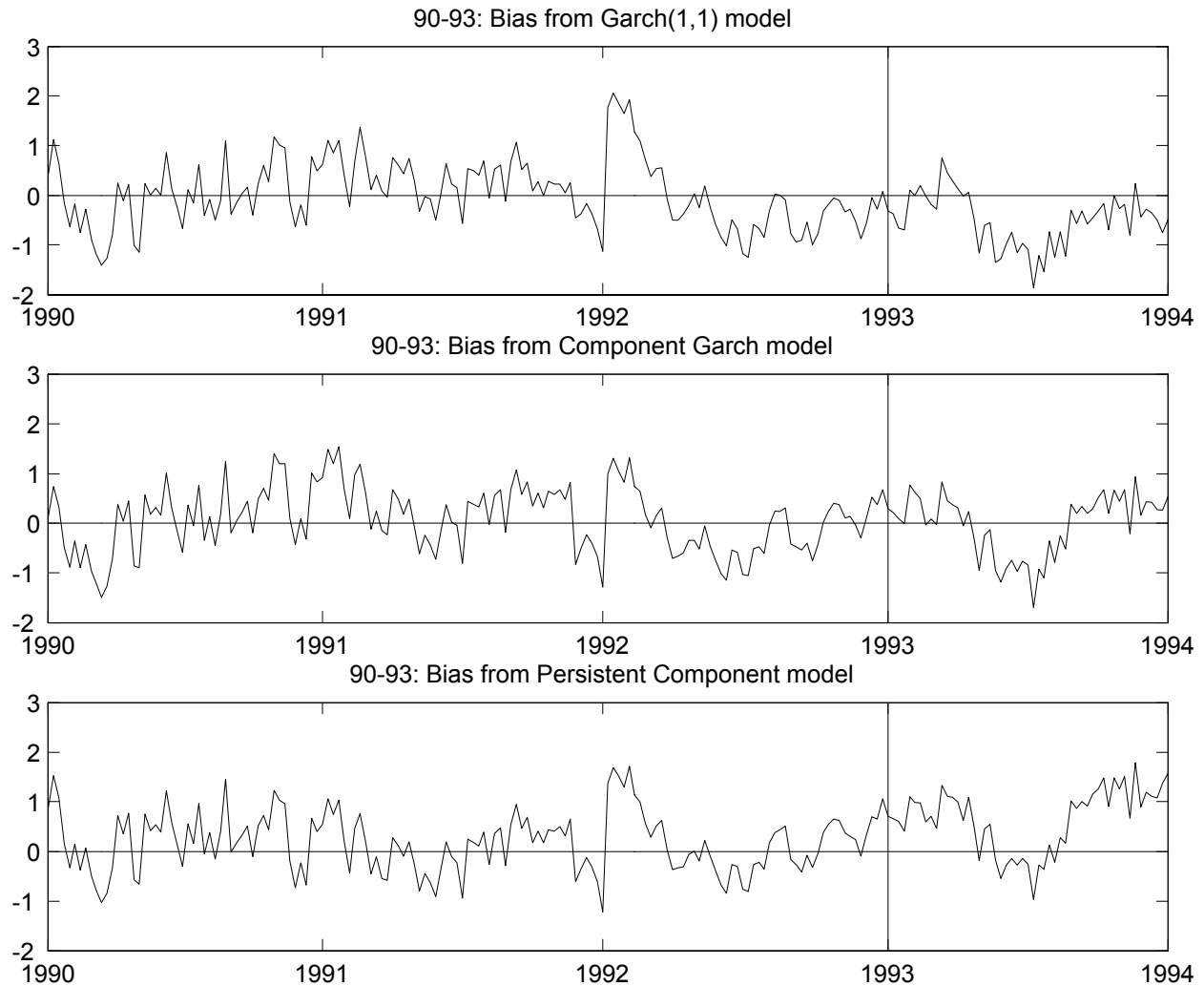
Notes to Figure: The left-hand panels plot the variance paths from the persistent component ( $\rho = 1$ ) and GARCH(1,1) models. The right-hand panels plot the individual components. The parameter values are obtained from MLE estimation on returns in Table 2.

Figure 11. Average Implied Volatility Smiles: Data and Models.  
 Estimates Obtained from NLS.



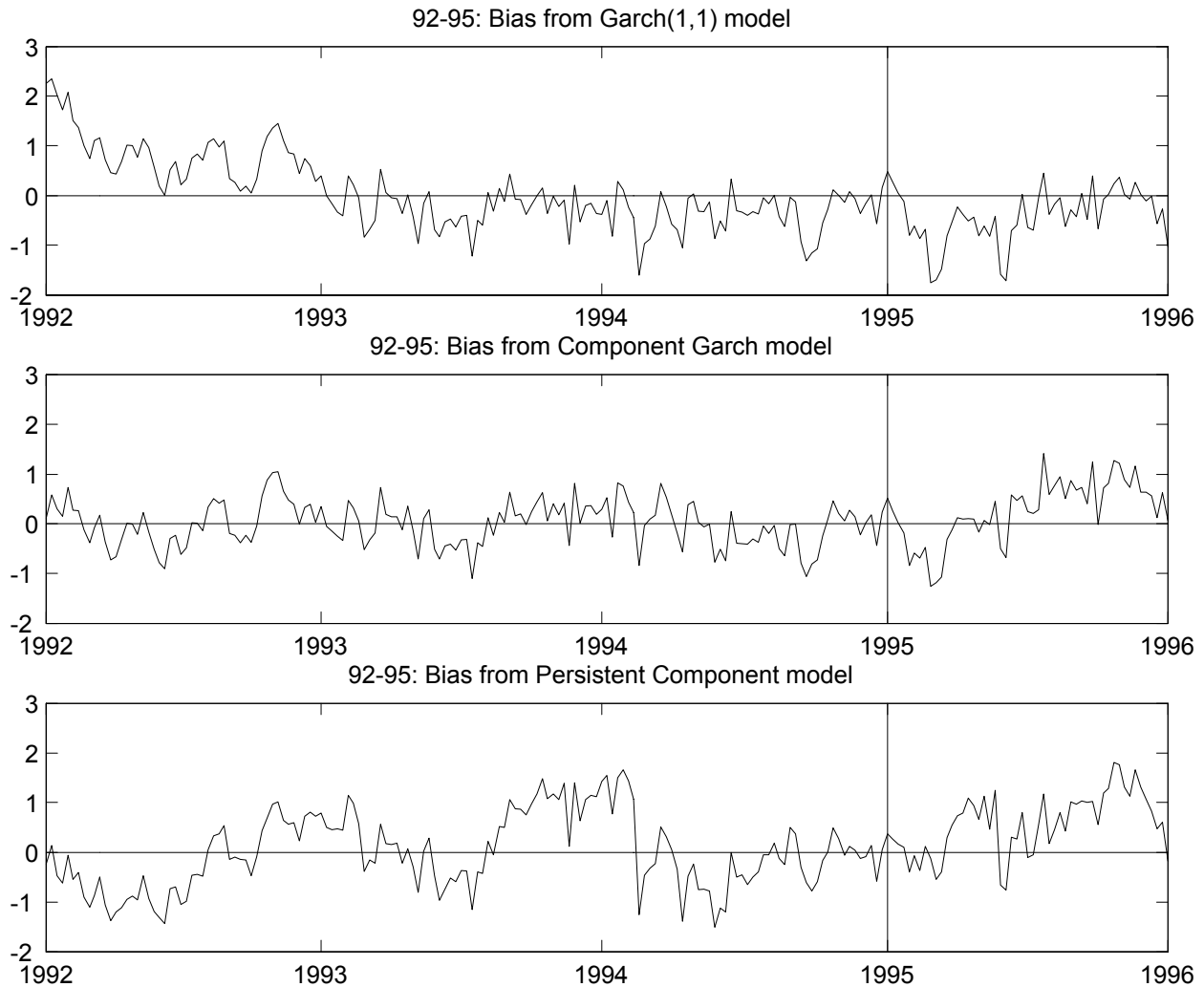
Notes to Figure: We plot the average Black-Scholes implied volatility from observed price data (solid line) and from our three sets of model prices against moneyness. The options are from the 1990-1992 sample, and the option valuation model parameter values are taken from the NLS estimation in Table 3.

Figure 12. Weekly Average Dollar Bias from Sample 90-93.  
Estimates Obtained from NLS.



Notes to Figure: We plot the average weekly bias (market price less model price) for the three GARCH models during the 1990-1993 sample. The parameter values are obtained from NLS estimation in Table 3 on options quoted during the 1990-1992 period. The vertical lines denote the end of the estimation sample period. The horizontal lines are at zero and the scales are identical across panels to facilitate comparison across models.

Figure 13. Weekly Average Dollar Bias from Sample 92-95.  
Estimates Obtained from NLS.



Notes to Figure: We plot the average weekly bias (market price less model price) for the three GARCH models during the 1992-1995 sample. The parameter values are obtained from NLS estimation in Table 5 on options quoted during the 1992-1994 period. The vertical lines denote the end of the estimation sample period. The horizontal lines are at zero and the scales are identical across panels to facilitate comparison across models.

**Table 1: S&P 500 Index Call Option Data (1990-1995)**

<b>Panel A. Number of Call Option Contracts</b>					
	<u>DTM&lt;20</u>	<u>20&lt;DTM&lt;80</u>	<u>80&lt;DTM&lt;180</u>	<u>DTM&gt;180</u>	<u>All</u>
S/X<0.975	147	2,503	2,322	1,119	6,091
0.975<S/X<1.00	365	1,604	871	312	3,152
1.00<S/X<1.025	378	1,524	890	382	3,174
1.025<S/X<1.05	335	1,462	797	311	2,905
1.05<S/X<1.075	307	1,315	713	297	2,632
1.075<S/X	<u>736</u>	<u>3,096</u>	<u>2,112</u>	<u>982</u>	<u>6,926</u>
All	2,268	11,504	7,705	3,403	24,880

<b>Panel B. Average Call Price</b>					
	<u>DTM&lt;20</u>	<u>20&lt;DTM&lt;80</u>	<u>80&lt;DTM&lt;180</u>	<u>DTM&gt;180</u>	<u>All</u>
S/X<0.975	0.91	2.67	6.86	11.94	5.93
0.975<S/X<1.00	2.64	7.95	16.99	27.50	11.77
1.00<S/X<1.025	9.37	15.37	24.90	34.41	19.62
1.025<S/X<1.05	19.64	24.53	33.13	42.14	28.21
1.05<S/X<1.075	30.06	34.33	41.98	48.83	37.54
1.075<S/X	<u>57.42</u>	<u>59.05</u>	<u>65.29</u>	<u>68.34</u>	<u>62.10</u>
All	27.65	26.66	32.07	36.07	29.71

<b>Panel C. Average Implied Volatility from Call Options</b>					
	<u>DTM&lt;20</u>	<u>20&lt;DTM&lt;80</u>	<u>80&lt;DTM&lt;180</u>	<u>DTM&gt;180</u>	<u>All</u>
S/X<0.975	0.1553	0.1284	0.1348	0.1394	0.1335
0.975<S/X<1.00	0.1331	0.1329	0.1461	0.1562	0.1389
1.00<S/X<1.025	0.1555	0.1489	0.1572	0.1605	0.1534
1.025<S/X<1.05	0.1940	0.1676	0.1679	0.1656	0.1705
1.05<S/X<1.075	0.2445	0.1855	0.1792	0.1739	0.1894
1.075<S/X	<u>0.3877</u>	<u>0.2371</u>	<u>0.1996</u>	<u>0.1869</u>	<u>0.2345</u>
All	0.2484	0.1738	0.1642	0.1607	0.1758

Notes to Table: We use European call options on the S&P500 index. The prices are taken from quotes within 30 minutes from closing on each Wednesday during the January 1, 1990 to December 31, 1995 period. The moneyness and maturity filters used by Bakshi, Cao and Chen (1997) are applied here as well. The implied volatilities are calculated using the Black-Scholes formula.

**Table 2: MLE Estimates and Properties**  
**Sample: Daily Returns, 1963-1995**

<b>GARCH(1,1)</b>			<b>Component GARCH</b>			<b>Persistent Component</b>		
<u>Parameter</u>	<u>Estimate</u>	<u>Std. Error</u>	<u>Parameter</u>	<u>Estimate</u>	<u>Std. Error</u>	<u>Parameter</u>	<u>Estimate</u>	<u>Std. Error</u>
w	2.101E-17	1.120E-07	$\tilde{\beta}$	6.437E-01	1.892E-01	$\tilde{\beta}$	7.643E-01	5.963E-03
b <sub>1</sub>	9.013E-01	4.678E-03	$\alpha$	1.580E-06	1.200E-07	$\alpha$	7.639E-07	1.230E-07
a <sub>1</sub>	3.313E-06	1.380E-07	$\gamma_1$	4.151E+02	3.156E+02	$\gamma_1$	7.645E+02	1.121E+01
c <sub>1</sub>	1.276E+02	8.347E+00	$\gamma_2$	6.324E+01	7.279E+00	$\gamma_2$	1.137E+02	8.202E+00
$\lambda$	2.231E+00	1.123E+00	$\omega$	8.208E-07	1.860E-07	$\omega$	2.448E-07	7.280E-09
			$\phi$	2.480E-06	1.200E-07	$\phi$	1.482E-06	3.500E-08
			$\rho$	9.896E-01	1.950E-03	$\rho$	1.000E+00	
			$\lambda$	2.092E+00	7.729E-01	$\lambda$	-6.659E+00	5.410E+00
Total Persist	0.9552		Total Persist	0.9963		Total Persist	1.0000	
Annual Vol	0.1366		Annual Vol	0.1413				
Var of Var	8.652E-06		Var of Var	1.557E-05				
Leverage	-8.455E-04		Leverage	-1.626E-03		Leverage	-1.505E-03	
Ln Likelihood	33,955		Ln Likelihood	34,102		Ln Likelihood	34,055	

Notes to Table: We use daily total returns from January 1, 1963 to December 31, 1995 on the S&P500 index to estimate the three GARCH models using Maximum Likelihood. Robust standard errors are calculated from the outer product of the gradient at the optimum parameter values. Total Persist refers to the persistence of the conditional variance in each model. Annual Vol refers to the annualized unconditional standard deviation as implied by the parameters in each model. Var of Var refers to the unconditional variance of the conditional variance in each model. Leverage refers to the unconditional covariance between the return and the conditional variance. Ln Likelihood refers to the logarithm of the likelihood at the optimal parameter values.

**Table 3: NLS Estimates and Properties**  
**Sample: 1990-1992 (in-sample) 1993 (out-of-sample).**  
**7 - 365 Days to Maturity**

<b>GARCH(1,1)</b>			<b>Component GARCH</b>			<b>Persistent Component</b>		
<u>Parameter</u>	<u>Estimate</u>	<u>Std. Error</u>	<u>Parameter</u>	<u>Estimate</u>	<u>Std. Error</u>	<u>Parameter</u>	<u>Estimate</u>	<u>Std. Error</u>
w	3.891E-14	3.560E-12	$\tilde{\beta}$	6.998E-01	1.345E-01	$\tilde{\beta}$	6.870E-01	2.049E-01
b <sub>1</sub>	6.801E-01	3.211E-03	$\alpha$	1.788E-06	7.121E-09	$\alpha$	1.127E-06	4.409E-09
a <sub>1</sub>	2.666E-07	6.110E-09	$\gamma_1$	5.592E+02	4.524E+01	$\gamma_1$	7.386E+02	6.904E+01
c <sub>1</sub>	1.092E+03	5.432E+01	$\gamma_2$	5.612E+02	2.136E+02	$\gamma_2$	4.651E+02	1.204E+02
			$\omega$	2.382E-07	1.093E-07	$\omega$	4.466E-07	1.909E-08
			$\phi$	5.068E-07	2.305E-10	$\phi$	7.474E-07	8.344E-09
			$\rho$	9.966E-01	9.970E-04	$\rho$	1.000E+00	
Total Persist	0.9981		Total Persist	0.9990		Total Persist	1.0000	
Annual Vol	0.1857		Annual Vol	0.1320				
Var of Var	6.820E-06		Var of Var	2.161E-05				
Leverage	-5.822E-04		Leverage	-2.569E-03		Leverage	-2.360E-03	
RMSE (in)	1.038		RMSE (in)	0.931		RMSE (in)	0.991	
Normalized	1.000		Normalized	0.897		Normalized	0.955	
RMSE (out)	1.284		RMSE (out)	0.983		RMSE (out)	1.247	
Normalized	1.000		Normalized	0.765		Normalized	0.971	

Notes to Table: We use Wednesday option prices from from January 1, 1990 to December 31, 1992 on the S&P500 index to estimate the three GARCH models using Nonlinear Least Squares on the valuation errors. Robust standard errors are calculated from the outer product of the gradient at the optimum parameter values. RMSE refers to the square root of the mean-squared valuation errors. RMSE(in) refers to 1990-1992 and RMSE(out) to 1993. Normalized values are divided by the RMSE from GARCH(1,1).

**Table 4: NLS Estimates and Properties**  
**Sample: 1990-1992 (in-sample) 1993 (out-of-sample)**  
**80 - 365 Days to Maturity**

<b>GARCH(1,1)</b>			<b>Component GARCH</b>			<b>Persistent Component</b>		
<u>Parameter</u>	<u>Estimate</u>	<u>Std. Error</u>	<u>Parameter</u>	<u>Estimate</u>	<u>Std. Error</u>	<u>Parameter</u>	<u>Estimate</u>	<u>Std. Error</u>
w	1.023E-14	1.346E-14	$\tilde{\beta}$	6.031E-01	2.599E-01	$\tilde{\beta}$	7.964E-01	3.935E-01
b <sub>1</sub>	6.842E-01	4.673E-02	$\alpha$	4.707E-06	7.896E-10	$\alpha$	2.757E-07	7.099E-08
a <sub>1</sub>	2.679E-07	7.836E-09	$\gamma_1$	3.378E+02	1.838E+01	$\gamma_1$	1.891E+03	6.921E+02
c <sub>1</sub>	1.082E+03	5.024E+01	$\gamma_2$	6.922E+02	2.683E+02	$\gamma_2$	5.369E+02	2.300E+02
			$\omega$	1.596E-07	9.790E-08	$\omega$	4.612E-07	2.964E-07
			$\phi$	3.793E-07	7.540E-10	$\phi$	6.643E-07	8.733E-09
			$\rho$	9.975E-01	2.900E-03	$\rho$	1.000E+00	
Total Persist	0.9980		Total Persist	0.9990		Total Persist	1.0000	
Annual Vol	0.1833		Annual Vol	0.1277				
Var of Var	6.705E-06		Var of Var	3.065E-05				
Leverage	-5.798E-04		Leverage	-3.705E-03		Leverage	-1.756E-03	
RMSE (in)	1.133		RMSE (in)	1.013		RMSE (in)	1.112	
Normalized	1.000		Normalized	0.895		Normalized	0.982	
RMSE (out)	1.452		RMSE (out)	1.048		RMSE (out)	1.553	
Normalized	1.000		Normalized	0.722		Normalized	1.070	

Notes to Table: See notes to Table 3. Only options with at least 80 days to maturity are used here.



**Table 5: Model Estimates and Properties**  
**Sample: 1992-1994 (in-sample) 1995 (out-of-sample)**  
**7 to 365 Days to Maturity**

<b>GARCH(1,1)</b>			<b>Component GARCH</b>			<b>Persistent Component</b>		
<u>Parameter</u>	<u>Estimate</u>	<u>Std. Error</u>	<u>Parameter</u>	<u>Estimate</u>	<u>Std. Error</u>	<u>Parameter</u>	<u>Estimate</u>	<u>Std. Error</u>
w	7.521E-16	3.498E-09	$\tilde{\beta}$	9.241E-01	3.780E-01	$\tilde{\beta}$	9.763E-01	3.435E-01
b <sub>1</sub>	4.694E-01	1.251E-01	$\alpha$	1.849E-06	1.103E-09	$\alpha$	1.678E-06	3.430E-08
a <sub>1</sub>	1.936E-06	3.986E-07	$\gamma_1$	5.827E+02	1.505E+02	$\gamma_1$	2.552E+02	1.123E+02
c <sub>1</sub>	5.078E+02	1.041E+02	$\gamma_2$	5.714E+02	2.110E+02	$\gamma_2$	1.924E+02	3.425E+01
			$\omega$	2.043E-07	1.301E-07	$\omega$	1.246E-07	2.054E-08
			$\phi$	2.420E-07	1.035E-08	$\phi$	7.191E-07	2.453E-08
			$\rho$	9.958E-01	1.039E-03	$\rho$	1.000E+00	
Total Persist	0.9687		Total Persist	0.9997		Total Persist	1.0000	
Annual Vol	0.1250		Annual Vol	0.1113				
Var of Var	1.572E-05		Var of Var	1.731E-05				
Leverage	-1.967E-03		Leverage	-2.432E-03		Leverage	-1.133E-03	
RMSE (in)	1.107		RMSE (in)	0.855		RMSE (in)	0.994	
Normalized	1.000		Normalized	0.773		Normalized	0.898	
RMSE (out)	1.227		RMSE (out)	0.972		RMSE (out)	1.076	
Normalized	1.000		Normalized	0.792		Normalized	0.877	

Notes to Table: See notes to Table 3. RMSE(in) now refers to 1992-1994 and RMSE(out) to 1995.

**Table 6: Model Estimates and Properties**  
**Sample: 1992-1994 (in-sample) 1995 (out-of-sample)**  
**80 to 365 Days to Maturity**

<b>GARCH(1,1)</b>			<b>Component GARCH</b>			<b>Persistent Component</b>		
<u>Parameter</u>	<u>Estimate</u>	<u>Std. Error</u>	<u>Parameter</u>	<u>Estimate</u>	<u>Std. Error</u>	<u>Parameter</u>	<u>Estimate</u>	<u>Std. Error</u>
w	3.238E-07	1.099E-08	$\tilde{\beta}$	9.448E-01	2.935E-01	$\tilde{\beta}$	9.756E-01	2.104E-01
b <sub>1</sub>	1.341E-01	9.100E-02	$\alpha$	1.125E-06	2.542E-09	$\alpha$	4.569E-07	9.353E-10
a <sub>1</sub>	1.894E-06	5.232E-07	$\gamma_1$	7.337E+02	2.400E+02	$\gamma_1$	9.492E+02	3.091E+02
c <sub>1</sub>	6.624E+02	8.010E+01	$\gamma_2$	5.318E+02	1.769E+02	$\gamma_2$	7.317E+02	6.055E+01
			$\omega$	2.260E-07	1.390E-07	$\omega$	2.127E-07	8.785E-08
			$\varphi$	2.864E-07	1.109E-08	$\varphi$	3.319E-07	4.936E-10
			$\rho$	9.957E-01	1.009E-02	$\rho$	1.000E+00	
Total Persist	0.9650		Total Persist	0.9998		Total Persist	1.0000	
Annual Vol	0.1264		Annual Vol	0.1147				
Var of Var	2.016E-05		Var of Var	1.427E-05				
Leverage	-2.509E-03		Leverage	-1.956E-03		Leverage	-1.353E-03	
RMSE (in)	1.190		RMSE (in)	0.890		RMSE (in)	0.926	
Normalized	1.000		Normalized	0.748		Normalized	0.778	
RMSE (out)	1.743		RMSE (out)	1.052		RMSE (out)	1.201	
Normalized	1.000		Normalized	0.604		Normalized	0.689	

Notes to Table: See notes to Tables 3. RMSE(in) refers to 1992-1994 and RMSE(out) to 1995. Only options with at least 80 days to maturity are used here.

**Table 7: 1990-1992 (in-sample) MSE and Ratio MSE by moneyness and maturity  
Contracts with 7-365 days to maturity**

<b>Panel A. GARCH(1,1) MSE</b>					
	<u>DTM&lt;20</u>	<u>20&lt;DTM&lt;80</u>	<u>80&lt;DTM&lt;180</u>	<u>DTM&gt;180</u>	<u>All</u>
S/X<0.975	0.191	0.791	1.205	1.628	1.162
0.975<S/X<1.00	0.441	1.112	1.260	1.297	1.110
1.00<S/X<1.025	0.331	0.914	1.100	0.987	0.913
1.025<S/X<1.05	0.309	0.822	1.060	0.901	0.844
1.05<S/X<1.075	0.472	0.979	1.360	1.236	1.064
1.075<S/X	<u>0.412</u>	<u>1.156</u>	<u>1.511</u>	<u>1.044</u>	<u>1.164</u>
All	0.372	0.953	1.262	1.324	1.079

<b>Panel B. Ratio of Component GARCH to GARCH(1,1) MSE</b>					
	<u>DTM&lt;20</u>	<u>20&lt;DTM&lt;80</u>	<u>80&lt;DTM&lt;180</u>	<u>DTM&gt;180</u>	<u>All</u>
S/X<0.975	0.882	0.666	0.718	0.855	0.762
0.975<S/X<1.00	0.802	0.761	0.852	1.101	0.860
1.00<S/X<1.025	0.851	0.839	0.912	0.999	0.896
1.025<S/X<1.05	0.760	0.777	0.914	1.130	0.876
1.05<S/X<1.075	0.813	0.721	0.821	1.005	0.813
1.075<S/X	<u>0.942</u>	<u>0.769</u>	<u>0.718</u>	<u>0.900</u>	<u>0.780</u>
All	0.851	0.749	0.780	0.922	0.808

<b>Panel C. Ratio of Persistent Component to GARCH(1,1) MSE</b>					
	<u>DTM&lt;20</u>	<u>20&lt;DTM&lt;80</u>	<u>80&lt;DTM&lt;180</u>	<u>DTM&gt;180</u>	<u>All</u>
S/X<0.975	0.720	0.702	0.819	1.263	0.972
0.975<S/X<1.00	0.707	0.749	0.777	1.206	0.848
1.00<S/X<1.025	0.824	0.805	0.807	1.205	0.886
1.025<S/X<1.05	0.789	0.805	0.794	1.112	0.843
1.05<S/X<1.075	0.840	0.807	0.775	1.090	0.849
1.075<S/X	<u>0.950</u>	<u>0.834</u>	<u>0.785</u>	<u>0.894</u>	<u>0.830</u>
All	0.830	0.780	0.799	1.173	0.891

Notes to Table: We use the NLS estimates from Table 3 to compute the mean squared option valuation error (MSE) for various moneyness and maturity bins during 1990-1992. Panel A shows the MSEs for the GARCH(1,1) model. Panel B shows the ratio of the component GARCH MSEs to the GARCH(1,1) MSEs from Panel A. Panel C shows the ratio of the persistence component GARCH MSEs to the GARCH(1,1) MSEs.

**Table 8: 1993 (out-of-sample) MSE and Ratio MSE by moneyness and maturity  
Contracts with 7-365 days to maturity**

<b>Panel A. GARCH(1,1) MSE</b>					
	<u>DTM&lt;20</u>	<u>20&lt;DTM&lt;80</u>	<u>80&lt;DTM&lt;180</u>	<u>DTM&gt;180</u>	<u>All</u>
S/X<0.975	0.083	1.339	1.764	3.780	2.133
0.975<S/X<1.00	0.335	2.282	3.241	5.924	2.659
1.00<S/X<1.025	0.248	1.316	2.132	5.243	1.839
1.025<S/X<1.05	0.351	0.524	1.309	4.056	1.015
1.05<S/X<1.075	0.422	0.427	0.696	2.496	0.740
1.075<S/X	<u>1.316</u>	<u>1.345</u>	<u>0.983</u>	<u>1.965</u>	<u>1.359</u>
All	0.661	1.263	1.582	3.318	1.648

<b>Panel B. Ratio of Component GARCH to GARCH(1,1) MSE</b>					
	<u>DTM&lt;20</u>	<u>20&lt;DTM&lt;80</u>	<u>80&lt;DTM&lt;180</u>	<u>DTM&gt;180</u>	<u>All</u>
S/X<0.975	0.513	0.371	0.340	0.259	0.309
0.975<S/X<1.00	0.638	0.453	0.434	0.284	0.415
1.00<S/X<1.025	1.181	0.712	0.569	0.347	0.560
1.025<S/X<1.05	0.933	1.158	0.758	0.475	0.780
1.05<S/X<1.075	1.256	1.076	1.080	0.386	0.813
1.075<S/X	<u>0.981</u>	<u>0.943</u>	<u>1.091</u>	<u>0.862</u>	<u>0.954</u>
All	0.989	0.685	0.606	0.425	0.586

<b>Panel C. Ratio of Persistent Component to GARCH(1,1) MSE</b>					
	<u>DTM&lt;20</u>	<u>20&lt;DTM&lt;80</u>	<u>80&lt;DTM&lt;180</u>	<u>DTM&gt;180</u>	<u>All</u>
S/X<0.975	0.440	0.306	0.714	1.664	1.065
0.975<S/X<1.00	0.629	0.297	0.495	0.454	0.394
1.00<S/X<1.025	1.207	0.557	0.770	0.710	0.680
1.025<S/X<1.05	1.007	1.499	1.124	0.413	0.985
1.05<S/X<1.075	1.390	1.511	2.135	0.920	1.417
1.075<S/X	<u>0.984</u>	<u>1.094</u>	<u>1.889</u>	<u>1.119</u>	<u>1.259</u>
All	1.010	0.690	0.990	1.139	0.934

Notes to Table: See Table 7. We use the NLS estimates from Table 3 to compute the out-of-sample mean squared option valuation error (MSE) for various moneyness and maturity bins during 1993.

**Table 9: 1992-1994 (in-sample) MSE and Ratio MSE by moneyness and maturity  
Contracts with 7-365 days to maturity**

<b>Panel A. GARCH(1,1) MSE</b>					
	<u>DTM&lt;20</u>	<u>20&lt;DTM&lt;80</u>	<u>80&lt;DTM&lt;180</u>	<u>DTM&gt;180</u>	<u>All</u>
S/X<0.975	0.233	0.862	1.199	1.861	1.259
0.975<S/X<1.00	0.977	1.646	1.673	1.953	1.625
1.00<S/X<1.025	0.818	1.469	1.401	2.248	1.507
1.025<S/X<1.05	0.347	0.908	0.997	1.818	1.004
1.05<S/X<1.075	0.617	0.646	0.785	2.398	0.982
1.075<S/X	<u>0.850</u>	<u>0.750</u>	<u>0.735</u>	<u>2.094</u>	<u>1.065</u>
All	0.734	1.018	1.092	2.023	1.225

<b>Panel B. Ratio of Component GARCH to GARCH(1,1) MSE</b>					
	<u>DTM&lt;20</u>	<u>20&lt;DTM&lt;80</u>	<u>80&lt;DTM&lt;180</u>	<u>DTM&gt;180</u>	<u>All</u>
S/X<0.975	0.661	0.410	0.371	0.332	0.365
0.975<S/X<1.00	0.597	0.592	0.530	0.479	0.558
1.00<S/X<1.025	0.750	0.679	0.529	0.395	0.578
1.025<S/X<1.05	0.922	0.669	0.511	0.619	0.624
1.05<S/X<1.075	0.845	0.706	0.513	0.564	0.616
1.075<S/X	<u>0.992</u>	<u>0.906</u>	<u>0.738</u>	<u>0.830</u>	<u>0.844</u>
All	0.826	0.654	0.514	0.553	0.591

<b>Panel C. Ratio of Persistent Component to GARCH(1,1) MSE</b>					
	<u>DTM&lt;20</u>	<u>20&lt;DTM&lt;80</u>	<u>80&lt;DTM&lt;180</u>	<u>DTM&gt;180</u>	<u>All</u>
S/X<0.975	0.652	0.770	1.086	1.335	1.114
0.975<S/X<1.00	0.488	0.746	1.083	1.290	0.905
1.00<S/X<1.025	0.582	0.658	0.984	1.213	0.867
1.025<S/X<1.05	0.917	0.698	0.988	0.993	0.858
1.05<S/X<1.075	0.971	0.795	1.012	0.727	0.822
1.075<S/X	<u>0.989</u>	<u>1.162</u>	<u>1.180</u>	<u>0.958</u>	<u>1.061</u>
All	0.780	0.808	1.072	1.110	0.978

Notes to Table: See Table 7. We use the NLS estimates from Table 5 to compute the mean squared option valuation error (MSE) for various moneyness and maturity bins during 1992-1994.

**Table 10: 1995 (out-of-sample) MSE and Ratio MSE by moneyness and maturity  
Contracts with 7-365 days to maturity**

<b>Panel A. GARCH(1,1)</b>					
	<u>DTM&lt;20</u>	<u>20&lt;DTM&lt;80</u>	<u>80&lt;DTM&lt;180</u>	<u>DTM&gt;180</u>	<u>All</u>
S/X<0.975	0.150	0.745	2.120	6.033	3.135
0.975<S/X<1.00	0.991	1.381	2.954	4.381	2.391
1.00<S/X<1.025	0.566	1.134	2.292	3.505	1.930
1.025<S/X<1.05	0.289	0.827	1.599	2.103	1.233
1.05<S/X<1.075	0.816	0.380	0.751	1.963	0.803
1.075<S/X	<u>0.415</u>	<u>0.380</u>	<u>0.326</u>	<u>0.929</u>	<u>0.463</u>
All	0.553	0.716	1.408	3.415	1.507

<b>Panel B. Ratio of Component GARCH to GARCH(1,1) MSE</b>					
	<u>DTM&lt;20</u>	<u>20&lt;DTM&lt;80</u>	<u>80&lt;DTM&lt;180</u>	<u>DTM&gt;180</u>	<u>All</u>
S/X<0.975	1.700	1.404	0.947	0.378	0.572
0.975<S/X<1.00	0.988	0.815	0.571	0.481	0.613
1.00<S/X<1.025	0.703	0.562	0.543	0.424	0.501
1.025<S/X<1.05	1.074	0.559	0.432	0.465	0.497
1.05<S/X<1.075	0.959	0.691	0.588	0.550	0.634
1.075<S/X	<u>1.016</u>	<u>1.160</u>	<u>1.190</u>	<u>0.870</u>	<u>1.052</u>
All	0.957	0.863	0.717	0.449	0.613

<b>Panel C. Ratio of Persistent Component to GARCH(1,1) MSE</b>					
	<u>DTM&lt;20</u>	<u>20&lt;DTM&lt;80</u>	<u>80&lt;DTM&lt;180</u>	<u>DTM&gt;180</u>	<u>All</u>
S/X<0.975	0.749	0.987	0.647	0.372	0.475
0.975<S/X<1.00	0.824	0.780	0.564	0.660	0.670
1.00<S/X<1.025	0.748	0.678	0.675	0.605	0.648
1.025<S/X<1.05	1.216	0.899	0.671	0.712	0.767
1.05<S/X<1.075	1.059	1.492	1.364	0.641	1.041
1.075<S/X	<u>0.927</u>	<u>1.753</u>	<u>2.457</u>	<u>1.099</u>	<u>1.589</u>
All	0.922	1.034	0.822	0.536	0.718

Notes to Table: See Table 7. We use the NLS estimates from Table 5 to compute the out-of-sample mean squared option valuation error (MSE) for various moneyness and maturity bins during 1995.