

Option Valuation with Conditional Heteroskedasticity and Non-Normality*

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Abstract

We provide results for the valuation of European style contingent claims for a large class of specifications of the underlying asset returns. Our valuation results obtain in a discrete time, infinite state-space setup using the no-arbitrage principle and an equivalent martingale measure. Our approach allows for general forms of heteroskedasticity in returns, and valuation results for homoskedastic processes can be obtained as a special case. It also allows for conditional non-normal return innovations, which is critically important because heteroskedasticity alone does not suffice to capture the option smirk. The resulting risk-neutral return dynamics are from the same family of distributions as the physical return dynamics. Our framework nests the valuation results obtained by Duan (1995) and Heston and Nandi (2000) by allowing for a time-varying price of risk and non-normal innovations. An empirical example demonstrates the usefulness of conditional non-normality for the modeling of the index option smirk.

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1 Introduction

A contingent claim is a security whose payoff depends upon the value of another underlying security. A valuation relationship is an expression that relates the value of the contingent claim to the value of the underlying security and other variables. The most popular approach for valuing contingent claims is the use of a Risk Neutral Valuation Relationship (RNVR).

Most of the literature on contingent claims and most of the applications of the RNVR have been cast in continuous time. While the continuous-time approach offers many advantages, the valuation of contingent claims in discrete time is also of substantial interest. For example, when hedging option positions, rebalancing decisions must be made in discrete time. In the case of American and exotic options, early exercise decisions must be made in discrete time as well. Moreover, as only discrete observations are available for empirical study, discrete time models are often more econometrically tractable.

As a result, most of the stylized facts characterizing the underlying securities have been studied in discrete time models. One very important feature of returns is conditional heteroskedasticity, which can be addressed in the GARCH framework of Engle (1982) and Bollerslev (1986).¹ Presumably, because of this evidence, most of the recent empirical work on discrete time option valuation has also focused on GARCH processes.² The GARCH model amounts to an infinite state space setup, with the innovations for underlying asset returns described by continuous distributions. In this case the market is incomplete, and it is in general not possible to construct a portfolio containing the contingent claim and the underlying asset in some proportions so that the resulting portfolio becomes riskless.³

To obtain a RNVR, the GARCH option valuation literature builds on the approach of Rubinstein (1976) and Brennan (1979), who demonstrate how to obtain RNVRs for lognormal and normal returns in the case of constant mean return and volatility, by specifying a representative agent economy.⁴ The resulting first order condition yields an Euler equation that can be used to price any asset. For a given dynamic of the underlying security, specific assumptions have to be made on preferences in order to obtain a risk neutralization result. For lognormal stock returns

¹See for example French, Schwert and Stambaugh (1987) and Schwert (1989) for early studies on stock returns. The literature is far too voluminous to cite all relevant papers here. See Bollerslev, Chou and Kroner (1992) and Diebold and Lopez (1995) for reviews on GARCH modeling.

²See Bollerslev and Mikkelsen (1996), Satchell and Timmermann (1996), Garcia and Renault (1998), Heston and Nandi (2000), Christoffersen and Jacobs (2004), and Christoffersen, Heston and Jacobs (2006) for applications to option valuation.

³In a discrete time finite state space setting, Harrison and Pliska (1981) provide the mathematical framework to obtain the existence of the risk neutral probability measure, to demonstrate uniqueness in the case of complete markets, and to get a RNVR for any contingent claim.

⁴Camara (2003) uses this approach to obtain valuation results for transformed normal dynamics of returns and state variables. See also Schroder (2004). Perrakis (1986), Perrakis and Ryan (1984) and Ritchken and Kuo (1988) provide alternative discrete time approaches.

and a conditionally heteroskedastic (GARCH) volatility dynamic, the standard result is the one in Duan (1995). Duan's result relies on the existence of a representative agent with constant relative risk aversion or constant absolute risk aversion.

However, because it is difficult to characterize the general equilibrium setup underlying a RNVR, very few valuation results are currently available for heteroskedastic processes with non-normal innovations.⁵ In this paper, we argue that it is possible to investigate option valuation for a large class of conditionally non-normal heteroskedastic processes, provided that the conditional moment generating function exists. It is also possible to accommodate a large class of time-varying risk premia. Our framework differs from the approach in Brennan (1979) and Duan (1995), and is more intimately related to the approach adopted in continuous-time option valuation: we only use the no-arbitrage assumption and some technical conditions on the investment strategies to show the existence of an RNVR. We demonstrate the existence of an EMM and characterize it, without first making an explicit assumption on the utility function of a representative agent. We then show that the price of the contingent claim defined as the expected value of the discounted payoff at maturity is a no-arbitrage price and characterize the risk-neutral dynamic.

Why are we able to provide more general valuation results than the existing literature? In our opinion, the analysis in Brennan (1979) and Duan (1995) addresses two important questions simultaneously: First, a mostly technical question that characterizes the risk-neutral dynamic and the valuation of options; second, a more economic one that characterizes the equilibrium underlying the valuation procedure. The existing discrete-time literature for the most part has viewed these two questions as inextricably linked, and has therefore largely limited itself to (log)normal return processes as well as a few special non-normal cases. We argue that it is possible and desirable to treat these questions one at a time, and we provide some general results on the valuation of options under conditionally non-normal asset returns without resorting to equilibrium techniques. We also show how the normal model and the available conditional non-normal models are special cases of our setup.

The same separation of questions occurs in the literature on option valuation using continuous-time stochastic volatility models, such as for instance in Heston's (1993a) model.⁶ For any assumption on the price of volatility risk in Heston, we can find the risk neutral dynamic and the price of contingent claims. The question of which utility function supports this price of risk

⁵Duan, Ritchken and Sun (2005) analyze a heteroskedastic model with Poisson-normal innovations and Duan (1999) analyzes a conditionally fat-tailed heteroskedastic model. Christoffersen, Heston and Jacobs (2006) use a heteroskedastic return dynamic with inverse Gaussian innovations.

⁶Interestingly, GARCH models can sometimes be viewed as discrete time approximations to underlying continuous time diffusions. See for example Nelson and Foster (1994), Foster and Nelson (1996), Nelson (1996) and Ritchken and Trevor (1999). Corradi (2000) points out that such limiting results must be interpreted with caution.

is an interesting one in its own right, but it can be treated separately. See for instance Heston (1993a) and Bates (1996, 2000) for a discussion.

The paper proceeds as follows. In Section 2 we define the class of conditional stock return processes we can accommodate, and derive an appropriate class of EMMs which in turn is used to derive a no-arbitrage option price. Section 3 characterizes the risk-neutral dynamics, and Section 4 discusses several return dynamics that can be analyzed using our approach. In Section 5, an empirical illustration demonstrates the importance of allowing for volatility dynamics as well as conditional non-normality in option valuation models. Section 6 discusses related research, and Section 7 concludes.

2 Theoretical results

We define the probability space (Ω, \mathbb{F}, P) to describe the physical distribution of the states of nature. The financial market consists of a zero-coupon risk-free bond index and a stock. The dynamics of the bond are described by the process $\{B_t\}_{t=1}^T$ normalized to $B_0 = 1$ and the dynamics of the stock price by $\{S_t\}_{t=1}^T$. The information structure is given by the filtration $\mathbb{F} = \{F_t | t = 1, \dots, T\}$ generated by the stock and the bond process.

2.1 The stock price process

The underlying stock price process is assumed to follow the conditional distribution D under the physical measure P . We write

$$R_t \equiv \ln \left(\frac{S_t}{S_{t-1}} \right) = \mu_t - \gamma_t + \varepsilon_t \quad \varepsilon_t | F_{t-1} \sim D(0, \sigma_t^2) \quad (2.1)$$

where S_t is the stock price at time t , and σ_t^2 is the conditional variance of the log return in period t . The mean correction factor, γ_t , is defined from

$$\exp(\gamma_t) \equiv E_{t-1} [\exp(\varepsilon_t)]$$

and it serves to ensure that the conditional expected gross rate of return, $E_{t-1} [S_t/S_{t-1}]$, is equal to $\exp(\mu_t)$. More explicitly,

$$\begin{aligned} E_{t-1} [S_t/S_{t-1}] &= E_{t-1} [\exp(\mu_t - \gamma_t + \varepsilon_t)] = \exp(\mu_t) \\ \iff \exp(\gamma_t) &= E_{t-1} [\exp(\varepsilon_t)] \end{aligned}$$

Note that our specification (2.1) does not restrict the risk premium in any way nor does it

assume conditional normality.

We follow most of the existing discrete-time empirical finance literature by focusing on conditional means μ_t and conditional variances σ_t^2 that are F_{t-1} measurable. We do not constrain the interest rate r_t to be constant. It is instead assumed to be an element of F_{t-1} as well. Our framework is able to accommodate the class of ARCH and GARCH processes proposed by Engle (1982) and Bollerslev (1986) and used for option valuation by Amin and Ng (1993), Duan (1995, 1999), and Heston and Nandi (2000).⁷

In the following, we show that we can find an EMM by defining a probability measure that makes the discounted security process a martingale. We derive more general results on option valuation for heteroskedastic processes compared to the available literature, because we focus on the narrow question of option valuation while ignoring the economic question regarding the preferences of the representative agent that support this valuation argument in equilibrium.

We use a no-arbitrage argument that is similar to the one used in the continuous-time literature. We first prove the existence of an EMM. Subsequently we demonstrate the existence of a RNVR by demonstrating that the price of the contingent claim, defined as the expected value of the discounted payoff at maturity, is a no-arbitrage price under this EMM.⁸ The proof uses an argument similar to the one used in the continuous-time literature, but is arguably more straightforward as it avoids the technical issues involved in the analysis of local and super martingales.

2.2 Specifying an equivalent martingale measure

The objective in this section is to find a measure equivalent to the physical measure P that makes the price of the stock discounted by the riskless asset a martingale. An EMM is defined as long as the Radon-Nikodym derivative is defined. We start by specifying a candidate Radon-Nikodym derivative of a probability measure. We then show that this Radon-Nikodym derivative defines an EMM that makes the discounted stock price process a martingale. This result in turn allows us to obtain the distribution of the stock return under this EMM.

For a given sequence of a random variable, ν_t , we define the following candidate Radon-

⁷Our results will also hold for different types of GARCH specifications, such as the EGARCH model of Nelson (1991) or the specification of Glosten, Jagannathan and Runkle (1993). For our results to apply, all that matters is that the volatility process is predetermined. While our framework can accommodate a wide range of interesting processes, it must be noted that it is not able to handle potentially interesting processes such as discrete-time stochastic volatility models. See Ghysels, Harvey and Renault (1995) for a review of these models.

⁸Duan (1995) refers to RNVR as Local RNVR in the case of GARCH. The reason for the distinction is that the conditional volatility is identical under the two measures only one period ahead. In the remainder of the paper we will drop this distinction for ease of exposition. We emphasize that the result that the conditional volatility differs between the two measures for more than one period ahead is to be expected as volatility is random in this case. This feature is very similar to the continuous time case, which has random volatility for any horizon.

Nikodym derivative

$$\frac{dQ}{dP} \Big| F_t = \exp \left(- \sum_{i=1}^t (\nu_i \varepsilon_i + \Psi_i(\nu_i)) \right) \quad (2.2)$$

where $\Psi_t(u)$ is defined as the natural logarithm of the moment generating function

$$E_{t-1} [\exp(-u\varepsilon_t)] \equiv \exp(\Psi_t(u))$$

Note that we can think of the mean correction factor in (2.1) as $\gamma_t = \Psi_t(-1)$. Note also that in the normal case we have $\Psi_t(u) = \frac{1}{2}\sigma_t^2 u^2$.

We can now show the following lemma

Lemma 1 $\frac{dQ}{dP} \Big| F_t$ is a Radon-Nikodym derivative

Proof. We need to show that $\frac{dQ}{dP} \Big| F_t > 0$ which is immediate. We also need to show that $E_0^P \left[\frac{dQ}{dP} \Big| F_t \right] = 1$. We have

$$E_0^P \left[\frac{dQ}{dP} \Big| F_t \right] = E_0^P \left[\exp \left(- \sum_{i=1}^t (\nu_i \varepsilon_i + \Psi_i(\nu_i)) \right) \right].$$

Using the law of iterative expectations we can write

$$\begin{aligned} E_0^P \left[\frac{dQ}{dP} \Big| F_t \right] &= E_0^P \left[E_1^P \dots E_{t-1}^P \exp \left(- \sum_{i=1}^t (\nu_i \varepsilon_i + \Psi_i(\nu_i)) \right) \right] \\ &= E_0^P \left[E_1^P \dots E_{t-2}^P \exp \left(- \sum_{i=1}^{t-1} \nu_i \varepsilon_i - \sum_{i=1}^t \Psi_i(\nu_i) \right) E_{t-1}^P \exp(-\nu_t \varepsilon_t) \right] \\ &= E_0^P \left[E_1^P \dots E_{t-2}^P \exp \left(- \sum_{i=1}^{t-1} \nu_i \varepsilon_{i+1} - \sum_{i=1}^t \Psi_i(\nu_i) \right) \exp(\Psi_t(\nu_t)) \right] \\ &= E_0^P \left[E_1^P \dots E_{t-2}^P \exp \left(- \sum_{i=1}^{t-1} \nu_i \varepsilon_i - \sum_{i=1}^{t-1} \Psi_i(\nu_i) \right) \right] \end{aligned}$$

Iteratively, using this result we get

$$\begin{aligned} E_0^P \left[\frac{dQ}{dP} \Big| F_t \right] &= E_0^P [\exp(-\nu_1 \varepsilon_1 - \Psi_1(\nu_1))] \\ &= \exp(-\Psi_1(\nu_1)) \exp(\Psi_1(\nu_1)) \\ &= 1 \end{aligned}$$

and the lemma obtains. ■

We are now ready to show that we can specify an EMM using this Radon-Nikodym derivative.

Proposition 1 *The probability measure Q defined by the Radon-Nikodym derivative in (2.2) is an EMM if and only if*

$$\Psi_t(\nu_t - 1) - \Psi_t(\nu_t) - \gamma_t + \alpha_t \sigma_t^2 = 0$$

where $\alpha_t = \frac{\mu_t - r_t}{\sigma_t^2}$.

Proof. We need $E^Q \left[\frac{S_t}{B_t} \middle| F_{t-1} \right] = \frac{S_{t-1}}{B_{t-1}}$ or equivalently $E^Q \left[\frac{S_t}{S_{t-1}} / \frac{B_t}{B_{t-1}} \middle| F_{t-1} \right] = 1$. We have

$$\begin{aligned} E^Q \left[\frac{S_t}{S_{t-1}} / \frac{B_t}{B_{t-1}} \middle| F_{t-1} \right] &= E^P \left[\left(\frac{\frac{dQ}{dP} | F_t}{\frac{dQ}{dP} | F_{t-1}} \right) \frac{S_t}{S_{t-1}} / \frac{B_t}{B_{t-1}} \middle| F_{t-1} \right] \\ &= E^P \left[\left(\frac{\frac{dQ}{dP} | F_t}{\frac{dQ}{dP} | F_{t-1}} \right) \frac{S_t}{S_{t-1}} \exp(-r_t) \middle| F_{t-1} \right] \\ &= E^P [\exp(-\nu_t \varepsilon_t - \Psi_t(\nu_t)) \exp(\mu_t - \gamma_t + \varepsilon_t) \exp(-r_t) | F_{t-1}] \\ &= \exp(-\Psi_t(\nu_t) + \mu_t - r_t - \gamma_t) E^P [\exp((1 - \nu_t) \varepsilon_t) | F_{t-1}] \\ &= \exp(-\Psi_t(\nu_t) + \mu_t - r_t - \gamma_t + \Psi_t(\nu_t - 1)) \\ &= \exp(\Psi_t(\nu_t - 1) - \Psi_t(\nu_t) - \Psi_t(-1) + \alpha_t \sigma_t^2) \end{aligned}$$

Thus Q is a probability measure that makes the stock discounted by a riskless asset a martingale if and only if

$$\Psi_t(\nu_t - 1) - \Psi_t(\nu_t) - \Psi_t(-1) + \alpha_t \sigma_t^2 = 0 \quad (2.3)$$

This result implies that we can construct an EMM by choosing the sequence, ν_t , to make (2.3) hold. ■

2.3 The valuation of European style contingent claims

We have demonstrated that in a general return model with time-varying conditional mean and volatility and non-normal shocks, there exists an EMM Q that makes the stock discounted by the riskless asset a martingale.

We now turn our attention to the pricing of European style contingent claims. Existing papers on the pricing of contingent claims in a discrete-time infinite state space setup, such as the literature on GARCH option pricing in Duan (1995), Amin and Ng (1993) and Heston and Nandi (2000) value such contingent claims by making an assumption on the bivariate distribution of the stock return and the endowment, or an equivalent assumption. While this approach, which most often amounts to the characterization of the equilibrium that supports the pricing, is an

elegant way to deal with the incompleteness that characterizes these markets, we argue that it is not strictly necessary to characterize the equilibrium. Instead, we adopt an approach which is more prevalent in the continuous-time literature, and proceed to pricing derivatives using a no-arbitrage argument alone.

To understand our approach, the analogy with option valuation for the stochastic volatility model of Heston (1993a) is particularly helpful. In this incomplete markets setting, an infinity of no-arbitrage contingent claims prices exist, one for every different specification of the price of risk. When one fixes the price of volatility risk, however, there is a unique no-arbitrage price. For the purpose of option valuation, one can simply pick a price of volatility risk, and the resulting valuation exercise is purely mechanical.

The question whether a particular price of risk is reasonable is of substantial interest in its own right, and an analysis of the representative agent utility function that support a particular price of risk is very valuable. However, this question can be analyzed separately from the option valuation problem. For the heteroskedastic discrete-time models we consider, a similar remark applies. We can value options provided we specify the price of risk. The link between our approach and the utility-based approach in Brennan (1979), Rubinstein (1976) and Duan (1995) is that assumptions on the utility function are implicit in the specification of the risk premium in the return dynamic in our case.⁹ The representative agent preferences underlying this assumption are of interest, but it is not necessary to analyze them in order to value options. Of course, we note that the main difference with the continuous-time stochastic volatility models is that GARCH models are one-shock models, and that therefore there is only one price of risk.

We have already found an EMM Q . We therefore want to demonstrate that the price at time t is defined as

$$C_t = E^Q \left[\frac{C_T(S_T)}{B_T} B_t \middle| F_t \right].$$

The proof proceeds in a number of steps and requires defining a number of concepts that are well-known in the literature. Fortunately, even though our methodology closely follows the continuous-time case, we economize on the number of technical conditions in the continuous-time setup, such as admissibility, and avoid the concepts of local martingale and super martingale. The reason is that the integration over an infinite number of trading times in the continuous-time case is replaced by a finite sum over the trading days in discrete time.

Definitions

1. We denote by η_t , δ_t and ψ_t the units of the stock, the contingent claim and the bond held

⁹See Bick (1990) and He and Leland (1993) for a discussion of assumptions on the utility function implicit in the specification of the return dynamic for the market portfolio. We proceed along the lines of Jacob and Shiryaev (1998), and Shiryaev (1999).

at date t . We refer to the F_t predictable processes η_t , δ_t and ψ_t as investment strategies.

2. The value process

$$V_t = \eta_t S_t + \delta_t C_t + \psi_t B_t$$

describes the total dollar amount available for investments at date t .

3. The gain process

$$G_t = \sum_{i=0}^{t-1} \eta_i (S_{i+1} - S_i) + \sum_{i=0}^{t-1} \delta_i (C_{i+1} - C_i) + \sum_{i=0}^{t-1} \psi_i (B_{i+1} - B_i).$$

captures the total financial gains between dates 0 and t .

4. We call the process $\{\eta_t, \delta_t, \psi_t\}_{t=0}^{T-1}$ a self financing strategy if and only if $V_t = G_t \forall t = 1, \dots, T$.

5. The definition of an arbitrage opportunity is standard: we have an arbitrage opportunity if a self financing strategy exists with either $V_0 < 0, V_T \geq 0$ a.s. or $V_0 \leq 0, V_T > 0$ a.s.

6. We denote the discounted stock price at time t as $S_t^B = \frac{S_t}{B_t}$ and the discounted contingent claim as $C_t^B = \frac{C_t}{B_t}$. Similarly, the discounted value process is denoted $V_t^B = \frac{V_t}{B_t}$ and the discounted gain process $G_t^B = \frac{G_t}{B_t}$.

Note that for a self financing strategy, we have $V_t^B = G_t^B$ because $V_t = G_t$ and $B_t > 0$. Furthermore, we can show the following.

Lemma 2 *For a self financing strategy we have*

$$G_t^B = \sum_{i=0}^{t-1} \eta_i (S_{i+1}^B - S_i^B) + \sum_{i=0}^{t-1} \delta_i (C_{i+1}^B - C_i^B) \quad \forall t = 1, \dots, T$$

Proof. The proof involves straightforward but somewhat cumbersome algebraic manipulations of the above definitions. See the Appendix for the details. ■

We know that under the EMM we defined, the stock discounted by the risk free asset is a martingale. We now need to show that the contingent claims prices obtained by computing the expected value of the final payoff discounted by the risk free asset also constitute a martingale under this EMM.

Lemma 3 *The stochastic process defined by the discounted values of the candidate contingent claims prices is an F_t martingale under the EMM.*

Proof. We defined our candidate process for the contingent claims price under the EMM as $C_t = E^Q \left[\frac{C_T(S_T)}{B_T} B_t \middle| F_t \right]$. The process for the discounted values of the contingent claims prices is then defined as

$$C_t^B \equiv \frac{C_t}{B_t} = E^Q \left[\frac{C_T(S_T)}{B_T} \middle| F_t \right]$$

We use the fact that the conditional expectation itself is a Q martingale. This in turn follows from the law of iterated expectations and the European style payoff function. Taking conditional expectations with respect to F_s on both sides of the above equation yields

$$E^Q \left[\frac{C_t}{B_t} \middle| F_s \right] = E^Q \left[E^Q \left[\frac{C_T(S_T)}{B_T} \middle| F_t \right] \middle| F_s \right] \quad \forall t > s$$

Now using the law of iterated expectations we get

$$E^Q \left[\frac{C_t}{B_t} \middle| F_s \right] = E^Q \left[\frac{C_T(S_T)}{B_T} \middle| F_s \right] = \frac{C_s}{B_s} = C_s^B \quad \forall t > s$$

which gives the desired result. ■

Lemma 4 *Under the EMM defined by (2.2), the discounted gain process is a martingale.*

Proof. Under the EMM Q , the process $\{S_t^B\}_{t=1}^T$ is a Q martingale. Using a standard property of martingales the process defined as $SS_t^B = \sum_{i=0}^{t-1} \eta_i (S_{i+1}^B - S_i^B)$ then is a Q martingale, since the investment strategy η_t is included in the information set.¹⁰ Furthermore, from Lemma 3 we get that $\{C_t^B\}_{t=1}^T$ is also a Q martingale. Then using the fact that δ_t is an F_t predetermined process and using the same martingale property as above we get that the process $CC_t^B = \sum_{i=0}^{t-1} \delta_i (C_{i+1}^B - C_i^B)$ is a Q martingale. Then since from Lemma 2 the discounted gain process $\{G_t^B\}_{t=1}^T$ is the sum of two Q martingales, SS_t^B and CC_t^B , it is itself a Q martingale. ■

At this stage, we have all the ingredients to show the following main result.

Proposition 2 *If we have an EMM that makes the discounted price of the stock a martingale, then defining the price of any contingent claim as the expected value of its payoff, taken under this EMM and discounted at the riskless interest rate constitutes a no-arbitrage price.*

Proof. From Lemma 4 G_t^B is a Q martingale. Because we are considering self financing strategies we get that V_t^B is a martingale. We prove the absence of arbitrage by contradiction. If we assume the existence of an arbitrage opportunity, then there exists a self financing strategy with type 1

¹⁰Note that because we are working in discrete time there is no need to investigate the integrability of SS_t^B .

arbitrage ($V_0 < 0, V_T \geq 0$ a.s.) or type 2 arbitrage ($V_0 \leq 0, V_T > 0$ a.s.). Both cases lead to a clear contradiction. Consider type 1 arbitrage: we start from the existence of a self financing strategy with $V_0 < 0$ that ends up with a positive final value. $V_0 < 0$ implies that $V_0^B < 0$ since the numeraire is always positive by definition. Also since $V_T \geq 0$ we have $V_T^B \geq 0$. Taking expectations and using the fact that V_t^B is a Q martingale yields $V_0^B = E_0^Q[V_T^B] \geq 0$. This is a contradiction because we assumed that we start with a negative value $V_0 < 0$. A similar argument works for type 2 arbitrage. Thus, the C_t from the EMM Q must be a no-arbitrage price. ■

In summary, we have demonstrated that in a discrete-time infinite state space setting, if we have an EMM that makes the underlying asset price a martingale, then the expected value of the payoff of the contingent claim taken under this EMM, discounted at the riskless asset, is a no-arbitrage price. In Section 2.2, we derived such an EMM. Altogether, we have therefore demonstrated that for any contingent claim paying a final payoff $C_T(S_T)$ the current price C_t can be computed as

$$C_t = E^Q \left[\frac{C_T(S_T)}{B_T} B_t \middle| F_t \right].$$

3 Characterizing the risk-neutral distribution

The previous section demonstrates how options can be priced using the EMM directly. However, when pricing options using Monte Carlo simulation, knowing the risk neutral distribution is valuable. In this section, we derive an important result that shows that for the class of models we investigate, the risk neutral distribution is from the same family as the original physical distribution.

We first need the following lemma, where we recall that $\Psi_t(u)$, denotes the one-day log conditional moment generating function of the innovation ε_t

Lemma 5

$$E_{t-1}^Q [\exp(-u\varepsilon_t)] = \exp(\Psi_t(\nu_t + u) - \Psi_t(\nu_t))$$

Proof.

$$\begin{aligned} E_{t-1}^Q [\exp(-u\varepsilon_t)] &= E^P \left[\left(\frac{\frac{dQ}{dP} | F_t}{\frac{dQ}{dP} | F_{t-1}} \right) \exp(-u\varepsilon_t) | F_{t-1} \right] \\ &= E^P [\exp(-\nu_t \varepsilon_t - \Psi_t(\nu_t)) \exp(-u\varepsilon_t) | F_{t-1}] \\ &= \exp(\Psi_t(\nu_t + u) - \Psi_t(\nu_t)) \end{aligned}$$

■

From this lemma, if we define $\Psi_t^Q(u)$ to be the log conditional moment generating function of ε_t under the risk neutral probability measure, then we have

$$\Psi_t^Q(u) = \Psi_t(\nu_t + u) - \Psi_t(\nu_t)$$

From this we can derive

$$E_{t-1}^Q[\varepsilon_t] = \left. \frac{\partial \exp(\Psi_t^Q(-u))}{\partial u} \right|_{u=0} = -\Psi_t'(\nu_t)$$

which represents the risk premium. Define the risk neutral innovation

$$\varepsilon_t^* = \varepsilon_t - E_{t-1}^Q[\varepsilon_t]$$

The risk-neutral log-conditional moment generating function of ε_t^* , labeled $\Psi_{t-1}^{Q*}(u)$, is then

$$\Psi_t^{Q*}(u) = -u\Psi_t'(\nu_t) + \Psi_t^Q(u) \tag{3.1}$$

We are now ready to show the following

Proposition 3 *If the physical conditional distribution of ε_t is an infinitely divisible distribution with finite second moment, then the risk-neutral conditional distribution of ε_t^* is also an infinitely divisible distribution with finite second moment.*

Proof. See the appendix. ■

Because of the one-to-one mapping between moment generating functions and distribution functions, this result can be used to derive specific parametric risk-neutral distributions corresponding to the parametric physical distributions assumed by the researcher.

4 Parametric examples

In this section we demonstrate how a number of existing models are nested in our setup. We also give an example of a model that has not yet been discussed in the literature but can be handled by our setup.

4.1 Conditionally normal returns

In the conditional normal case we have the return dynamics

$$R_t = \mu_t - \gamma_t + \varepsilon_t \quad \varepsilon_t | F_{t-1} \sim N(0, \sigma_t^2)$$

where the conditional variance, σ_t^2 , can take on any GARCH-type specification.

The normal log MGF is $\Psi_t(u) = \frac{1}{2}\sigma_t^2 u^2$ so that $\gamma_t = \Psi_t(-1) = \frac{1}{2}\sigma_t^2$ and our EMM condition

$$\Psi_t(\nu_t - 1) - \Psi_t(\nu_t) - \Psi_t(-1) + \alpha_t \sigma_t^2 = 0$$

from (2.3) is solved by choosing

$$\nu_t = \alpha_t = \frac{\mu_t - r_t}{\sigma_t^2}$$

In this normal case, the probability measure Q defined by the Radon-Nikodym derivative

$$\frac{dQ}{dP} \Big|_{F_t} = \exp \left(- \sum_{i=1}^t (\nu_i \varepsilon_i + \Psi_i(\nu_i)) \right) = \exp \left(- \sum_{i=1}^t \left(\alpha_i \varepsilon_i + \frac{1}{2} \alpha_i^2 \sigma_i^2 \right) \right)$$

is therefore an EMM.

From Section 3 we have the risk neutral conditional log MGF in the general case

$$\Psi_t^{Q^*}(u) = -u \Psi_t'(\nu_t) + \Psi_t(\nu_t + u) - \Psi_t(\nu_t)$$

Using $\Psi_t(u) = \frac{1}{2}\sigma_t^2 u^2$, we get

$$\Psi_t^{Q^*}(u) = \frac{1}{2}\sigma_t^2 u^2.$$

so that in the normal case the risk neutral distribution is also normal. The results in Section 3 also imply that the risk neutral innovation generally can be written

$$\varepsilon_t^* = \varepsilon_t + \Psi_t'(\nu_t)$$

so that in the normal case we have

$$\varepsilon_t^* = \varepsilon_t + \nu_t \sigma_t^2 = \varepsilon_t + \alpha_t \sigma_t^2 = \varepsilon_t + \mu_t - r_t$$

4.2 Flexible risk premium specifications

One of the advantages of our approach is that we can allow for time-varying risk premia. Here we discuss some potentially interesting ways to specify the risk premium in the return process

for the underlying asset. In order to demonstrate the link with the available literature and for computational simplicity, we assume conditional normal returns, although this assumption is by no means necessary.

The conditional normal models in the Duan (1995) and Heston and Nandi (2000) models are special cases of our set-up. In our notation, Duan (1995) assumes

$$r_t = r, \text{ and } \mu_t = r + \lambda\sigma_t$$

which in our framework corresponds to a Radon-Nikodym derivative of

$$\frac{dQ}{dP} \Big|_{F_t} = \exp \left(- \sum_{i=1}^t \left(\frac{\varepsilon_i}{\sigma_i} \lambda - \frac{1}{2} \lambda^2 \right) \right)$$

and risk neutral innovations of the form

$$\varepsilon_t^* = \varepsilon_t + \lambda\sigma_t.$$

Heston and Nandi (2000) instead assume

$$r_t = r, \text{ and } \mu_t = r + \lambda\sigma_t^2 + \frac{1}{2}\sigma_t^2$$

which in our framework corresponds to a Radon-Nikodym derivative of

$$\frac{dQ}{dP} \Big|_{F_t} = \exp \left(- \sum_{i=1}^t \left(\left(\lambda + \frac{1}{2} \right) \varepsilon_i - \frac{1}{2} \left(\lambda + \frac{1}{2} \right)^2 \sigma_i^2 \right) \right)$$

and risk neutral innovations of the form

$$\varepsilon_t^* = \varepsilon_t + \lambda\sigma_t^2 + \frac{1}{2}\sigma_t^2.$$

However, many empirically relevant cases are not covered by existing theoretical results. For example, in the original ARCH-M paper, Engle, Lilien and Robins (1987) find the strongest empirical support for a risk premium specification of the form

$$\mu_t = r_t + \lambda \ln(\sigma_t) + \frac{1}{2}\sigma_t^2$$

which cannot be used for option valuation using the available theory. In our framework it simply

corresponds to a Radon-Nikodym derivative of

$$\frac{dQ}{dP} \Big|_{F_t} = \exp \left(- \sum_{i=1}^t \left(\frac{\lambda \ln(\sigma_i) + \frac{1}{2} \sigma_i^2}{\sigma_i^2} \varepsilon_i - \frac{1}{2} \left(\frac{\lambda \ln(\sigma_i) + \frac{1}{2} \sigma_i^2}{\sigma_i^2} \right)^2 \sigma_i^2 \right) \right)$$

and risk neutral innovations

$$\varepsilon_t^* = \varepsilon_t + \lambda \ln(\sigma_t) + \frac{1}{2} \sigma_t^2$$

Our approach allows for option valuation under such specifications whereas the existing literature does not.

4.3 Conditionally inverse Gaussian returns

Christoffersen, Heston and Jacobs (2006) analyze a GARCH model with an inverse Gaussian innovation, $y_t \sim IG(\sigma_t^2/\eta^2)$. We can write their return dynamic as

$$R_t = r + (\lambda + \eta^{-1}) \sigma_t^2 + \varepsilon_t$$

where ε_t is a zero-mean innovation defined by

$$\varepsilon_t = \eta y_t - \eta^{-1} \sigma_t^2$$

and where the conditional return variance, σ_t^2 , is of the GARCH form.

From the MGF of an inverse Gaussian variable, we can derive the conditional log MGF of ε_t as

$$\Psi_t(u) = \left(u + \frac{1 - \sqrt{1 + 2u\eta}}{\eta} \right) \frac{\sigma_t^2}{\eta}$$

The EMM condition

$$\Psi_t(\nu_t - 1) - \Psi_t(\nu_t) - \Psi_t(-1) + \alpha_t \sigma_t^2 = 0$$

is now solved by the constant

$$\nu_t = \nu = \frac{1}{2\eta} \left[\frac{(2 + \lambda\eta^3)^2}{4\lambda^2\eta^2} - 1 \right], \forall t$$

which in turn implies that the EMM is given by

$$\begin{aligned} \frac{dQ}{dP} \Big|_{F_t} &= \exp \left(- \sum_{i=1}^t \left(\nu \varepsilon_i + \left(\nu + \frac{1 - \sqrt{1 + 2\nu\eta}}{\eta} \right) \frac{\sigma_i^2}{\eta} \right) \right) \\ &= \exp \left(-\nu t \bar{\varepsilon}_t - \delta t \bar{\sigma}_t^2 \right) \end{aligned}$$

where $\bar{\varepsilon}_t = \frac{1}{t} \sum_{i=1}^t \varepsilon_i$, $\overline{\sigma_t^2} = \frac{1}{t} \sum_{i=1}^t \sigma_i^2$, and $\delta = \frac{\nu}{\eta} + \frac{1 - \sqrt{1 + 2\nu\eta}}{\eta^2}$.

These expressions can be used to obtain the risk-neutral distribution from Christoffersen, Heston and Jacobs (2006) using the results in Section 3. Recall that in general the risk neutral log MGF is

$$\Psi_t^{Q^*}(u) = -u\Psi_t'(\nu) + \Psi_t(\nu + u) - \Psi_t(\nu)$$

In the GARCH-IG case we can write

$$\Psi_t^{Q^*}(u) = \left(u + \frac{1 - \sqrt{1 + 2u\eta^*}}{\eta^*} \right) \frac{\sigma_t^{*2}}{\eta^*}$$

where

$$\eta^* = \frac{\eta}{1 + 2\nu\eta} \text{ and } \sigma_t^{*2} = \frac{\sigma_t^2}{(1 + 2\nu\eta)^{3/2}}$$

This implies that the risk neutral model can be written as

$$R_t \equiv \ln \left(\frac{S_t}{S_{t-1}} \right) = r - \Psi_t^{Q^*}(-1) + \varepsilon_t^* = r + (\lambda^* + \eta^{*-1}) h_t^* + \varepsilon_t^*$$

where

$$\lambda^* = \frac{1 - 2\eta^* - \sqrt{1 - 2\eta^*}}{\eta^{*2}} \text{ and } \varepsilon_t^* = \eta^* y_t^* - \eta^{*-1} \sigma_t^{*2}$$

The risk neutral process thus takes the same form as the physical process which is exactly what our Proposition 3 in Section 3 shows.

4.4 Conditionally Poisson-normal jumps

Another interesting model that can be easily nested in our framework is the heteroskedastic model with Poisson-normal innovations in Duan, Ritchken and Sun (2005).¹¹ For expositional simplicity, we consider the simplest version of the model. More complex models, for instance with time-varying Poisson intensities, can also be accommodated. We can write the underlying asset return as

$$R_t = \kappa_t + \varepsilon_t$$

The zero-mean innovation ε_t equals

$$\varepsilon_t = \sigma_t (J_t - \lambda \bar{\mu})$$

where J_t is a Poisson jump process with N_t jumps each with distribution $N(\bar{\mu}, \bar{\gamma}^2)$ and jump intensity λ . The conditional return variance equals $(1 + \lambda(\bar{\mu}^2 + \bar{\gamma}^2)) \sigma_t^2$, where σ_t^2 is of the GARCH

¹¹Maheu and McCurdy (2004) consider a different discrete-time jump model.

form. The log return mean κ_t is a function of σ_t^2 as well as the jump and risk premium parameters.

We can derive the conditional log MGF of ε_t as

$$\begin{aligned}\Psi_t(u) &= \ln(E_{t-1}[\exp(-u\sigma_t(J_t - \lambda\bar{\mu}))]) \\ &= u\lambda\bar{\mu}\sigma_t + \frac{1}{2}u^2\sigma_t^2 + \lambda \left[e^{(-\bar{\mu}u\sigma_t + \frac{1}{2}\bar{\gamma}^2 u^2 \sigma_t^2)} - 1 \right]\end{aligned}$$

The approach taken in Duan et al (2005) corresponds to fixing $\nu_t = \nu$ and setting

$$\kappa_t = r + \Psi_t(\nu) - \Psi_t(\nu - 1)$$

which in turn implies that the EMM is given by

$$\frac{dQ}{dP} \Big|_{F_t} = \exp \left(-\nu t \bar{\varepsilon}_t - \nu \lambda \bar{\mu} t \bar{\sigma}_t - \frac{1}{2} t \nu^2 \bar{\sigma}_t^2 + \lambda t - \lambda \sum_{i=1}^t e^{(-\bar{\mu} \nu_i \sigma_i + \frac{1}{2} \bar{\gamma}^2 \nu_i^2 \sigma_i^2)} \right)$$

where $\bar{\varepsilon}_t$ and $\bar{\sigma}_t^2$ are the historical averages as above.

We can again show that the risk-neutral distribution of the risk neutral innovation is from the same family as the physical

$$\begin{aligned}\Psi_t^{Q^*}(u) &= \ln E_{t-1}^Q[\exp(-u\varepsilon_t^*)] \\ &= u\lambda_t^* \bar{\mu}_t^* \sigma_t + \frac{1}{2}u^2\sigma_t^2 + \lambda_t^* \left[e^{(-\bar{\mu}_t^* u \sigma_t + \frac{1}{2}\bar{\gamma}^2 u^2 \sigma_t^2)} - 1 \right]\end{aligned}$$

where

$$\lambda_t^* = \lambda \exp \left(-\bar{\mu} \nu \sigma_t + \frac{1}{2} \bar{\gamma}^2 \nu^2 \sigma_t^2 \right) \text{ and } \bar{\mu}_t^* = \bar{\mu} - \bar{\gamma}^2 \sigma_t \nu$$

4.5 Conditionally skewed variance gamma returns

We now introduce a new model where the conditional skewness, s , and excess kurtosis, k , are given directly by two parameters in the model.¹² Consider the return of the underlying asset specified as follows

$$\begin{aligned}R_t &= \mu_t - \gamma_t + \varepsilon_t \\ &= \mu_t - \gamma_t + \sigma_t z_t, \quad z_t \stackrel{i.i.d}{\sim} SVG(0, 1, s, k)\end{aligned}$$

¹²In Christoffersen, Heston and Jacobs (2006), conditional skewness and kurtosis are driven by functions of the same parameter.

The distribution of the shocks, $SVG(0, 1, s, k)$, is a standardized skewed variance gamma distribution which is constructed as a mixture of two gamma variables.¹³ The conditional variance, σ_t^2 , can take on any GARCH specification. We will provide an empirical illustration in the next section using a leading GARCH dynamic.

Let z_1 and z_2 be independent draws from two gamma distributions

$$z_{i,t} \stackrel{i.i.d.}{\sim} \Gamma(4/\tau_i^2), \quad i = 1, 2$$

parameterized as

$$\tau_1 = \sqrt{2} \left(s - \sqrt{\frac{2}{3}k - s^2} \right) \text{ and } \tau_2 = \sqrt{2} \left(s + \sqrt{\frac{2}{3}k - s^2} \right)$$

If we construct the SVG random variable from the two gamma variables as

$$z_t = \frac{1}{2\sqrt{2}} (\tau_1 z_{1,t} + \tau_2 z_{2,t}) - \sqrt{2} \left(\frac{1}{\tau_1} + \frac{1}{\tau_2} \right)$$

then z_t will have a mean of zero, a variance of one, a skewness of s , and an excess kurtosis of k , thus allowing for conditional skewness and kurtosis in the GARCH model as intended.¹⁴

The log moment generating function of ε_t can be derived from the gamma distribution MGF as

$$\Psi_t(u) = \sqrt{2} (\tau_1^{-1} + \tau_2^{-1}) u \sigma_t - 4\tau_1^{-2} \ln \left(1 + \frac{1}{2\sqrt{2}} \tau_1 u \sigma_t \right) - 4\tau_2^{-2} \ln \left(1 + \frac{1}{2\sqrt{2}} \tau_2 u \sigma_t \right)$$

so that the mean correction variable, γ_t , for the return can be found as $\gamma_t = \Psi_t(-1)$.

Using the formula for the risk neutral conditional log MGF

$$\Psi_t^{Q^*}(u) = -u \Psi_t'(\nu_t) + \Psi_t(\nu_t + u) - \Psi_t(\nu_t)$$

we can show that the risk neutral model is

$$R_t = r_f - \gamma_t^* + \varepsilon_t^* \tag{4.1}$$

¹³See Madan and Seneta (1990) for an early application of the symmetric and i.i.d. variance gamma distribution in finance.

¹⁴The special cases where τ_1 or τ_2 are zero can be handled easily by drawing from the normal distribution for the relevant mixing variable $z_{1,t}$ or $z_{2,t}$. When both τ_1 and τ_2 are zero then the normal distribution obtains for z_t .

where

$$\Psi_t^{Q^*}(u) = \sqrt{2} (\tau_1^{-1} \sigma_{1,t}^* + \tau_2^{-1} \sigma_{2,t}^*) u - 4\tau_1^{-2} \ln \left(1 + \frac{1}{2\sqrt{2}} \tau_1 \sigma_{1,t}^* u \right) - 4\tau_2^{-2} \ln \left(1 + \frac{1}{2\sqrt{2}} \tau_2 \sigma_{2,t}^* u \right)$$

with

$$\sigma_{i,t}^* = \frac{\sigma_t}{\sqrt{2} + \frac{1}{2} \tau_i \sigma_t \nu_t}, \quad \text{for } i = 1, 2. \quad (4.2)$$

We see that $\Psi_t^{Q^*}(u)$ is exactly of the same form as $\Psi_t(u)$, and therefore that $\gamma_t^* = \Psi_t^{Q^*}(-1)$. This model will be investigated empirically in the next section.

5 Empirical illustration

In this section we demonstrate how the greater flexibility and generality allowed for by our approach can lead to more realistic option valuation models. To do so, we analyze the GARCH-SVG model in Section 4.5, which allows for conditional skewness and kurtosis, and which has not yet been analyzed in the literature. We compare its empirical implications with the more standard conditional normal model of Section 4.1. We compute option prices from both models using parameters estimated from return data, and subsequently construct option implied volatility smiles. We also compare the two heteroskedastic models to two benchmark models with independent returns.

5.1 Parameter estimates from index returns and stylized facts

We start by illustrating some key stylized facts of daily equity index returns using the S&P500 as a running example.

Figure 1 shows a normal quantile-quantile plot (QQ plot) of daily S&P500 returns, using data from January 2, 1980 through December 30, 2005 for a total of 6,564 observations. The returns are standardized by the sample mean and standard deviation. The data quantiles on the vertical axis are plotted against the normal distribution quantiles on the horizontal axis. The plot reveals the well-known stark deviations from normality in daily asset returns: actual returns include much more extreme observations than the normal distribution allows for in a sample of this size. The largest negative return is the famous 20 standard deviation crash in October 1987, but the normal distribution has trouble fitting a large number of extremes in both tails of the return distribution. The actual returns range from -20 to +9 standard deviations but the normal distribution only ranges from -4 to +4 standard deviations in a sample of this size.

Figure 2 shows the sample autocorrelation function of the squared daily returns for the sample. The significantly positive correlations at short lags suggest the need for a dynamic

volatility model allowing for clustering in volatility.

Figures 1 and 2 clearly suggest the need for a GARCH model which can capture potentially both the volatility clustering in Figure 2 and the non-normality in Figure 1.

As a benchmark, we use the conditional normal NGARCH model of Engle and Ng (1993)

$$R_t = \mu_t - \gamma_t + \sigma_t z_t, \quad z_t \stackrel{i.i.d}{\sim} N(0, 1) \quad (5.1)$$

where

$$\begin{aligned} \mu_t &= r_t + \lambda \sigma_t \\ \gamma_t &= \frac{1}{2} \sigma_t^2 \\ \sigma_t^2 &= \beta_0 + \beta_1 \sigma_{t-1}^2 + \beta_2 \sigma_{t-1}^2 (z_{t-1} - \beta_3)^2 \end{aligned}$$

Notice that the β_3 parameter in the GARCH variance specification allows for an asymmetric variance response to positive versus negative shocks, z_{t-1} . This captures the so-called leverage effect, which is another important empirical regularity in daily equity index returns.

Table 1 reports the maximum likelihood estimates of the GARCH parameters. We also report parameter estimates for a version of the model where the GARCH dynamics have been shut down, that is, where $\beta_1 = \beta_2 = \beta_3 = 0$. Notice the large increase in the Log-likelihood function from including the GARCH dynamics.

Figure 3 shows the autocorrelation function for the observed squared GARCH shocks, z_t^2 . If the GARCH model has adequately captured the volatility clustering then the shocks should be independent and in particular the squared shocks should be uncorrelated. Figure 3 suggests that the GARCH model does a good job of capturing the volatility dynamics in the daily index returns.

Figure 4 assesses the conditional normality assumption by plotting a QQ plot of z_t against the normal distribution. It is clear from Figure 4 that much of the non-normality in the raw returns has been removed by the GARCH model. This is particularly true for the right tail, where the non-normality was least pronounced to begin with. Unfortunately, the left tail of the shock distribution still exhibits strong evidence of non-normality with negative shocks as large as -10 standard deviations compared with the normal distribution's -4.

From Figures 3 and 4, we conclude that while the normal GARCH model appears to provide adequate dynamics for capturing volatility clustering, the conditional normality assumption is violated in the data and must be modified in the model.

For the implementation of the GARCH-SVG model, μ_t and σ_t^2 are the same as in the conditional normal model in (5.1). We can calibrate the s and k parameters in the GARCH-SVG

model from Section 4.5 by simply equating them to the sample moments from the z_t sequence from the QMLE estimation of the GARCH model. These sample moments are reported in Table 1.

Figure 5 shows the QQ plot of the GARCH shocks against the SVG distribution. Compared with the normal QQ plot in Figure 4, we see that the SVG captures the left tail of the shock distribution much better than the normal does. Impressively, the SVG model only has trouble fitting the two most extreme negative shocks, whereas the normal distribution misses a whole string of large negative shocks.

5.2 Option prices and implied volatilities

Armed with estimated return processes we are ready to assess the option pricing implications of the different models. From Section 2.3 we have the general option price relationship which for a European call option with strike price K is

$$C_t(T, K) = E_t^Q \left[\text{Max}(S_T - K, 0) \frac{B_t}{B_T} \right]$$

Using the estimated physical process from Section 4 we can now simulate future paths for S_T from the current S_t and compute the option price as the simulated sample analogue to this discounted expectation.

We present evidence on the option pricing properties of the various models in Figures 6 and 7. Figure 6 considers an i.i.d. normal and an i.i.d. SVG model where the GARCH dynamics have been shut down ($\beta_1 = \beta_2 = \beta_3 = 0$), and s and k have been set to the the sample skewness and kurtosis from the raw returns which are reported in Table 1. Figure 7 considers the normal GARCH-Normal and GARCH-SVG models. The parameter estimates used are again from Table 1.

We first compute option prices for various moneyness and maturities and we then compute implied Black and Scholes (1973) volatilities from the model option prices. Implied volatilities are plotted against moneyness on the horizontal axis. The three panels correspond to maturities of 1 day, 1 week, and 1 month respectively.

The i.i.d. SVG model in Figure 6 (solid lines) shows a strong implied volatility “smile” for the 1-day maturity driven by the large excess kurtosis of 27.33 from Table 1. Interestingly, as the maturity increases the smile becomes an asymmetric “smirk” driven by the skewness parameter of -1.21 in Table 1. The i.i.d. normal model in Figure 6 (dashed line) results in a flat implied volatility curve.

The GARCH-SVG model in Figure 7 shows a smirk at the 1 day maturity compared with the

flat implied volatility for the GARCH-Normal model where the conditional 1 day distribution is normal. The GARCH-Normal model generates a non-trivial volatility smirk for horizons beyond 1 day where the conditional distribution is no longer normal. However, the GARCH-SVG model is capable of capturing much more non-normality than the GARCH-Normal model at all horizons. This is important because the empirical option valuation literature often finds that existing models are unable to fit short term option prices where the implied degree of non-normality is large.¹⁵

From this empirical illustration we conclude that it is possible to build relatively simple models capturing the conditional volatility and non-normality found in index returns data, and more importantly that such models provide the flexibility needed to price options.

6 Relationship with the existing literature

Our results are intimately related to the theoretical and empirical literature on GARCH option valuation, which in turn builds on the discrete-time option valuation results of Brennan (1979) and Rubinstein (1976). The aim of this literature is to obtain a risk-neutral valuation relationship, but these papers typically obtain such relationship by characterizing conditions on preferences needed to obtain risk-neutral valuation. For example, Brennan (1979) characterizes the bivariate distribution of returns on aggregate wealth and the underlying asset under which a risk-neutral valuation relationship obtains in the homoskedastic case. Duan (1995) extends this framework to the case of heteroskedasticity of the underlying asset return. Amin and Ng (1993) also study the heteroskedastic case. Although they formulate the problem in terms of the economy's stochastic discount factor, they start by making an assumption on the bivariate distribution of the stochastic discount factor and the underlying return process.

There is also a growing literature that values options for discrete-time return dynamics with non-normal innovations. A number of other papers obtain risk-neutral valuation relationships either under the maintained assumption of non-normal innovations, or under the maintained assumption of heteroskedasticity, or both. Madan and Seneta (1990) use the symmetric and i.i.d. variance gamma distribution. Heston (1993b) presents results for the gamma distribution and Heston (2004) analyzes a number of infinitely divisible distributions. Camara (2003) uses a transformed normal innovation and Duan (1999) uses a heteroskedastic model with a transformed normal innovation. Christoffersen, Heston and Jacobs (2006) analyze a heteroskedastic return process with inverse Gaussian innovations.

Our paper differs in a subtle but important way from most of the studies that use heteroskedastic processes, in the sense that we do not attempt to characterize the bivariate distribu-

¹⁵See Bates (2003) for an excellent discussion of this and other stylized facts in option markets.

tion of preferences and returns that gives rise to the risk-neutral valuation relationship. Strictly speaking, the only assumption we make is on the return dynamic. Establishing the equivalent martingale measure that makes the discounted stock price process a martingale does not amount to an additional assumption. It is simply a mathematical manipulation required to obtain the benefits of risk-neutral valuation. All assumptions needed for risk-neutral valuation are given by the specification of the return dynamic, or, in other words, the assumptions on the equilibrium supporting the valuation problems are implicitly incorporated in the risk premium assumption for the return dynamic. The specification of the price of risk may be—but does not need to be—explicitly motivated by a utility-based argument.

To motivate our approach, consider the available literature on option valuation in continuous time, and in particular option valuation with continuous-time stochastic volatility models, such as the one in Heston (1993a). It is well-known (see e.g. Karatzas and Shreve (1998)) that in this case there are different equivalent martingale measures for different specifications of the volatility risk premium. However, for a given specification of the volatility risk premium, we can find an EMM and characterize the risk-neutral dynamic using Girsanov’s theorem. To perform this manipulation, and to value options, there is no need to characterize the utility function underlying the volatility risk premium. Characterizing the utility function that generates a particular volatility risk premium is a very interesting question in its own right, but differs from characterizing the risk-neutral dynamic and the option value for a given physical return dynamic.¹⁶ The latter is a purely mathematical exercise. The former provides the economic background behind a particular choice of volatility premium, and therefore helps us understand whether a particular choice of functional form for the risk premium, which is often made for convenience, is also reasonable from an economic perspective.

In the same sense, our paper should be interpreted as providing a set of tools that can be used to value options for a large class of discrete-time return dynamics that are characterized by heteroskedasticity and non-normal innovations. Whether this valuation exercise makes sense from an economic perspective depends on the nature of the assumed risk premium, and the general equilibrium setup that gives rise to such risk premium. There are two questions: a mostly technical one that characterizes the risk-neutral dynamic and the valuation of options, and a more economic one that characterizes the equilibrium underlying this valuation procedure. In our opinion, the existing discrete-time literature for the most part has viewed these two questions as inextricably linked, and has therefore largely limited itself to (log)normal return processes. We argue that it is possible and desirable to treat these questions one at a time, and we provide new results on the question of option valuation with conditionally non-normal returns.

¹⁶See Bollerslev, Gibbons and Zhou (2005) for a recent treatment.

There are many other papers that are in some way related to our contribution. First and foremost, we emphasize that we do not claim to be the first to analyze no-arbitrage pricing in discrete-time models. There is a rich tradition of discrete-time finite state space modeling in discrete time, going back to Harrison and Kreps (1979), Cox, Ross and Rubinstein (1979) and Cox and Ross (1976). However, the infinite state space, conditionally non-normal return dynamics we analyze are arguably the most empirically relevant descriptions of return data available,¹⁷ and the option valuation literature that uses GARCH processes has hitherto focused on equilibrium arguments. Because of this, the available valuation results in this literature are quite limited, and our paper shows that we can obtain additional results by using a simple no-arbitrage approach. Second, it is likely that our risk neutralizations can equivalently be derived using the specification of a candidate stochastic discount factor, rather than through our approach which starts with the specification of a Radon-Nikodym derivative and derives the EMM.¹⁸ However, in most applications that we are aware of, existing work actually starts out by assuming a bivariate distribution for the stochastic discount factor and the stock return (see for example Amin and Ng (1993)).¹⁹ This assumption clearly goes beyond the existence of no-arbitrage and is closer in spirit to the general equilibrium setup of Duan (1995) and Brennan (1979). See Garcia, Ghysels and Renault (2006) for a discussion on how some of these assumed joint distributions effectively amount to degenerate distributions. Our approach is also related to the risk-neutral valuation argument used in Heston (1993b, 2004) and Christoffersen, Heston and Jacobs (2006), but in our opinion our approach is more transparent. Duan, Ritchken and Sun (2005) use a risk neutralization for a Poisson-normal heteroskedastic model that has some similarities with our approach. However, they do not apply their principle to the investigation of more general return dynamics.

Finally, at an empirical level, combining non-normality with heteroskedasticity attempts to correct the biases associated with the conditionally normal GARCH model. These biases are similar to those displayed by the Heston (1993) model, which the continuous-time literature has sought to remedy by adding (potentially correlated) jumps in returns and volatility. This paper is therefore also related to empirical studies of jump models. See for example Bakshi, Cao and Chen (1997), Bates (2000), Broadie, Chernov and Johannes (2006), Carr and Wu (2004), Eraker, Johannes and Polson (2003), Eraker (2004), Huang and Wu (2004) and Pan (2002).

¹⁷The empirical evidence suggesting GARCH type processes is strong. See Bollerslev, Chou and Kroner (1992) and Diebold and Lopez (1995) for overviews.

¹⁸See for example Hansen and Richard (1987) for a characterization of risk neutralization using the stochastic discount factor.

¹⁹See Gouriéroux and Montfort (2006) for a notable exception.

7 Conclusion

This paper provides valuation results for contingent claims in a discrete time infinite state space setup. Our valuation argument applies to a large class of conditionally normal and non-normal stock returns with flexible time-varying mean and volatility, as well as a potentially time-varying price of risk, provided that these moments are predetermined one period ahead. Our setup generalizes the result in Duan (1995) in the sense that we do not restrict the returns to be conditionally normal, nor do we restrict the price of risk to be constant. Our results apply to some of the most widely used discrete time processes in finance, such as GARCH processes. For the class of processes we analyze in this paper, the risk neutral return dynamic is the same as the physical dynamic, but with a different parameterization which we characterize.

To demonstrate the empirical relevance of our approach, we provide an empirical analysis of a heteroskedastic return dynamic with a standardized skewed variance gamma distribution, which is constructed as the mixture of two gamma variables. In the resulting dynamic, conditional skewness and kurtosis are directly governed by two distinct parameters. We estimated the model on return data using quasi maximum likelihood and compare its performance with the heteroskedastic conditional normal model which is standard in the literature. Diagnostics clearly indicate that the conditionally nonnormal model outperforms the conditionally normal model, and an analysis of the option smirk demonstrates that this model provides substantially more flexibility to value options.

We leave a couple of important issues unaddressed. First, while we obtain a unique EMM given the choice of Radon-Nikodym derivative, we cannot exclude that even for a given specification of the risk premium, there exist other EMMs corresponding to different functional forms of the Radon-Nikodym derivative. Second, while we advocate separating the valuation issue and the general equilibrium setup that supports it, the general equilibrium foundations of our results are of course very important. It may prove possible to characterize the equilibrium setup that gives rise to the risk neutralization proposed for some of the processes considered in this paper, such as the empirically interesting dynamics considered in Section 5. However, this is by no means a trivial problem, and it is left for future work.

8 Appendix

Proof of Lemma 2. For a self financing strategy we have

$$\begin{aligned} G_{t+1} &= V_{t+1} = \eta_t S_{t+1} + \delta_t C_{t+1} + \psi_t B_{t+1} \\ &= \eta_{t+1} S_{t+1} + \delta_{t+1} C_{t+1} + \psi_{t+1} B_{t+1} \end{aligned}$$

We also have

$$G_t = \sum_{i=0}^{t-1} \eta_i (S_{i+1} - S_i) + \sum_{i=0}^{t-1} \delta_i (C_{i+1} - C_i) + \sum_{i=0}^{t-1} \psi_i (B_{i+1} - B_i).$$

It follows that

$$G_{t+1} - G_t = \eta_t (S_{t+1} - S_t) + \delta_t (C_{t+1} - C_t) + \psi_t (B_{t+1} - B_t)$$

We can trivially also write

$$G_{t+1}^B - G_t^B = G_{t+1}^B - G_t^B + \underbrace{\left(\frac{G_{t+1}}{B_t} - \frac{G_{t+1}}{B_t} \right)}_{=0}$$

This implies that

$$\begin{aligned} G_{t+1}^B - G_t^B &= (\eta_t S_{t+1} + \delta_t C_{t+1} + \psi_t B_{t+1}) \left(\frac{1}{B_{t+1}} - \frac{1}{B_t} \right) \\ &\quad + \frac{1}{B_t} (\eta_t (S_{t+1} - S_t) + \delta_t (C_{t+1} - C_t) + \psi_t (B_{t+1} - B_t)). \\ &= \eta_t \left[S_{t+1} \left(\frac{1}{B_{t+1}} - \frac{1}{B_t} \right) + \frac{1}{B_t} (S_{t+1} - S_t) \right] \\ &\quad + \delta_t \left[C_{t+1} \left(\frac{1}{B_{t+1}} - \frac{1}{B_t} \right) + \frac{1}{B_t} (C_{t+1} - C_t) \right] \\ &\quad + \underbrace{\psi_t B_{t+1} \left(\frac{1}{B_{t+1}} - \frac{1}{B_t} \right) + \frac{1}{B_t} \psi_t (B_{t+1} - B_t)}_{=0} \end{aligned}$$

Then

$$G_{t+1}^B - G_t^B = \eta_t \left[S_{t+1} \left(\frac{1}{B_{t+1}} - \frac{1}{B_t} \right) + \frac{1}{B_t} (S_{t+1} - S_t) \right] + \delta_t \left[C_{t+1} \left(\frac{1}{B_{t+1}} - \frac{1}{B_t} \right) + \frac{1}{B_t} (C_{t+1} - C_t) \right]$$

$$= \eta_t(S_{t+1}^B - S_t^B) + \delta_t(C_{t+1}^B - C_t^B) + \left(\eta_t \frac{S_{t+1}}{B_t} - \eta_t \frac{S_{t+1}}{B_t} \right) + \left(\delta_t \frac{C_{t+1}}{B_t} - \delta_t \frac{C_{t+1}}{B_t} \right)$$

and therefore

$$G_{t+1}^B - G_t^B = \eta_t(S_{t+1}^B - S_t^B) + \delta_t(C_{t+1}^B - C_t^B). \quad \forall t = 1, \dots, T-1$$

Because $G_0 = G_0^B = 0$ the discounted gain can be written as the sum of past changes

$$G_t^B = \sum_{i=0}^{t-1} (G_{i+1}^B - G_i^B) \quad \forall t = 1, \dots, T.$$

Therefore the discounted gain can be written

$$G_t^B = \sum_{i=0}^{t-1} \eta_i(S_{i+1}^B - S_i^B) + \sum_{i=0}^{t-1} \delta_i(C_{i+1}^B - C_i^B)$$

and the proof is complete.

Proof of Proposition 3. From Lukacs (1970), page 119, we have the Kolmogorov canonical representation of the log-moment generating function of an infinitely divisible distribution function. This result stipulates that a function Ψ is the log-moment generating function of an infinitely divisible distribution with finite second moment if, and only if, it can be written in the form

$$\Psi(u) = -uc + \int_{-\infty}^{+\infty} (e^{-ux} - 1 + ux) \frac{dK(x)}{x^2}$$

where c is a real constant while $K(u)$ is a nondecreasing and bounded function such that $K(-\infty) = 0$. Applying this theorem gives the following form for $\Psi_t(u)$,

$$\Psi_t(u) = -uc_{t-1} + \int_{-\infty}^{+\infty} (e^{-ux} - 1 + ux) \frac{dK_{t-1}(x)}{x^2} \quad (8.1)$$

where c_{t-1} is a random variable known at $t-1$, and $K_{t-1}(x)$ is a function known at $t-1$, which is nondecreasing and bounded so that $K_{t-1}(-\infty) = 0$. Using relation (3.1) and the characterisation (8.1) we can write $\Psi_t^{Q^*}(u)$ as

$$\Psi_t^{Q^*}(u) = \int_{-\infty}^{+\infty} (e^{-ux} - 1 + ux) \frac{dK_{t-1}^*(x)}{x^2}$$

where

$$K_{t-1}^*(x) = \int_{-\infty}^x e^{-\nu_{t-1}y} dK_{t-1}(y)$$

This implies that

$$K_{t-1}^*(-\infty) = 0$$

$K_{t-1}^*(x)$ is obviously non-decreasing since $K_{t-1}(x)$ is non-decreasing, $K_{t-1}^*(\infty) < \infty$, because $K_{t-1}(\infty) < \infty$, and $e^{-\nu_t y}$ is a decreasing function of y which converge to 0. Recall that ν_t is the price of risk, which is positive and known at time $t - 1$.

In conclusion we have constructed a constant c_{t-1}^* ($= 0$) and a non-decreasing bounded function $K_{t-1}^*(x)$, with $K_{t-1}^*(-\infty) = 0$, such that

$$\Psi_t^{Q^*}(u) = -uc_{t-1}^* + \int_{-\infty}^{+\infty} (e^{-ux} - 1 + ux) \frac{dK_{t-1}^*(x)}{x^2}.$$

Hence, according to the Kolmogorov canonical representation, the conditional distribution of ε_t^* is infinitely divisible.

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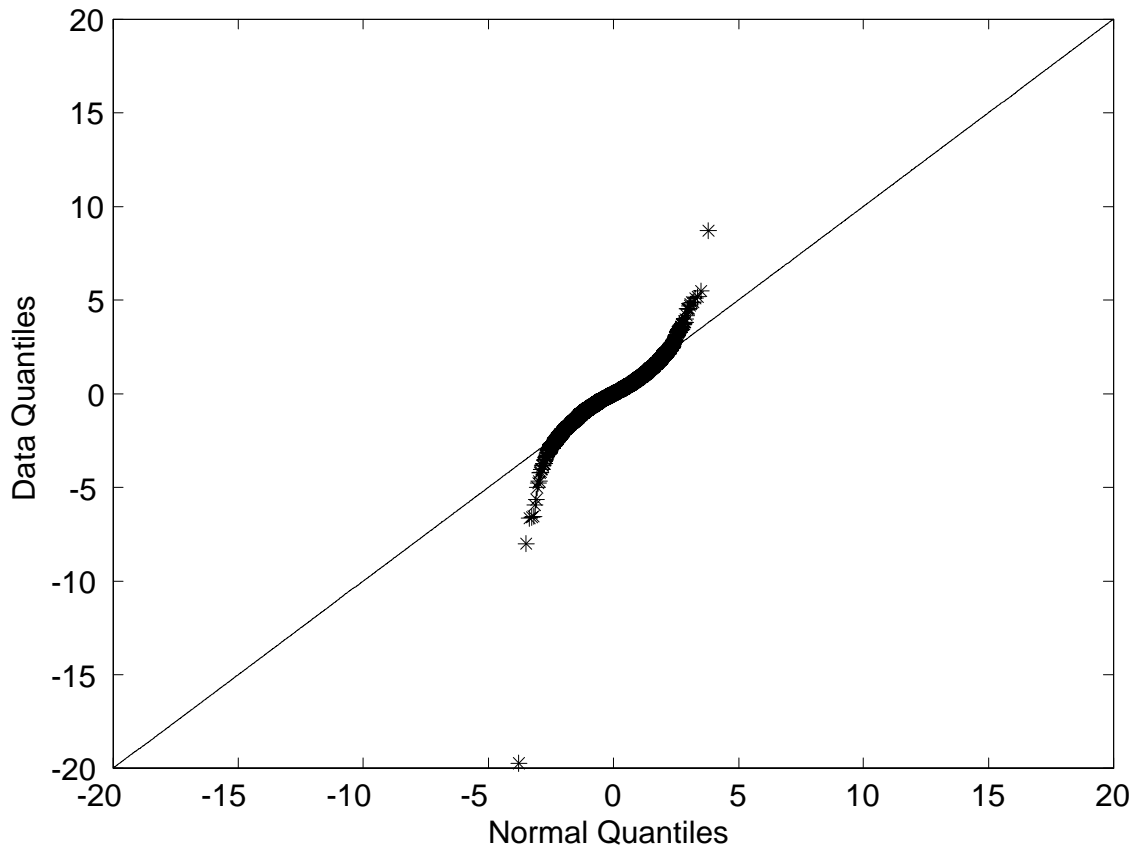
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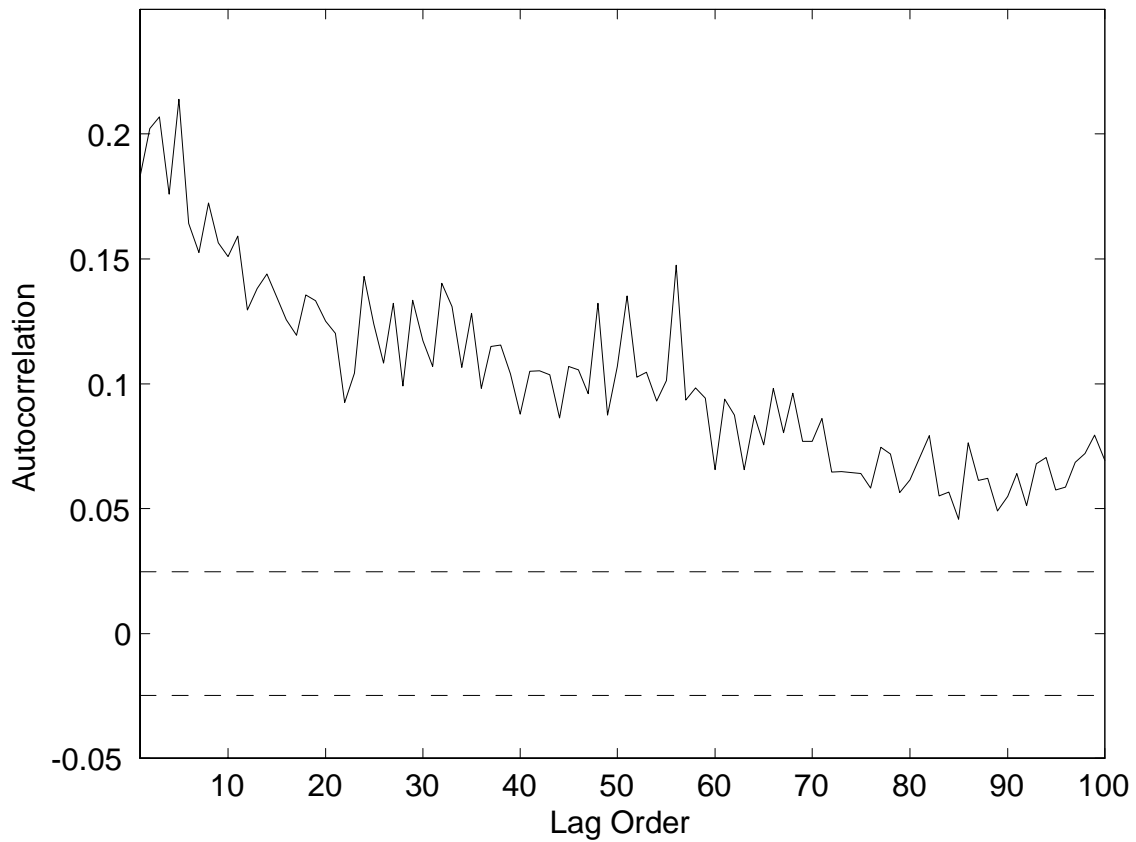
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Figure 1: Quantile-Quantile Plot of S&P500 Returns Against the Normal Distribution



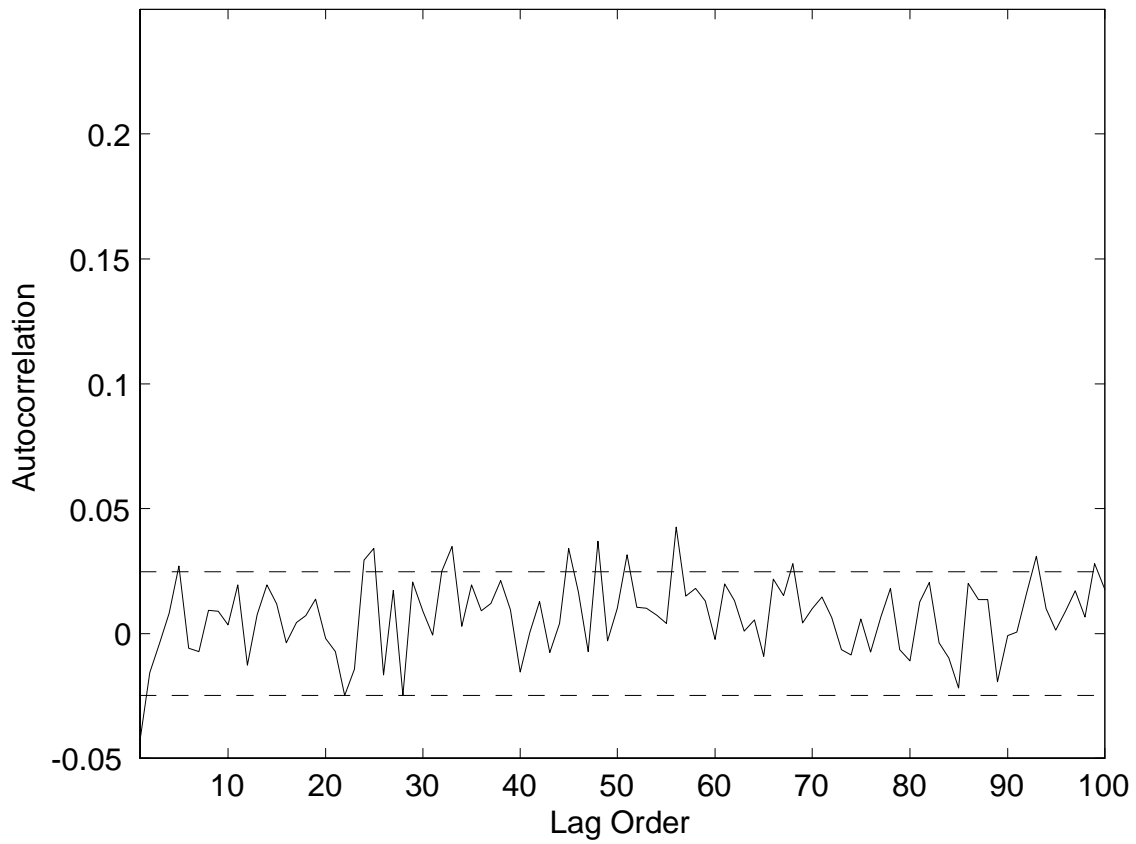
Notes to Figure: We take daily returns on the S&P500 from January 2, 1980 to December 30, 2005 and standardize them by the sample mean and sample standard deviation. The quantiles of the standardized returns are plotted against the quantiles from the standard normal distribution.

Figure 2: Autocorrelation Function of Absolute S&P500 Returns



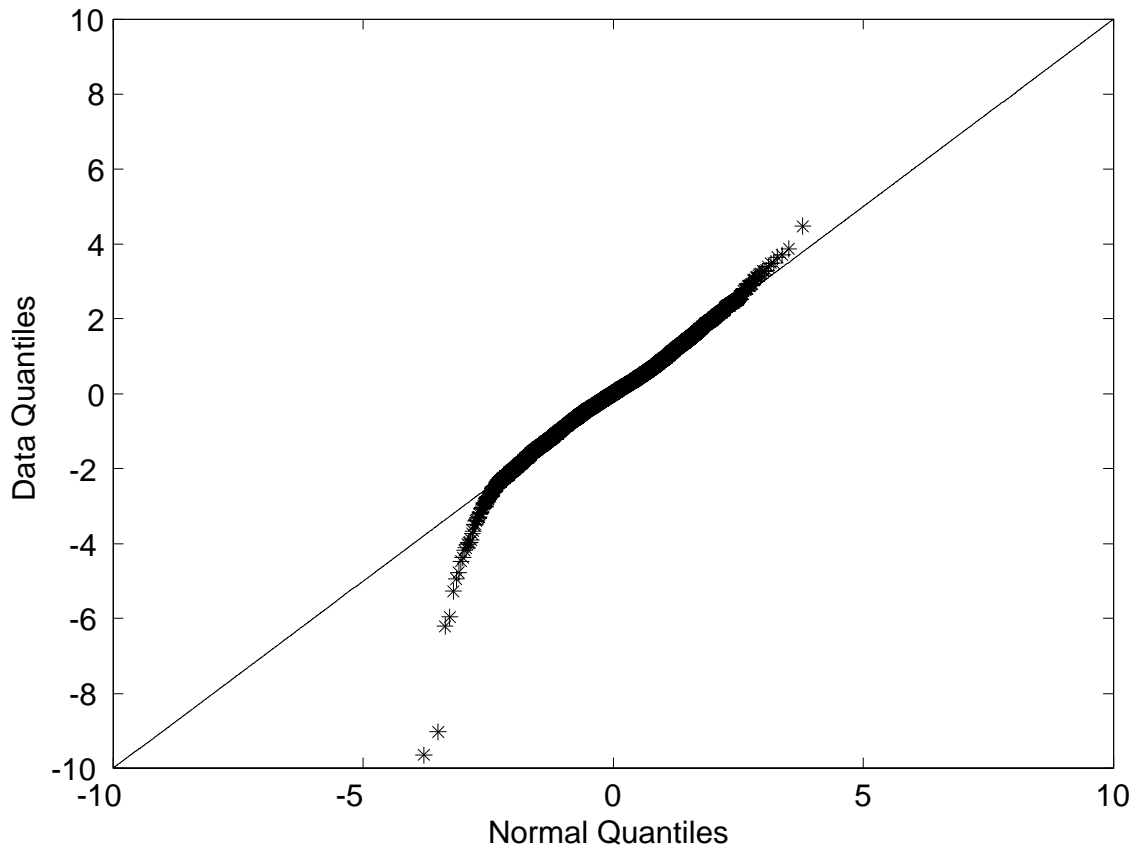
Notes to Figure: From daily absolute returns on the S&P500 from January 2, 1980 to December 30, 2005 we compute and plot the sample autocorrelations for lags one through 100 days. The horizontal dashed lines denote 95% Bartlett confidence intervals around zero.

Figure 3: Autocorrelation Function of Absolute GARCH Innovations



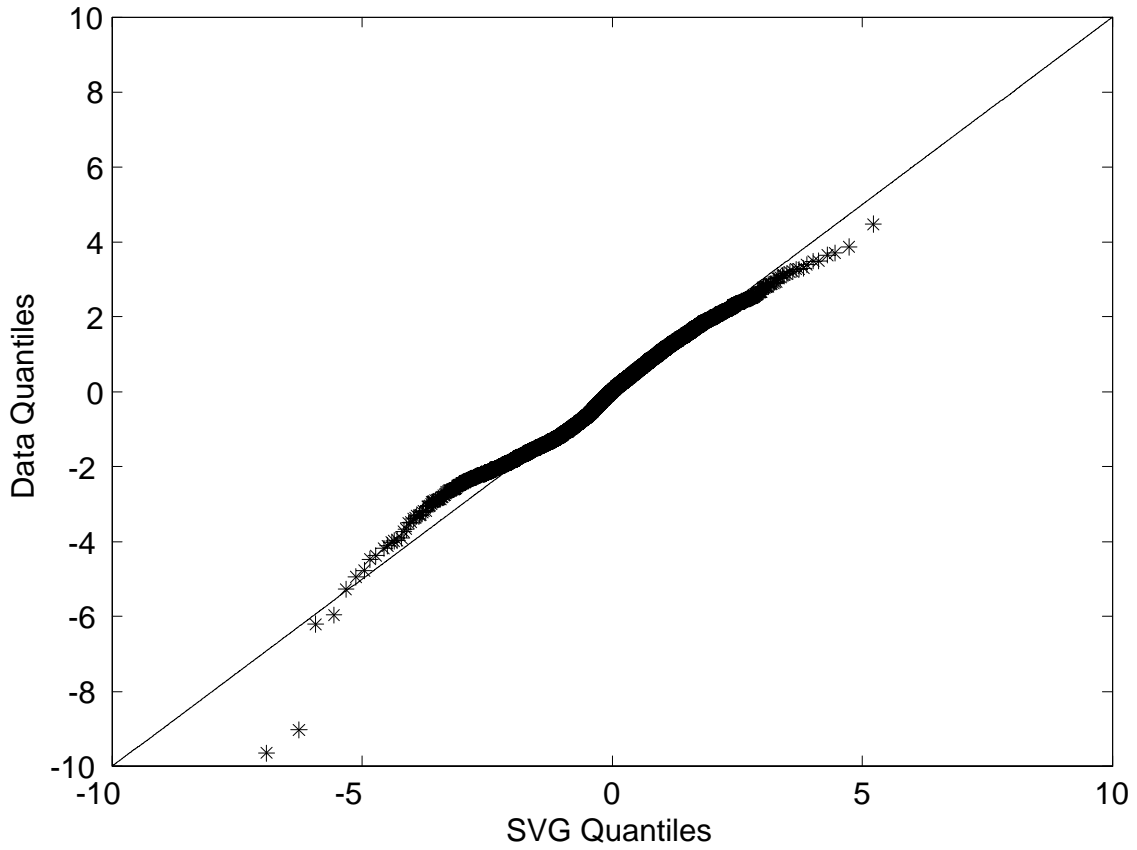
Notes to Figure: From the estimated GARCH model in Table 1 we construct the absolute standardized sequence of shocks and plot the sample autocorrelations for lags one through 100 days. The horizontal dashed lines denote 95% Bartlett confidence intervals around zero.

Figure 4: Quantile-Quantile Plots of GARCH Innovations Against the Normal Distribution



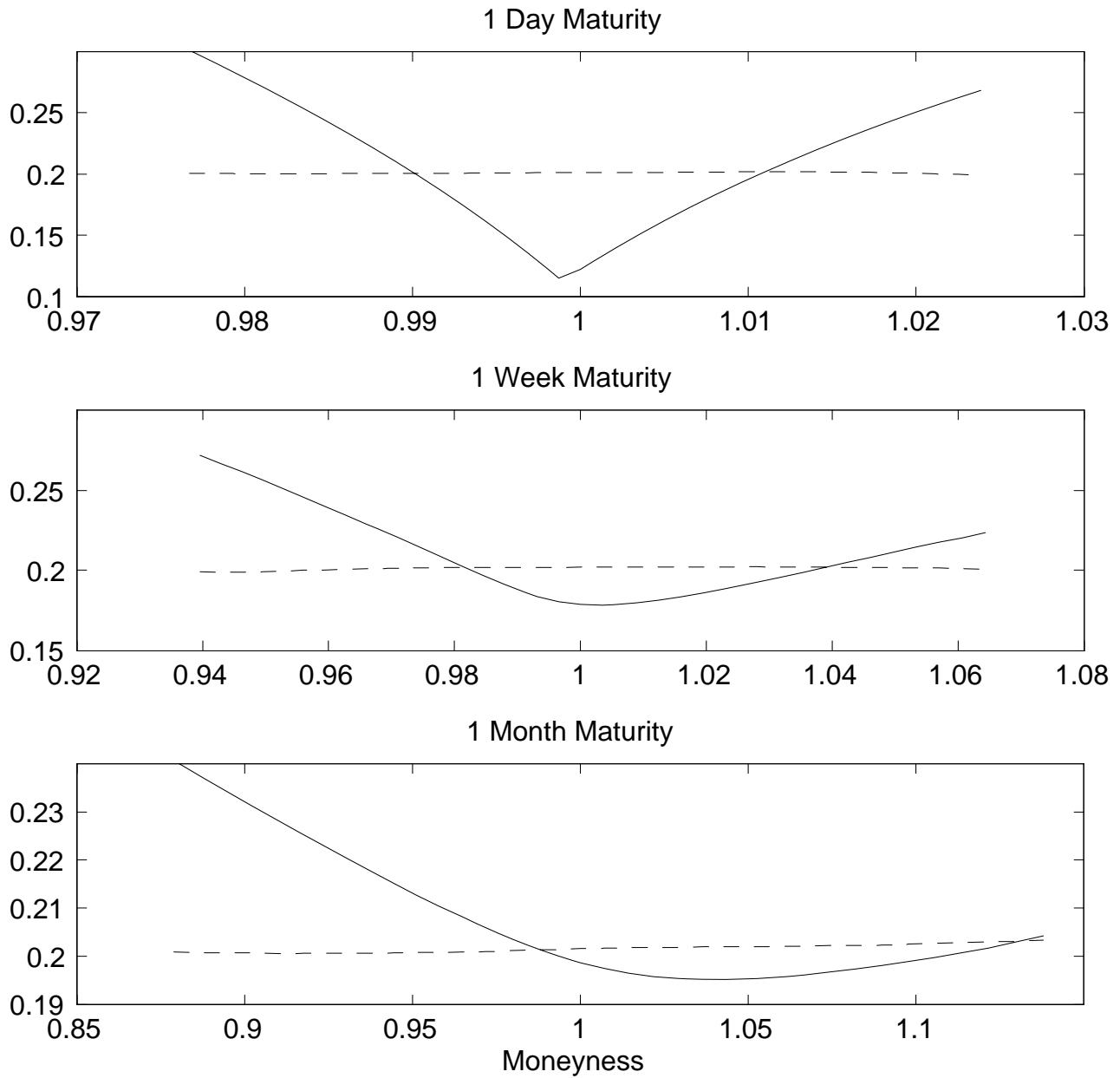
Notes to Figure: From the estimated GARCH models in Table 1 we compute the time series of dynamically standardized S&P500 returns. The quantiles of these GARCH innovations are plotted against the quantiles from the standard normal distribution.

Figure 5: Quantile-Quantile Plots of GARCH Innovations Against the SVG Distribution



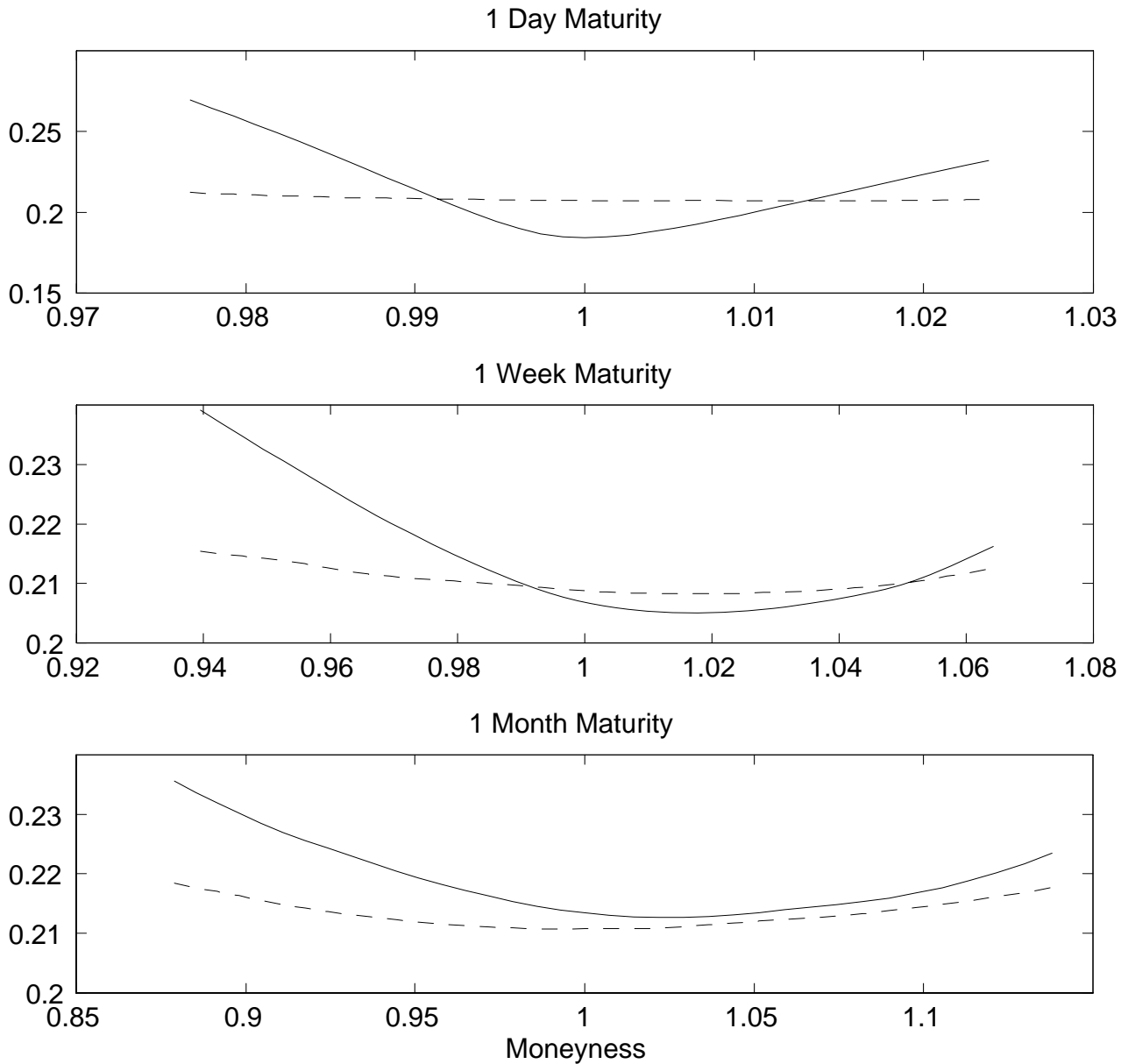
Notes to Figure: From the estimated GARCH models in Table 1 we compute the time series of dynamically standardized S&P500 returns. The quantiles of these GARCH innovations are plotted against the quantiles from the skewed variance gamma (SVG) distribution.

Figure 6: Implied Volatility Functions for Normal and SVG Independent Return Models



Notes to Figure: From the estimated independent return model in Table 1 we compute call option prices for various moneyness and maturities and we then compute implied Black-Scholes volatilities from the model option prices. Implied volatility is plotted against moneyness on the horizontal axis. The three panels correspond to maturities of 1 day, 1 week, and 1 month respectively. The solid lines show the i.i.d. SVG model and the dashed lines the i.i.d. Normal models.

Figure 7: Implied Volatility Functions for Normal and SVG GARCH Models



Notes to Figure: From the estimated GARCH model in Table 1 we compute call option prices for various moneyness and maturities and then we compute implied Black-Scholes volatilities from the model option prices. The implied volatilities are plotted with moneyness on the horizontal axis. The three panels correspond to maturities of 1 day, 1 week, and 1 month respectively. The solid lines show the SVG GARCH model and the dashed lines the Normal GARCH model.

Table 1: Parameter Estimates and Model Properties
 Daily S&P500 Returns. January 2, 1980 - December 30, 2005.

<u>Parameters</u>	Independent Returns		GARCH Returns	
	<u>Estimate</u>	<u>Standard Error</u>	<u>Estimate</u>	<u>Standard Error</u>
r	1.370E-04		1.370E-04	
λ	0.0313	0.0129	0.0312	0.0121
β_0	1.111E-04	9.9781E-06	1.516E-06	6.050E-07
β_1			0.8916	0.0274
β_2			0.0617	0.0154
β_3			0.7422	0.0808
<u>Properties</u>	Independent Returns		GARCH Returns	
Log-Likelihood	20,615.00		21,586.28	
Volatility Persistence	0		0.9873	
Annual Volatility	0.1673		0.1734	
Conditional Skewness	-1.2105		-0.4127	
Conditional Kurtosis	27.3304		3.4935	

Notes: We use quasi maximum likelihood to estimate an independent return and a GARCH return model on daily S&P500 returns from January 2, 1980 to December 30, 2005 for a total of 6,564 observations. We report various properties of the two models including conditional skewness and excess kurtosis which are later used as parameter estimates in the SVG models.