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What we can learn from pricing 139,879 Individual Stock Options

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Abstract

The GARCH framework has been used for option pricing with quite some success. While the initial work assumed conditional Gaussian innovations, recent contributions relax this assumption and allow for more flexible parametric specifications of the underlying distribution. However, until now the empirical applications have been limited to index options or options on only a few stocks and this using only few potential distributions and variance specifications. In this paper we test the GARCH framework on 30 stocks in the Dow Jones Industrial Average using two classical volatility specifications and 7 different underlying distributions. Our results provide clear support for using an asymmetric volatility specification together with non-Gaussian distribution, particularly of the Normal Inverse Gaussian type, and statistical tests show that this model is most frequently among the set of best performing models.

JEL Classification: C22, C53, G13

Keywords: American options, GARCH models, Model Confidence Set, Simulation.

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1 Introduction

Pricing options, especially those with early exercise features, in a realistic setting remains one of the most important challenges in finance. In particular, models which can accommodate time varying volatility and allow for non-Gaussian innovations are required and this complicates not only the actual pricing of the options but also the estimation of the necessary parameters. A framework that can accommodate these features while remaining simple to implement is that of the generalized autoregressive conditional heteroskedasticity, or GARCH, models of Engle (1982) and Bollerslev (1986). GARCH models offer a very flexible framework which constitutes an obvious extension to the constant volatility framework of Black & Scholes (1973) and Merton (1973). In terms of option pricing the added flexibility comes at a cost since with time varying volatility the market is no longer complete. However, in Duan (1995) a GARCH option pricing model is derived under the assumption of conditionally Gaussian innovations and under some familiar assumptions on investor preferences. The theoretical foundation for option pricing in a more general framework is provided in Duan (1999) which extends the Gaussian GARCH option pricing model to situations with conditional leptokurtic distributions. See also Christoffersen, Elkamhi, Feunou & Jacobs (2010) and Gourieroux & Monfort (2007) for alternative approaches to derive the appropriate option pricing model.

When the Gaussian GARCH models are compared to e.g. the constant volatility model smaller pricing errors are obtained empirically. In particular, this is found for European style options on the Standard & Poor's 500 Index in e.g. Bollerslev & Mikkelsen (1996), Bollerslev & Mikkelsen (1999), Heston & Nandi (2000), Christoffersen & Jacobs (2004), and Hsieh & Ritchken (2005). Another recent contribution is Christoffersen, Jacobs, Ornthanalai & Wang (2008) where the volatility is allowed to have both short run and long run components. Empirical applications of the non-Gaussian framework can be found in e.g. Christoffersen, Heston & Jacobs (2006) and Christoffersen, Dorion, Jacobs & Wang (2010). Although Christoffersen, Dorion, Jacobs & Wang (2010) find little improvement for the non-Gaussian models, Christoffersen et al. (2006) observe that allowing for non-Gaussian innovations is important when pricing out of the money put options on the Standard & Poor's 500 Index. In Rombouts & Stentoft (2010) mixture models, which are very flexible, are used for option pricing with very good results. In particular, the paper finds substantial improvements compared to several benchmark models for the Standard & Poor's 500 Index options. Finally, in addition to models with non-Gaussian innovations, GARCH models with jumps have been applied empirically by Christoffersen, Jacobs & Ornthanalai (2008) which shows that jumps are important empirically when pricing Standard & Poor's 500 Index options.[1]

However, while the GARCH framework has been used with success to price European style options like those on the Standard & Poor's 500 Index, most traded options are American style options. Hence, for a large scale test of the GARCH framework methods that can accommodate the potential early exercise are needed which further complicates the analysis as it entails determining the optimal early exercise strategy. The first methods which were proposed were the extended binomial model of Ritchken & Trevor (1999) and the Markov Chain approximation method of Duan & Simonato (2001), both of which can be used with the Gaussian GARCH model. However, though these models can accommodate the early exercise feature, the approaches are not very flexible. For example, it is not immediately clear how these approaches should be implemented for the generalized GARCH framework in which innovations are non-Gaussian. To provide a more flexible method, Stentoft (2005) suggests to use simulation methods together with the Least Squares Monte Carlo method Longstaff & Schwartz (2001) to price options in the Gaussian GARCH framework. The simulation method is used with non-Gaussian innovations in Stentoft (2008) and applied to price options on three individual stocks together with options on the Standard and Poor's 100 index using the generalized GARCH framework. The findings in the paper are encouraging although only four underlying assets are considered together with a limited number of underlying distributions.

[1] In addition to the mentioned applications to the Standard & Poor's 500 Index, GARCH models are found to perform well for European style options on the German DAX index in Härdle & Hafner (2000), on the Hang Seng Index in Duan & Zhang (2001), and on the FTSE 100 Index in Lehar, Scheicher & Schittenkopf (2002).

In the current paper we correct the main shortcoming of the existing literature on pricing of individual stock options; the fact that until now very few assets have been analyzed in a setting with time varying volatility and with underlying distributions which are leptokurtic and skewed. In fact, the paper offers what we believe to be the largest analysis ever conducted of individual stock options. To be specific, using 30 stocks from the Dow Jones Industrial Average, or DJIA, as our sample, we price a total of 139,879 option contracts over the 11 year period from 1996 to 2006. We compare the results for two classical GARCH models, the symmetric GARCH model and the asymmetric NGARCH model, and we consider 7 different distributions, 3 of which are leptokurtic and 3 of which are skewed and leptokurtic. These choices are first of all driven by the observation that asymmetric models like the NGARCH model, which can accommodate the well known leverage effect, has been shown to be important also for option pricing. Secondly, allowing for skewness and leptokurtosis of the conditional distribution has also been shown to be important for option pricing.

The contribution of the paper is twofold. The first contribution is to provide an empirical application in which we compare the overall pricing performance for all 30 stocks across 15 models using both dollar and implied standard deviation, or ISD, errors. We first provide maximum likelihood estimation results for the 15 models using the available return data. The results provide clear evidence in favor of the NGARCH specification and of the NIG distribution. In particular, this model minimizes the Schwartz Information Criteria. Next, in terms of option pricing the overall results also provide clear evidence in favor of the NGARCH specification and of the NIG distribution. For example, when considering the ISD errors the NIG NGARCH model is the best performing model for 25 of the 30 stocks. The NIG NGARCH model is also the best performing model for the aggregate sample of options. When plotting the difference in ISD between the observed prices and the estimated prices from this model the results also show that the NIG NGARCH model significantly reduces the so-called smile effect found when applying option pricing models to this type of data.

The second contribution is to use the theory of model confidence sets, or MCS, developed by Hansen, Lunde & Nason (2011) to compare and statistically test the pricing performance across the various models. The MCS approach is analogous to the confidence interval of a parameter and is constructed such that it will contain the best forecasting model with a given level of confidence. It does so taking the information available in the data into consideration and for very informative data the MCS will contain only the best model. The MCS approach has primarily been used to compare variance forecasts, however since our estimated prices are predicted prices the MCS can be directly applied to test the performance of the option pricing models. The results show that the model most often contained in the MCS is once again the NIG NGARCH model. For example, when considering the ISD errors this model is in the MCS for 29 of the 30 stocks. Moreover, the results provide strong support for the use of the NGARCH specification over the GARCH specification and for the use of NIG innovations. In particular, a NGARCH model is in the MCS for all the stocks and so is a model with NIG innovations. To support these conclusions, we conduct several robustness checks confirming that this holds for both call and put options as well as across option maturity and option moneyness.

Option pricing with our approach is straightforward first of all because we only use historical data on the underlying asset and secondly because we use models in the GARCH framework which can be estimated directly by maximum likelihood. However, historical option prices themselves contain important information on the model parameters, and an alternative approach is to infer these parameters either from historical option data alone or by using both returns and options data. However, for this to be feasible option pricing models for which closed or semi-closed form pricing formulas exist are needed and unfortunately this is not the case for American style options. Moreover, an alternative to the GARCH framework is to consider continuous time stochastic volatility models. However, these models require the unobserved volatility as a state variable and this complicates not only the estimation procedure but also the actual option pricing procedure. For these reasons, the present paper focuses on the discrete time GARCH framework.

The rest of the paper is structured as follows: In Section 2 we review the generalized GARCH framework which will be used. In Section 3 we present the historical return data and provide estimation results for the various models. In Section 4 we present the option data and we provide empirical results on the overall performance of the option pricing models. Section 5 then analyzes the model performance using the model confidence set approach. Finally, Section 6 concludes. The appendix contains additional details on the constituents of the DJIA and the data screening procedure used.

2 Theoretical framework

In this paper a skewed and leptokurtic generalized GARCH framework similar to that of Stentoft (2008) is used. To be specific, we assume that the log return process, R_t, can be modelled as

$$R_t = m_t\left(\cdot;\theta_m\right) + \sqrt{h_t}\varepsilon_t \text{ and} \tag{1}$$

$$h_t = g\left(h_s, \varepsilon_s; -\infty < s \leq t-1; \theta_h\right) \text{ with} \tag{2}$$

$$\varepsilon_t | \mathcal{F}_{t-1} \sim D\left(0, 1; \theta_D\right), \tag{3}$$

where $\mathcal{F}_{t-1}$ is the information set containing all information up to and including time $t-1$. This general framework can accommodate various different specifications for the variance. Moreover, it allows for flexible specifications of the conditional distribution.

In (1) we use $m_t\left(\cdot;\theta_m\right)$ to denote the conditional mean, which is allowed to be governed by a set of parameters θ_m provided that the process is measurable with respect to the information set $\mathcal{F}_{t-1}$. Likewise, in (2) the parameter set θ_h governs the variance process. This process is allowed to depend on lagged values of the innovations to the return process, lagged values of the volatility itself, and various transformations hereof. Finally, in (3) we use $D\left(0, 1; \theta_D\right)$ to denote a zero mean and unit variance distribution which is also allowed to depend on a set of parameters θ_D. For notational convenience if the following we let θ denote the set of all parameters in θ_m, θ_h, and θ_D.

2.1 The skewed and leptokurtic GARCH option pricing model

Using the Generalized Local Risk Neutral Valuation Relationship, or GLRNVR, of Duan (1999), it can be shown that the risk neutralized dynamics of the system in (1) – (3) are given by

$$R_t = m_t(\cdot;\theta_m) + \sqrt{h_t}\varepsilon_t \text{ and} \tag{4}$$

$$h_t = g(h_s, \varepsilon_s; -\infty < s \leq t-1, \theta_h) \text{ with} \tag{5}$$

$$\varepsilon_t = F_D^{-1}\left[\Phi(Z_t - \lambda_t)\right], \tag{6}$$

where Z_t, conditional on $\mathcal{F}_{t-1}$, is a standard Gaussian variable under the risk neutral measure $\mathcal{Q}$, F_D^{-1} denotes the inverse cumulative distribution function associated with the distribution $D(0,1;\theta_D)$, Φ denotes the standard Gaussian cumulative distribution function, and where λ_t is the solution to

$$E^{\mathcal{Q}}\left[\exp\left(m_t(\cdot;\theta_m) + \sqrt{h_t}F_D^{-1}\left[\Phi(Z_t - \lambda_t)\right]\right)\Big|\,\mathcal{F}_{t-1}\right] = \exp(r_t). \tag{7}$$

In the above equation r_t denotes the one period risk free interest rate at time t, and although this rate has to be deterministic it may in fact be time-varying.

Note that the same mean is used in the risk-neutral process as in (1) and instead risk-neutralization is obtained through a change in the innovation term as specified in (6). For example, in the special case when $D(0,1;\theta_D)$ corresponds to the Gaussian distribution it follows that $F_D^{-1}[\Phi(z)] = z$, for any z, and in this situation the innovations in the risk neutral world remain Gaussian although with non zero mean. When the underlying distribution departs from the Gaussian the transformation in $F_D^{-1}[\Phi(z)]$ yields innovations under the risk neutral measure with the appropriate properties to be used when pricing e.g. options. In particular, note that when $\lambda = 0$ the innovations in (6) correspond to random draws from the $D(0,1;\theta_D)$ distribution irrespective of what distribution this is.

2.2 Feasible option pricing

In principle the system above is completely self-contained. However, when it comes to implementing it problems may occur due to the requirement that λ_t be the solution to (7). In particular, an analytical expression for λ_t may not be available in general. In the present paper we circumvent this issue using the proposed solution of Stentoft (2008) and "imply" the mean directly as

$$m_t(\cdot;\theta_m) = r_t - \ln E^{\mathcal{Q}}\left[\exp\left(\sqrt{h_t}F_D^{-1}\left[\Phi\left(Z_t - \lambda_t\right)\right]\right)\Big|\,\mathcal{F}_{t-1}\right]. \tag{8}$$

Using this specification ensures that the restriction in (7) is always satisfied. A similar approach is taken in Rombouts & Stentoft (2010) using the risk-neutralization method of Christoffersen, Elkamhi, Feunou & Jacobs (2010) and in Rombouts & Stentoft (2011) using a multivariate generalization hereof.

In the special case where returns are Gaussian the following restriction on the mean equation obtains

$$m_t(\cdot;\theta_m) = r_t + \lambda_t\sqrt{h_t} - \frac{1}{2}h_t, \tag{9}$$

where the last factor is a correction for working with continuously compounded returns. Thus, in this situation an analytical expression exists and the parameter λ_t is often interpreted as the unit risk premium. In particular, if we were to specify $\lambda_t = \lambda$, that is as a constant, the implied mean specification corresponds to assuming a unit risk premium proportional to the level of the standard deviation. Alternatively, if $\lambda_t = \lambda\sqrt{h_t}$, the unit risk premium becomes proportional to the level of the variance and with $\lambda_t = \lambda/\sqrt{h_t}$ a constant unit risk premium is obtained. Thus, while it may appear that we by implying the gross rate of return through (8) are constraining the potential mean specification in an unreasonably way from an econometric point of view, this is in fact not the case. Also note that $\lambda_t = 0$ is permitted and which specification is the most appropriate one can be tested by simple likelihood ratio type tests. In the general case a similar interpretation can be given to λ_t as shown by Stentoft (2008), though there is no simple connection.

3 Return data and estimation results

We consider the 30 stocks in the Dow Jones Industrial Average, or DJIA, as of February 19, 2008. The 30 stocks are shown in Table 1 together with the ticker, OptionMetrics ID, CRSP Permno, CUSIP, dates for which data is available, and the total number of observations.[2] The table shows that the data availability varies somewhat from stock to stock. For example, the most recent companies to be quoted were Microsoft, MSFT, which went public on March 13, 1986, and Citigroup, C, for which data is available only from October 29, 1986, from CRSP. For consistency, we therefore only use data from 1986 and onwards in this paper.

In Figures 1 and 2 the time series of the log returns, R_t, are plotted for each of the stocks. The figures show a familiar pattern of time varying volatility which has been documented for many other financial data series. The GARCH framework has been shown to be able to accommodate such features of the data, and in the following we describe in detail the models which will be considered. Next, we discuss some issues related to the implementation of the models and we provide estimation results for the 30 stocks.

3.1 Models considered

The generalized GARCH framework allows for different specifications of the variance process and underlying distribution. In this section we provide details on the particular models considered.

3.1.1 Variance specifications

Though several specifications for the variance could be considered, in this paper we consider two particular choices. The first of these is the well-known GARCH specification for which θ_h consists of the parameters $\{\omega, \beta, \alpha\}$ and where the functional form in (2) is given by

$$h_t = \omega + \beta h_{t-1} + \alpha h_{t-1} \varepsilon_{t-1}^2. \tag{10}$$

[2] The appendix provides further details on the data collection and on issues occuring for particular stocks.

Obviously, using more lags can be considered as simple extensions. Alternatively, we may wish to consider specifications which can accommodate asymmetric responses to negative and positive return innovations. Such models are generally said to allow for a leverage effect, which refers to the tendency for changes in stock prices to be negatively correlated with volatility.

The particular asymmetric extension to the GARCH model we consider is the non-linear asymmetric GARCH model, or NGARCH, of Engle & Ng (1993). The NGARCH specification of the variance process is given by

$$h_t = \omega + \beta h_{t-1} + \alpha h_{t-1} \left(\varepsilon_{t-1} + \gamma \right)^2 , \tag{11}$$

and for this specification we have $\theta_h = \{\omega, \alpha, \beta, \gamma\}$. In the NGARCH model the leverage effect is modelled through the parameter γ, and if $\gamma < 0$ this effect is said to be found. It is clear that this model nests the ordinary GARCH specification, which obtains when $\gamma = 0$, and the model thus allows us to compare the contribution of the leverage effect directly by comparison to the GARCH specification.

3.1.2 Alternative distributions

In addition to the Gaussian distribution we use 6 alternative distributions. These fall within 3 families: the Generalized Error, or GED, distribution, the Normal Inverse Gaussian, or NIG, distribution, and the Variance Gamma, or VG, distribution. We consider both symmetric and skewed versions of these for which we now provide details. Note that the two latter distributions are special cases of the Generalized Hyperbolic distributions and in principle other versions could be considered also. However, in order to implement the generalized GARCH framework one needs standardized, i.e. zero mean and unit variance, versions of the distributions. For the Generalized Hyperbolic distributions in general this is difficult to obtain as the first two moments depend on the scale and location parameters in a non-linear way.

Generalized Error distribution The GED distribution was first used with the GARCH framework in Nelson (1991). The density of a GED distributed variable is given by

$$f_{GED}(x,a) = \frac{a}{2L\Gamma(1/a)} \exp\left(-\frac{|x|^a}{L^a}\right), \tag{12}$$

where $\Gamma(\cdot)$ is the gamma function and where $L = \sqrt{\Gamma(1/a)/\Gamma(3/a)}$. The Gaussian distribution is a special case of this when $a = 2$.

The GED distribution is symmetric by construction. However, using e.g. the method of Theodossiou (2000) one may obtain skewed versions. The density of a standardized skewed GED distributed variable is given by

$$f_{sGED}(x;a,b) = \frac{a}{2L\Gamma(1/a)} \exp\left(-\frac{|x+S|^a}{(1-sign(x+S)\,b)^a\,L^a}\right), \tag{13}$$

where $L = B^{-1}\sqrt{\Gamma(1/a)/\Gamma(3/a)}$ and $S = 2bAB^{-1}$, and where $B = \sqrt{1+3b^2-4A^2b^2}$ and $A = \Gamma(2/a)/\sqrt{\Gamma(1/a)\Gamma(3/a)}$. In (13) b is the asymmetry parameter. In particular, when $b = 0$ the symmetric GED distribution is obtained since $B = 1$ which means that $S = 0$. By construction the GED distribution has mean zero and unit variance and hence no standardization is needed. We refer to this distribution as the $GED(a,b)$ distribution.

Normal Inverse Gaussian distribution Following Jensen & Lunde (2001) the $NIG(a,b,\mu,\delta)$ distribution can be defined in terms of the location and scale invariant parameters as

$$f_{NIG}(x;a,b,\mu,\delta) = \frac{a}{\pi\delta} \exp\left(\sqrt{a^2-b^2} + b\frac{(x-\mu)}{\delta}\right) q\left(\frac{x-\mu}{\delta}\right)^{-1} K_1\left(aq\left(\frac{x-\mu}{\delta}\right)\right), \tag{14}$$

where $q(z) = \sqrt{1+z^2}$ and $K_1(\cdot)$ is the modified Bessel function of third order and index 1. For the distribution to be well defined we obviously need to ensure that $0 \leq |b| \leq a$ and $0 < \delta$. We can interpret a and b as shape parameters with a determining the degree of leptokurtosis and b

the asymmetry. In particular, for $b = 0$ we have a symmetric distribution and with a tending to infinity the Gaussian distribution is obtained in the limit.

In (14), μ is a location parameter and δ is a scale parameter, and if we define $\rho = b/a$ the mean and variance of a $NIG(a, b, \mu, \delta)$ distributed variable are given as

$$E(X) = \mu + \frac{\rho\delta}{\sqrt{1-\rho^2}} \text{ and } Var(X) = \frac{\delta^2}{a(1-\rho^2)^{3/4}}. \tag{15}$$

Thus, a zero mean and unit variance NIG distributed variable can be obtained by restricting μ and δ to have the following form:

$$\mu = \frac{-\rho\delta}{\sqrt{1-\rho^2}} \text{ and } \delta = \sqrt{a(1-\rho^2)^{3/4}}. \tag{16}$$

In the following we will refer to this standardized distribution as the $NIG(a, b)$ distribution. This procedure was also used in Stentoft (2008).

Variance Gamma distribution The $VG(a, b, \mu, \delta)$ distribution can be specified as

$$f_{VG}(x; a, b, \mu, \delta) = \frac{(a^2-b^2)^{\delta} |x-\mu|^{\delta-1/2} K_{\delta-1/2}(a|x-\mu|) \exp(b(x-\mu))}{\sqrt{\pi}\Gamma(\delta)(2a)^{\delta-1/2}}, \tag{17}$$

where $K_{\delta-1/2}(\cdot)$ is the modified Bessel function of third order and index $\delta-1/2$. For the distribution to be well defined we obviously need to ensure that $0 \leq |b| \leq a$ and $0 < \delta$. We can again interpret a and b as shape parameters with a determining the degree of leptokurtosis and b the asymmetry. In particular, for $b = 0$ we have a symmetric distribution.

In (17), μ is a location parameter and δ is a scale parameter, and if we define $\gamma = \sqrt{a^2 - b^2}$ the mean and variance of a $VG(a, b, \mu, \delta)$ distributed variable are given as

$$E(X) = \mu + \frac{2b\delta}{\gamma^2} \text{ and } Var(X) = \frac{\delta(2 + 4b^2/\gamma^2)}{\gamma^2}. \tag{18}$$

Thus, a zero mean and unit variance VG distributed variable can be obtained by restricting μ and δ to have the following form:

$$\mu = -\frac{2b\delta}{\gamma^2} \text{ and } \delta = \frac{\gamma^2}{(2 + 4b^2/\gamma^2)}. \tag{19}$$

In the following we will refer to this standardized distribution as the $VG(a,b)$ distribution.

3.2 Implementation

One important property of the GLRNVR framework of Duan (1999) is that a close link is provided between the observed asset return process and the process which has to be used for valuation of the corresponding options. To be specific, note that by substituting (8) into the system in (1) – (3) we obtain the following specification for the return process to be used for estimation:

$$R_t = r - \ln E^{\mathcal{Q}} \left[\exp\left(\sqrt{h_t} F_D^{-1} \left[\Phi \left(Z_t - \lambda \right) \right] \right) \middle| \mathcal{F}_{t-1} \right] + \sqrt{h_t} \varepsilon_t \text{ and} \tag{20}$$

$$h_t = g\left(h_s, \varepsilon_s; -\infty < s \leq t-1, \theta_h\right) \text{ with} \tag{21}$$

$$\varepsilon_t | \mathcal{F}_{t-1} \sim D\left(0, 1; \theta_D\right), \tag{22}$$

where Z_t is a standard Gaussian variable under the risk neutral measure $\mathcal{Q}$, and where we have assumed a constant interest rate as well as a constant value for $\lambda_t = \lambda$. Comparing this system to the one used for pricing in (4) – (6) it is immediately clear that it is in fact possible to estimate all the necessary parameters from the historical returns. Thus, one of the major strengths of the proposed generalized GARCH framework is that cumbersome calibration procedures involving matching model option prices to observed prices to derive the model parameters may be avoided.

However, before we can actually implement the generalized GARCH option pricing model we need to obtain procedures for evaluating the transformation of the random variables Z_t through $F_D^{-1} \left[\Phi \left(Z_t - \lambda \right) \right]$ as well as for evaluating the logarithm of the expectation of the scaled exponential value of this, that is $\ln E^{\mathbb{Q}}\left[\exp\left(\sqrt{h_t}F_D^{-1}\left[\Phi\left(Z_t-\lambda\right)\right]\right)\middle|\mathcal{F}_{t-1}\right]$. Note though that such procedures would be needed even if we were to use a calibration based method. In this paper we follow the procedure outlined in Stentoft (2008) for constructing these approximations. We note that though Stentoft (2008) only considers the NIG distribution the method is applicable to all the distributions considered here and it allows for estimation of all the models in a straightforward manner.

3.3 Estimation results

In the present setting with 30 stocks and 15 models, presenting detailed results for all models is clearly too cumbersome. Instead we first summarize the results and then provide detailed estimation results for the preferred model only. The detailed results for all other models are, however, available from the author upon request. In all estimations we use variance targeting originally proposed in Engle & Mezrich (1996), which ensures that the implied unconditional level of the variance corresponds to the historical volatility actually observed. The procedure can be implemented in our framework simply by setting $\omega = Var\left(R_t\right)*\left(1-\alpha\left(1+\gamma^2\right)-\beta\right)$ for the NGARCH model with $\gamma = 0$ in the GARCH model.

We start by reporting the Schwartz Information Criteria, or SIC, values in Table 2. This criteria penalizes models with additional parameters compared to the raw likelihood values. It has been shown that the SIC can be used to discriminate between alternative volatility models with good results (see e.g. Bollerslev & Mikkelsen (1996)). Comparing the values across stocks it is seen that the SIC is minimized by the NIG NGARCH specification in all the cases. For PFE the symmetric NIG NGARCH has the same value of the SIC. Moreover, the model ranked second is for 28 of the 30 stocks the symmetric NIG NGARCH. For the two exceptions, AA and MSFT, it is the skewed NIG GARCH model which is ranked second. Thus, in terms of estimation the top ranked models are in all cases models which uses the NIG distribution and in most of the cases models that use the NGARCH specification.

3.3.1 Estimation results for the NIG NGARCH model

In Table 3 we report the estimation results for the preferred NIG NGARCH model. From the table we see that all the β's are significantly different from zero, 29 of the α's are significantly different from zero, and 28 of the γ's are significantly different from zero when using a 5% significance level. Moreover, the majority, 21 out of 30, of the estimated risk premiums, i.e. the λ's, are significantly different from zero. With respect to the distributional parameters the table shows that on average a is estimated at a value of 2. This is quite small and indicates the importance of allowing for a fat tailed distribution. The skewness parameter b, on the other hand, is only significant for 3 of the stocks and its average value is only 0.05. Also both positive and negative values are obtained for this parameter. Finally, note that the test statistics for misspecification show that overall the NIG NGARCH model does a good job in explaining the features of the data. In particular, in the majority of the cases no significant correlation in the residuals or the squared residuals are observed as indicated by the insignificant values of the $Q(20)$ and $Q^2(20)$ statistics. The same holds for the ARCH5 test which is significant at the 5% level only for 9 of the 30 stocks.

3.3.2 Risk premium, leverage effects, and skewed distributions

In the framework above there are three potential ways to introduce asymmetries in the simulated distributions: through the risk premium, λ, through the leverage effect, γ, and from skewness in the distribution, b. Of these, only γ is consistently estimated different from zero for nearly all the 30 stocks. The risk premium λ is significantly different from zero for roughly two thirds of the stocks, whereas b is statistically significant for only 3 of the stocks. Similar results are obtained for the GED and VG distributions. Based on these results it thus appears that γ will be most important for generating asymmetries in the risk neutral distribution. However, of these three, the risk premium λ has a special status since this parameter drives a wedge between the physical and risk neutral dynamics. In particular, as discussed in Section 2.1 without λ the model used for pricing is identical to that estimated on the historical returns. We return to this issue below.

4 Option data and pricing results

Our option sample covers the 11 year period from 1996 through 2006 on a monthly basis and comes from the IvyDB OptionMetrics file.[3] In total our sample contains 139,879 options on individual stocks. To our knowledge this makes it the largest sample of individual stock options ever considered for empirical study. In Table 4 we provide the number of options in our sample for different categories of maturity and moneyness. The different categories of maturity, T, are labelled as follows: short term (ST) has $T \leq 21$, middle term (MT) has $21 < T \leq 63$. long term (LT) has $63 < T \leq 126$, and very long term (VLT) has $126 \leq T$. Moneyness, Mon, is calculated as the ratio of the asset price to the strike price. The different categories of moneyness are labelled as follows for call options: deep in the money, (DITM) has $Mon > 1.1$, in the money (ITM) has $1.1 \geq Mon > 1.025$, at the money (ATM) has $1.025 \geq Mon > 0.975$, out of the money (OTM) has $0.975 \geq Mon > 0.9$, and deep out of the money (DOTM) has $0.9 \geq Mon$. For put options the (D)ITM and (D)OTM categories are reversed. The table shows that the data considered corresponds to a very diverse sample of options. In particular, the options are spread out across the different categories in terms of maturity. For example, when considering the last row with the aggregate data we see that of the approximately $140,000$ options a minimum of roughly $33,000$ and a maximum of $38,000$ options fall in each category. In terms of moneyness the options are also spread out, though the number of DOTM options is somewhat larger than for the other categories. However, there is still at least $20,000$ options in each of the categories.

In Tables 5 and 6 we report the average prices and implied standard deviations, or ISDs, for the sample of options. The ISDs are backed out from the binomial model with daily early exercise and corrects for maturity and moneyness effects through the nonlinear transformation of the dollar price.[4] Again we see that the sample of options is very diverse with overall price averages ranging from around $1 dollar for the DOTM category to $14 for the DITM category. The highest priced

[3] The appendix provides further details on the data collection and on issues occuring for particular stocks.

[4] Of the $139,879$ options this method yields reasonable values for $136,144$ options. The rest, amounting to $3,735$ options or 2.7% of the sample, are not considered in the reported results.

options are for technological companies such as IBM, INTC, and MSFT. When considering the ISDs in Table 6 large differences are also found. For example, the average ISD of INTC is with 43% almost 20 percentage points larger than that of CVX for which the average ISD is 24%. The table also shows that across categories the largest variation is found in terms of moneyness. In particular, the table shows the well-known smile across moneyness categories. In Figure 3 we show this graphically. The figure plots the difference between the ISD and the historical volatility for each moneyness category. The top plot is for the first 10 assets, the middle plot for assets 11 to 20, and the bottom plot is for the last 10 assets in alphabetical order of the ticker symbol.

The GARCH framework has been shown to be able to accommodate the above features. In the following we provide details on how the options can be priced in this framework using simulation. Next, we evaluate the option pricing performance of the models considered using well-known metrics from the literature. Finally, we examine the best performing model's ability to explain the smile which is present for the individual options considered as documented in Figure 3.

4.1 Pricing procedure

The first thing to note is that within a framework as general as the one above it is difficult, if not impossible, to obtain closed form, or even semi-closed form, solutions for the option price. Thus, it is necessary to consider alternative numerical procedures. Moreover, although it is potentially possible to customize e.g. lattice methods to the particular dynamics of one such model, this approach would be specific to the assumed underlying dynamics and hence not a method which is generally applicable. In this paper we choose to use simulation based methods which are, on the other hand, flexible enough to accommodate all of the possible specifications of the dynamics for the variance process and the assumed distributions considered here. In the following we describe in detail how the simulation is performed and we explain how to accommodate the early exercise feature.

4.1.1 Pricing using simulation

By substituting (8) into the system in (4) – (6) it is possible to obtain the dynamics to be used for pricing. These are given by

$$R_t = r - \ln E^{\mathcal{Q}} \left[\exp \left(\sqrt{h_t} F_D^{-1} \left[\Phi \left(Z_t - \lambda \right) \right] \right) \middle| \mathcal{F}_{t-1} \right] + \sqrt{h_t} \varepsilon_t \text{ and} \tag{23}$$

$$h_t = g \left(h_s, \varepsilon_s; -\infty < s \leq t-1, \theta_h \right) \text{ with} \tag{24}$$

$$\varepsilon_t = F_D^{-1} \left[\Phi \left(Z_t - \lambda \right) \right], \tag{25}$$

where Z_t, conditional on $\mathcal{F}_{t-1}$, is a standard Gaussian variable under the risk neutral measure $\mathcal{Q}$. Thus, it is immediately clear that these depend only on parameters which can be estimated using historical returns, and given these a large number of paths of the risk-neutralized asset prices can be generated. Moreover, although the simulation involves transforming the Gaussian innovations, the Z's, at every step along all paths it is in fact feasible to simulate efficiently from this system when the approximations from Stentoft (2008) are used. In particular, because the approximations need only be calculated once at the beginning of the simulation the computational complexity remains approximately linear in the number of paths and in the number of steps in the simulation.

For the actual simulation we use $M = 20,000$ paths. This choice is primarily made to minimized the computational work and together with using only monthly option data means that option pricing can be done in reasonable time. As input to the simulation we use parameter estimates obtained using the available historical information on the day of pricing only. Thus, as we move forward in time, the sample used for estimation increases. Moreover, as a result of this procedure the estimated prices can be considered as out of sample forecasts of the observed option prices. As the interest rate we use the EURODOLLAR rate on the last day of the sample used for estimation. Thus, although the same constant interest rate is used both in the estimation and in the simulation at any given day, in fact the interest rate does vary from one month to the next month.

In the simulations, we make the following three assumptions about the effect of dividend payments: First of all, we assume that only cash dividend payments are important for our purpose. This assumption is reasonable since exchange traded options, in general, are protected against other forms of dividends like, say stock splits. Secondly, we assume that both the ex-dividend day and the size of the dividends are known in advance. Though this is not strictly correct, dividends are paid regularly with fairly stable amounts throughout the period we consider. Thirdly, we assume that the effect of a cash dividend payment fully spills over on the asset price. We note that these assumptions are standard in the literature.

4.1.2 Accommodating the early exercise feature

The simulation method described above is immediately applicable to European options and has been used at least since Boyle (1977). However, in our sample all the options are American style. Hence, to price these options we need to take into consideration the possible early exercise. Though it was for a long time believed that this would be impossible within a simulation framework this is no longer the case. Specifically, in this paper we use the Least Squares Monte Carlo, or LSM, method of Longstaff & Schwartz (2001) to price the individual options in a GARCH framework as outlined in Stentoft (2005) and Stentoft (2008). This method approximates the value of holding the option at a given point in time along a specific simulated path by the predicted value from a cross-sectional regression using all the in the money paths.

The LSM method for pricing American style options proceeds as follows: First of all, given the full sample of random paths, the pricing step is initiated at the maturity date of the option. At this time, it is possible to decide along each path if the option should be exercised since the future value trivially equals zero. Hence, the pathwise payoffs may be easily determined at maturity. Next, working backwards through time a cross-sectional regression is performed at the first point in time where early exercise is to be considered. In the regression the discounted future payoffs are regressed on transformations of the current asset prices and volatility levels.[5] The fitted values from

[5] In our application we use powers of and cross products between the asset price and the level of the volatility of order two or less in addition to a constant term in the cross-sectional regressions.

this regression are then used as estimates of the pathwise conditional expected values of holding the option for one more period. The decision of whether to exercise or not along each path can now be made by comparing the estimated conditional expected value of continuing to hold the option to the value of immediate exercise. Once the decision has been recorded for each path, we can move back through time to the previous early exercise point and perform a new cross-sectional regression with the appropriate pathwise payoffs based on the previously determined choices. Finally, with the optimal early exercise strategies along each path an estimate of the American option value can be obtained as a simple average of the discounted pathwise payoff.

4.2 Overall pricing results

We now compare the pricing performance of the 15 different option pricing models considered here for each of the 30 stocks in the sample. The natural benchmark model is the constant volatility model with Gaussian distribution since this corresponds to the Black-Scholes-Merton model. We consider two classical metrics for option pricing comparison using both the dollar errors and the errors in implied standard deviations. Specifically, letting P_k and $\tilde{P}_k$ denote the kth observed price respectively the kth estimated price we use the bias, $BIAS = K^{-1} \sum_{k=1}^{K} \left(P_k - \tilde{P}_k \right)$ and the root mean squared error, $RMSE = \sqrt{K^{-1} \sum_{k=1}^{K} \left(P_k - \tilde{P}_k \right)^2}$. For the ISD errors similar formulas are used.

4.2.1 Comparison using dollar errors

In Table 7 we report the dollar BIAS for each stock using the 15 different models. We also report the aggregate dollar BIAS in the last row. Moreover, in the last two columns we indicate which model is the best performing and the worst performing model. The first thing to note from the table is that there are very large differences in terms of option pricing performance across the 30 stocks. For example, for the CV model the average errors vary between 1.6 cents for MCD and 43.1 cents for BAC. Moreover, when considered across the stocks which model is the best and which is the worst performing also differs a lot. For example, the CV model is the worst performing model for 16 stocks but the best performing for 3. Also the skewed VG NGARCH model is the best performing model for one stock, MMM, and the worst performing model for one stock, BA. Thus, using the BIAS metric for the dollar errors leads to somewhat mixed results. The model which has the smallest errors for most stocks is the NIG GARCH model which is the best performing model for 8 of the 30 stocks.

In Table 8 we report the corresponding errors using the RMSE metric. The first thing to note from this table is that the results are somewhat clearer at least in terms of the worst performing model, which for all 30 stocks is the CV model. However, there is still a large degree of variation in terms of the best performing model, though for 23 of the 30 stocks the best performing model has a NGARCH specification. Moreover, when considering the aggregate numbers in the table support is found in general for models with non-Gaussian innovations. In particular, the performance of models 4 through 15 is very similar with an average error of 0.602. Compared to this value the Gaussian CV error is 52% larger and the Gaussian GARCH and NGARCH errors are 12% and 10% larger, respectively. The models which have the smallest errors for most stocks are the NIG NGARCH models which are the best performing models for 7 and 6 of the 30 stocks, respectively.

4.2.2 Comparison using ISD errors

As Table 5 shows, the dollar prices vary a lot between the stocks and comparing the pricing errors based on these may be problematic. An alternative is to use the ISD which attempts to correct for maturity and moneyness effects through a nonlinear transformation of the dollar price. In Table 9 we report the ISD BIAS for each stock using the 15 different models. For all model prices the ISDs are backed out from the binomial model with daily early exercise. We also report the aggregate ISD BIAS in the last row, and in the last two columns we indicate the best performing and the worst performing model. Again the table shows that when using the BIAS metric results differ a lot across the stocks. For example, using the ISDs the CV model is the worst performing model for 18 stocks and the best performing for 4 stocks. However, the table does show that for 15 of the stocks the best performing model has a NGARCH specification. The model which has the smallest errors for most stocks is the NIG NGARCH models which is the best performing model for 7 of the 30 stocks.

In Table 10 we report the corresponding errors using the RMSE metric. Again, the first thing to note from this table is that the results are somewhat clearer. In particular, this is the case in terms of the worst performing model, which for all 30 stocks is the CV model. The table also shows that the best performing model is model 7, the symmetric NIG NGARCH model, for 11 stocks and model 13, the skewed NIG NGARCH model, for 14 stocks. Thus, a NIG NGARCH model is the best performing model for 25 of the 30 stocks. Note that the best performing model for the last 5 stocks also has a NGARCH specification. For each of the seven different distributions the GARCH errors are between 9.5% and 12.8% larger than those obtained with the NGARCH specification. Thus, using the ISD errors with the RMSE metric we find strong evidence in favor of using an asymmetric specification for the variance process and for using a model with the NIG innovations.

4.3 Fitting the smile in option ISDs

The overall pricing performance in terms of dollar errors or even in terms of ISDs is one possible metric for comparison. However, when it comes to option pricing it is perhaps of more interest to examine how the models fit across moneyness. In particular, option prices are often quoted in terms of implied volatilities, and often such volatility quotes vary with moneyness. Thus, the ultimate test of any option pricing model may well be to fit this pattern which is known as the volatility smile, and which was documented graphically for our sample of options in Figure 3.

The previous analysis shows that overall the NGARCH model with NIG innovations is the best performing model of the models considered here. Thus, we now analyze this model's potential for accommodating the smile found in our option data. In Figure 4 we plot the difference between the ISD from the observed price and the ISD of the estimated NIG NGARCH option price. In the figure we have used the same scale as in Figure 3 to make the results directly comparable. The figure shows that the smile in ISDs is much less pronounced for this model. Though for some stocks there remains some variation across moneyness the size is much smaller than for the CV model. For example, for GM the ISD error for the DOTM category decreases from 19.53% for the CV model to 10.96% for the NIG NGARCH model. In Figure 5 we plot the average ISDs across all stocks. These results show that the NIG NGARCH model significantly reduces the smile effect often found when applying option pricing models to this type of data.

When it comes to option pricing the λ parameter plays a special role as it drives a wedge between the physical dynamics and the risk free dynamics used for option pricing. In particular, a positive value for λ increases the long run volatility under the risk free measure. For the 30 stocks considered λ is positive though only statistically so for roughly two thirds of the stocks when using the NIG NGARCH model. Moreover, the point estimates are relatively small and hence the overall effect could be minimal. To examine this we also plot the average volatility smile for the NIG NGARCH model with $\lambda = 0$ in Figure 5. The figure shows that, though the overall pattern is similar, incorporating the risk premium does decrease the overall errors across moneyness. The overall error is also somewhat smaller at 8.19% when the risk premium is included compared to a value of 8.31% when $\lambda = 0$.[6]

5 Model confidence sets for option pricing models

Section 4 reported on the model performance using different types of pricing errors and different metrics, and though this allowed us to point out which models perform best an actual test of model performance is not possible. In particular, based on the point estimates of the reported errors, it is impossible to decide if the best performing model is in fact significantly better than the next best performing model. Likewise, it is not immediately clear if the worst performing model or models

[6] Incorporating a fixed value for $\lambda = 0.03$, which is roughly the average across the 30 stocks, yields results that are essentially identical to those obtained when λ is estimated.

are in fact significantly worse than the best performing one.

In this section we apply the theory of Model Confidence Sets which can be used to compare the forecasting ability of multiple models, and which allows us to formally test if any model is significantly outperformed by others when it comes to its predictive ability. To our knowledge, this is the first time the MCS approach has been used for comparing option pricing models. In the following we explain the approach. Next, we provide the results for the option pricing models, and finally we analyze the robustness of the results.

5.1 The model confidence set approach

The model confidence set approach was developed in Hansen et al. (2011). The method is analogous to the confidence interval of a parameter and is constructed such that it will contain the best forecasting model with a given level of confidence. It does so taking the information available in the data into consideration. Thus, for very informative data the MCS will contain only the best model whereas for less informative data many models are contained in the MCS. This stands in stark contrast to the procedure used above which selects one model as the best performing model irrespective of the information content in the data. Another benefit of the MCS procedure is that it yields a p-value for each model which indicates how likely it is that the model belongs to the MCS.

The MCS approach has primarily been used to compare variance forecasts from e.g. a large set of GARCH models. However, since our model prices are forecasts the approach is equally applicable here, and by comparing the price forecasts to the actual observed prices we may use the method to examine the performance of the pricing models. Likewise, the forecasted ISDs can be compared. In this paper we use the software provided by Hansen & Lunde (2010) to implement the MCS approach. This software allows for different loss functions and for different test statistics. For the loss function we choose the daily root mean squared error given by $RMSE = \sqrt{K_t^{-1} \sum_{k=1}^{K_t} \left(P_k - \tilde{P}_k \right)^2}$, where K_t is the total number of options at date t. Note that the daily bias would not be a proper loss function to use for the MCS approach. As the test statistic we use the MaxT statistic (see Hansen & Lunde (2010) for details). Although alternative statistics are available, this particular statistic generally resulted in the smallest MCSs.[7] Finally, for all tests we set the confidence level to $\alpha = 10\%$ and in the bootstrap we set the block length to 25 and the number of samples to $25,000$.

5.2 Model confidence set results

We now apply the MCS approach to examine our option pricing models. We consider both of the errors considered in Section 4: the dollar error in predicted price and the error in the predicted ISD.

5.2.1 Comparison using dollar errors

In Table 11 we report the MCS for the predicted dollar price. The table first of all shows that overall the MCS contains 271 models, that is approximately 9 models per stock. In fact, the MCS contains all 15 models for 3 of the stocks and it contains 10 or more models for half the stocks. On the other hand, for 5 of the stocks the MCS contains less than 5 models, and for 2 of these stocks only 2 models are in the MCS. Next, when considering the individual models the table shows that the CV model is only in the MCS for 3 of the 30 stocks. The Gaussian models, models 2 and 3, also only rarely belong to the MCSs. The rest of the models on the other hand are in the MCS for at least half of the stocks. The model which is most often in the MCS is model 7, the symmetric NIG NGARCH model, which is in the MCS for 28 of the stocks. The NGARCH model with skewed NIG innovations is the next best model and contained in the MCS for 27 of the stocks, and in fact a model with NIG innovations is in the MCS for all 30 stocks. For the GED and VG distributions, models with symmetric innovations are also most often found in the MCS. However, models with these distributions are in the MCS for only 22 and 26 of the 30 stocks, respectively. Finally, the table shows that in terms of the variance specification models with the NGARCH specification are

[7] Results for alternative test statistics are available from the author.

found most often in the MCS irrespectively of the choice of underlying distribution. In fact, a model with NGARCH specification is in the MCS for 28 of the stocks, whereas for the GARCH specification this is the case for only 22 of the 30 stocks.

5.2.2 Comparison using ISD errors

In Table 12 we report the MCS for the predicted ISD. The table first of all shows that the MCS contains about two thirds the number of models, 183 to be precise, when ISDs are used than when dollar prices are used. In fact, the maximum number of models in the MCS is 14, which occurs only for HD, and the MCS contains more than 10 models for only 5 of the 30 stocks. On the other hand, the MCS contains only one model for the two stocks BA and GM, and for 11 of the stocks less than 5 models are in the MCS. Thus, the results indicate that it may be more appropriate to use the ISD errors than the dollar errors for model comparison. Next, when considering the individual models the table shows that the CV model is never in the MCS. Moreover, the Gaussian GARCH model is only found in the MCS for 1 of the stocks. The NGARCH model with skewed NIG innovations, model 13, is on the other hand found in the MCS for 29 of the 30 stocks with the exception being AXP. The model that is found next most often in the MCS is model 7, the symmetric NIG NGARCH model, which is in the MCS for 28 stocks, and again a model with NIG innovations is in the MCS for all 30 stocks. Models with GED and VG innovations are on the other hand in the MCS for only 20 and 25 of the stocks, respectively. Finally, the table shows that when considering the variance specification models with NGARCH specifications are found much more frequently in the MCS than those with GARCH specifications when using the ISD errors. For example, for the symmetric GED distribution the model with a NGARCH specification is in the MCS for 21 stocks whereas this is the case for only 5 stocks for the model with a GARCH specification. In fact, a model with NGARCH specification is in the MCS for all the stock whereas for the GARCH specification this is the case for only 11 of the 30 stocks.

5.3 Robustness checks

To support the results reported above we now analyze the robustness of the results from the MCS approach along three dimensions: option type, i.e. call and put, option maturity, and option moneyness. The results are reported in Table 13.

5.3.1 Across option type

Panel A reports the results for the two different option types, i.e. the call (75,966 options) and the put (60,178 options) options. The first thing to note from this panel is that the number of models belonging to the MCS is roughly 55% larger for put options than for call options. In particular, when considering put options the various NGARCH specifications occur more frequently in the MCS. For example, whereas model 5 is in the MCS for call options for only 13 stocks it is in the MCS for put options for 25 stocks. Similar results are observed for models 3, 9, 11, and 15, though the NIG NGARCH specifications continue to be the best performing models. Thus, the results show that for the put options the choice of conditional distribution appears to be of second order importance as long as the NGARCH volatility specification is used. For the call options on the other hand NGARCH specifications with NIG innovations are by far the best performing models. For example, the symmetric NIG NGARCH model belongs to the MCS almost twice as often as the corresponding GED model and the differences are even more pronounced when considering the skewed models. Thus, in spite of some differences the panel shows that the results are robust across option type as the NIG NGARCH models perform the best for both option types.

5.3.2 Across maturity

Panel B reports the results across maturity (option numbers can be found in Table 4). The first thing to note is that the number of models in the MCS increases with maturity. For example, there are roughly 54% more models in the MCS for the VLT options than for the ST options. The main reason for the increase in the number of models is that more models with GARCH specifications are found in the latter category. For example, model 6 which uses the GARCH specification occurs in the MCS 7 times for ST and MT options, 11 times for LT options, and 17 times for the VLT options. Similar results are found for the other GARCH models. Note also that large increases are found for models with VG innovations in general. For models 7 and 13 on the other hand, the number of times only increases from 25 for the ST options to 29 and 28, respectively, for the VLT options. Thus, the table shows that as the maturity increases option ISDs contains less information and therefore the number of models in the MCSs increases. Intuitively this makes sense since in the long run all the models have similar properties in terms of e.g. the level of volatility. However, the panel does show that the results reported above are robust across maturity as a NIG NGARCH model is the best performing for all maturities.

5.3.3 Across moneyness

Panel C reports the results across moneyness (option numbers can be found in Table 4). The first thing to note is that across this dimension the number of models occurring in the MCS varies a lot. For example, there are almost twice the number of models in the MCS for ITM and ATM options than for DOTM options. Though for the DITM, ITM, ATM and OTM options the number of models is relatively stable. The main reason that there are more models in the MCS for ITM and ATM options is that for these options more models with GARCH specifications belong to the MCS. For the DOTM options on the other hand the table clearly shows that the reason that a low number of models are found in the MCS is that all but the NIG NGARCH models are found much less frequently in the MCS when compared to e.g. the OTM options. For example, whereas model 7 belongs to the MCS for 28 and 29 stocks for the OTM and DOTM options, respectively, for model 5 the number of times decrease from 21 to 14. Likewise, the number of times model 6 is found in the MCS decreases from 18 to only 8. The decrease for models with VG innovations are even more dramatic. Nevertheless, in spite of the differences the panel shows that the overall results are quite robust across moneyness and NIG NGARCH models are consistently the best performing model.

6 Conclusion

This paper offers what we believe to be the largest analysis ever conducted of individual stock options. Using 30 stocks from the Dow Jones Industrial Average, or DJIA, we price 139,879 option contracts over a 11 year period from 1996 to 2006. We compare the results for two classical GARCH models, the symmetric GARCH model and the asymmetric NGARCH model, and we consider 7 different distributions, 3 of which are leptokurtic and 3 of which are skewed and leptokurtic. The contribution of the paper is twofold.

We first of all compare the overall pricing performance using dollar and implied standard deviation, or ISD, errors. The results provide clear evidence in favor of the asymmetric NGARCH specification and of the Normal Inverse Gaussian, or NIG, distribution. For example, when considering the RMSE of the ISDs this is the best performing model for 25 of the 30 stocks. The NIG NGARCH model is also the best performing model for the aggregate sample of options. When plotting the difference in ISD between the observed prices and the estimated prices from this model the results show that the NIG NGARCH model significantly reduces the smile effect found when applying option pricing models to this type of data.

Next, we propose to conduct actual statistical tests of the option pricing models using the model confidence set, or MCS, approach. The MCS approach is analogous to the confidence interval of a parameter and is constructed such that it will contain the best forecasting model with a given level of confidence. The results show that the model most often contained in the MCS is once again the NIG NGARCH model. For example, when considering the ISD errors this model is in the MCS for 29 of the 30 stocks. Moreover, the results provide strong support for the use of NGARCH specifications over the GARCH specification and for the use of NIG innovations. In particular, a NGARCH model is in the MCS for all the stocks and so is a model with NIG innovations. We conduct several robustness checks confirming that this holds for both call and put options as well as across option maturity and option moneyness.

The present paper clearly demonstrates that pricing American style options within the generalized GARCH framework is possible and that asymmetries in the volatility specifications along which non-Gaussian innovations are important. Interesting extensions are to consider even more underlying assets, other types of distributions, and more extensive specifications of the GARCH models. The MCS approach used here can easily be used to test the performance with these extensions.

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A Data, data issues, and corrections

In this paper we work with the 30 constituent stocks of Dow Jones Industrial Average, or DJIA, as of February 19, 2008, which at the time of writing was the last time changes were made to the index. In this appendix we describe this data in more detail. Moreover, as is often the case when working with empirical data errors occur and we explain how these issues were dealt with.

A.1 DJIA and constituents

Table 1 shows the constituents of the DJIA as of February 19, 2008. The table also reports the ticker, the security ID used by Option Metrics, the Permno assigned by CRSP, and CUSIP for these stocks. While tickers change the permno allows us to uniquely identify a company and the security ID allows us to uniquely identify options on this company. We therefore use these numbers to track the company through time. Lastly the table shows the sample for which data is available and the total number of observations in this sample.

While most of the companies in the DJIA exist in the sample with no major changes this happens to a few of the constituents. Specifically, this is the case for Bank of America Corporation, J.P. Morgan Chase & Company, and AT&T Incorporated. We now describe the significant changes which occurred for these cases in detail:

- Bank of America Corporation, BAC, as it exists today is the successor of the North Carolina National Bank since the merger in September 1998. Thus, the sample used for this ticker contains returns on North Carolina National Bank with permno 59408 as well as options on this company prior to the merger.

- J. P. Morgan Chase & Company, JPM, as it exists today was formed at the end of 2000 when Chase Manhattan Corporation acquired J.P. Morgan & Co. Thus, the sample used for this ticker contains returns on Chase Manhattan Corporation with permno 47896 as well as options on this company prior to the acquisition.

- AT&T Incorporated, T, as it exists today was formed in November of 2005, when SBC Communications Inc. purchased former AT&T Corporation. Thus, the sample used for this ticker contains returns on SBC Communications with permno 66093 as well as options on this company prior to the purchase.

A.2 Return data

The source of the return and distribution data is the CRSP file which provides data from the time of listing and onwards for each company as indicated in Table 1. At certain occasions data was double checked with alternative data sources to verify very large movements in the asset prices. In all cases though the original prices provided by CRSP were deemed to be correct.

A.2.1 Data used for estimation and for option pricing

Besides the actual date the following data series were used from the CRSP file:

- DISTCD: Distribution Code. This code was used to decide if dividends should be considered in the option pricing part as cash dividends.

- DIVAMT: Dividend Cash Amount. While the dividends are included by CRSP in the RET series the DIVAMT was used in the option pricing part as the actual future dividends paid.

- FACPR: Factor to adjust price. This factor was also used in the option pricing part as options are protected from stock splits etc.

- RET: Holding Period Return (per day). The log of this was used as the return series.

When using the CRSP file special care has to be taken when it comes to dividend payments as these may lead to multiple observations on a given day. For this reason all the files were checked for dividend payments and multiple observations were consolidated such that only one observation was available per day. Moreover, in doing so it was verified that only cash dividends occurred as dividend payments.

A.3 Option data

The source of the option data is the OptionMetrics data base provided by IvyDB which contains data from 1996 and onwards. The data base contains an end of day observation for each traded option contract. We screen the initial sample the following ways:

1. We eliminate options with more than a year to expiration which we in trading days take to be 252.

2. We eliminate options with less than 5 trading day to expiration.

3. We eliminate options for which the traded volume during the day was less than 5 contracts.

4. We eliminate options with non standard settlement as indicated by OptionMetrics when the variable "FLAG" equals 1.

A.3.1 Dates used for option pricing

With a sample spanning 11 years and 30 stocks it is infeasible to price all existing options. For this reason we chose to work only with one day per month for a total of 132 days. This also minimizes the number of estimations which are needed. The actual dates chosen are Wednesdays for which a one month option, which we take to be 18 trading days, is available. If Wednesday is a no trade day the Tuesday immediately before was used. This happens in December of 1996 and in December of 2002.

A.3.2 Option data errors

While the data available from OptionMetrics is generally of very high quality, a few errors were encountered. The errors relate to two options on AT&T, T, which on June 25, 2003, mistakenly were recorded with at strike price of 2530 instead of 30. This error was manually corrected in the original option data file.

B Figures and Tables

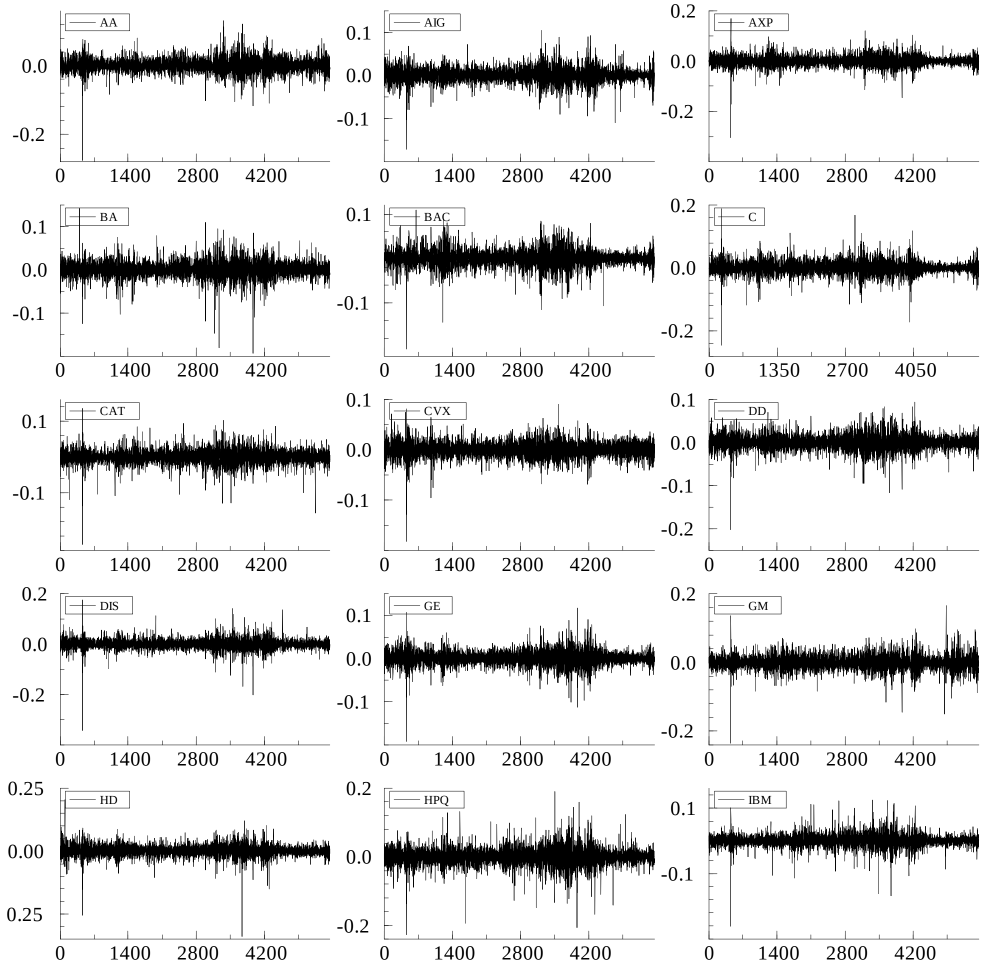

Figure 1: Timeseries of R_t, the log returns, for the first 15 stocks in alphabetical order.

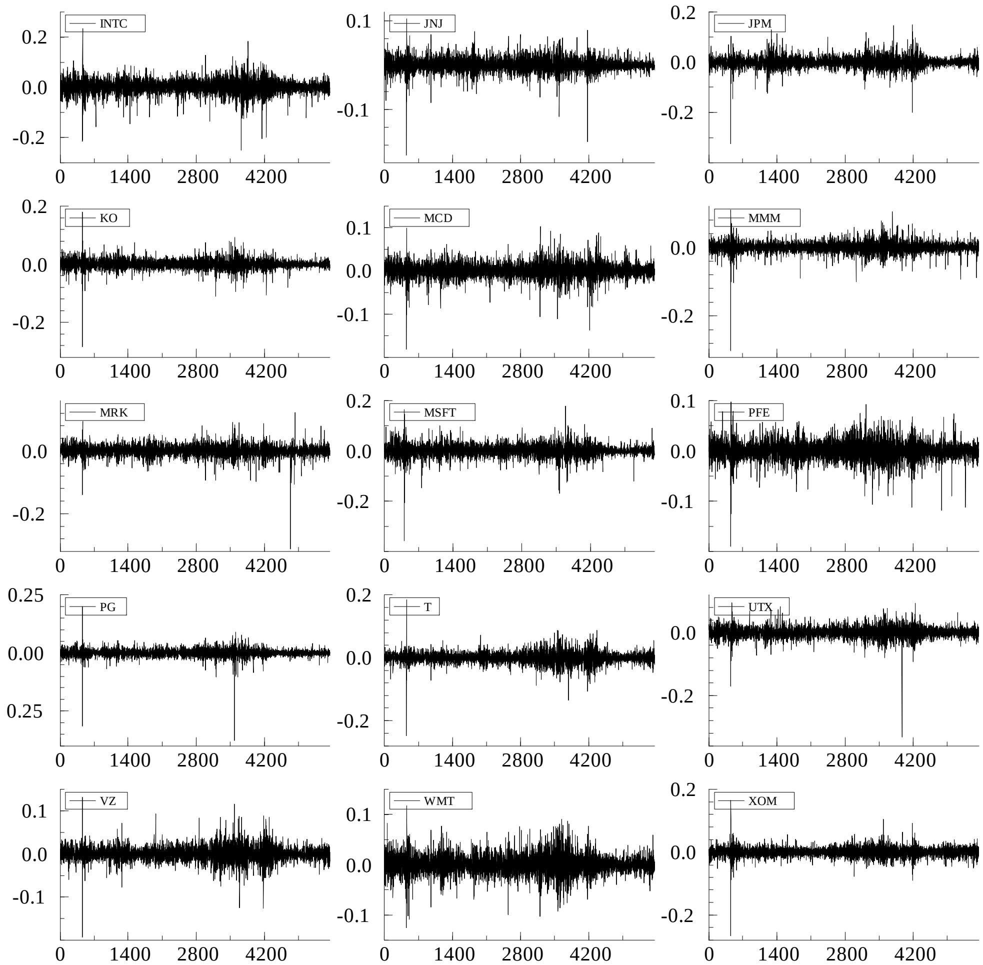

Figure 2: Time series of R_t, the log returns, for the last 15 stocks in alphabetical order.

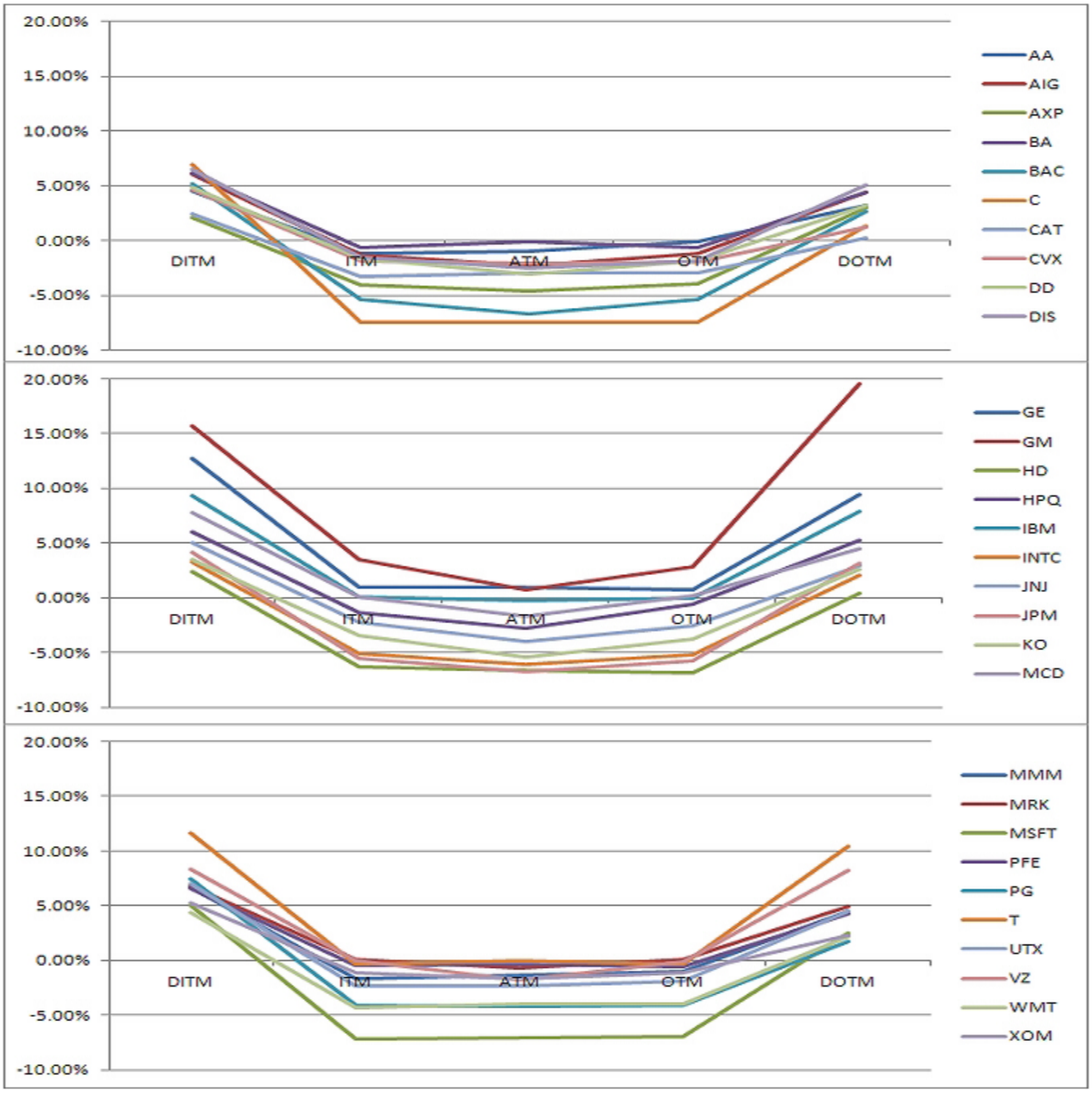

Figure 3: This figure plots the difference between the ISDs implied from the actual prices and the historical volatility for each moneyness category. The top plot is for the first 10 assets, middle plot for asset 11 to 20, and the bottom plot is for the last 10 assets in alphabetical order.

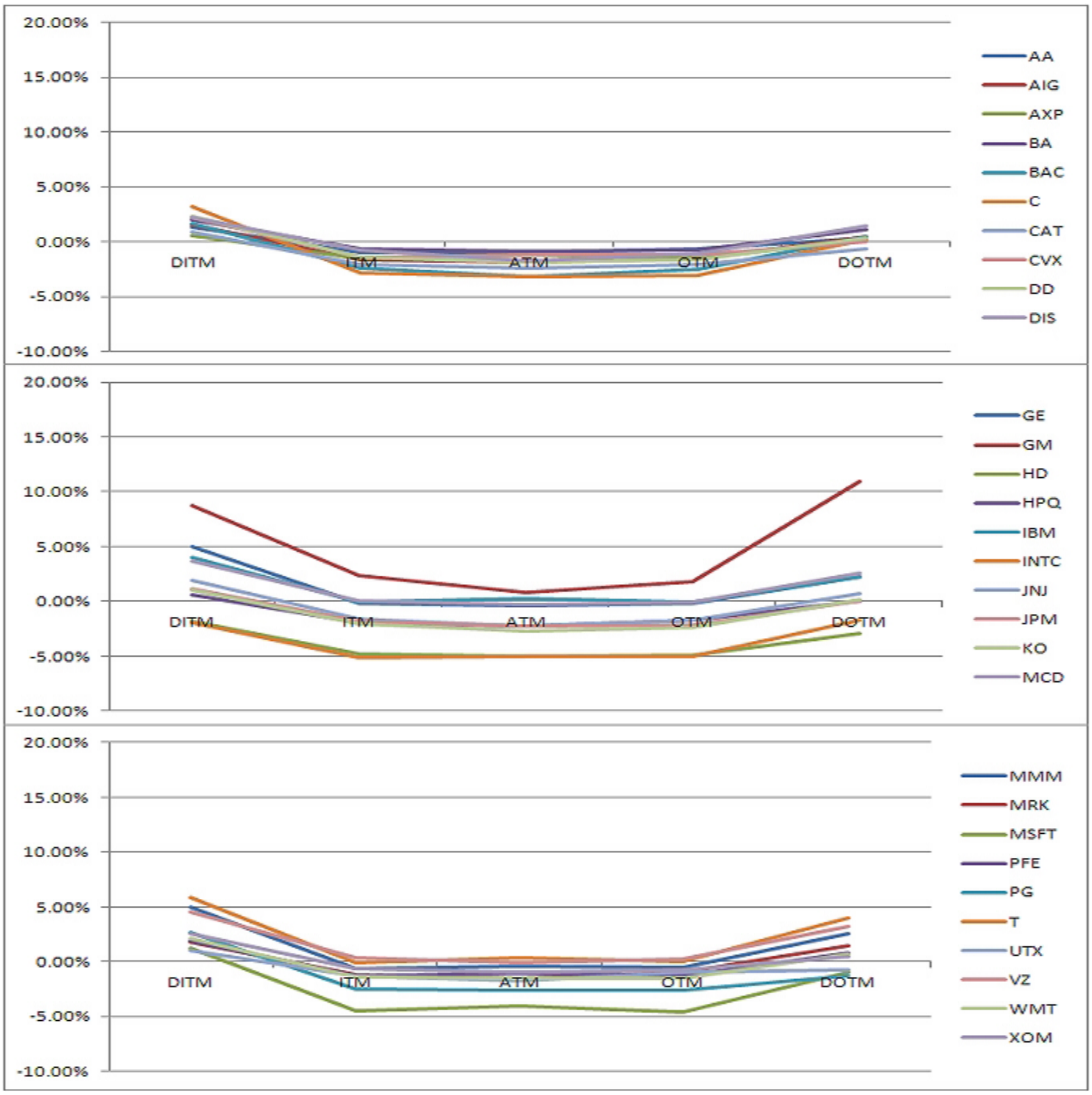

Figure 4: This figure plots the difference between the ISDs implied from the actual prices and from the price estimates from the skewed NIG NGARCH model for each moneyness category. The top plot is for the first 10 assets, middle plot for asset 11 to 20, and the bottom plot is for the last 10 assets in alphabetical order.

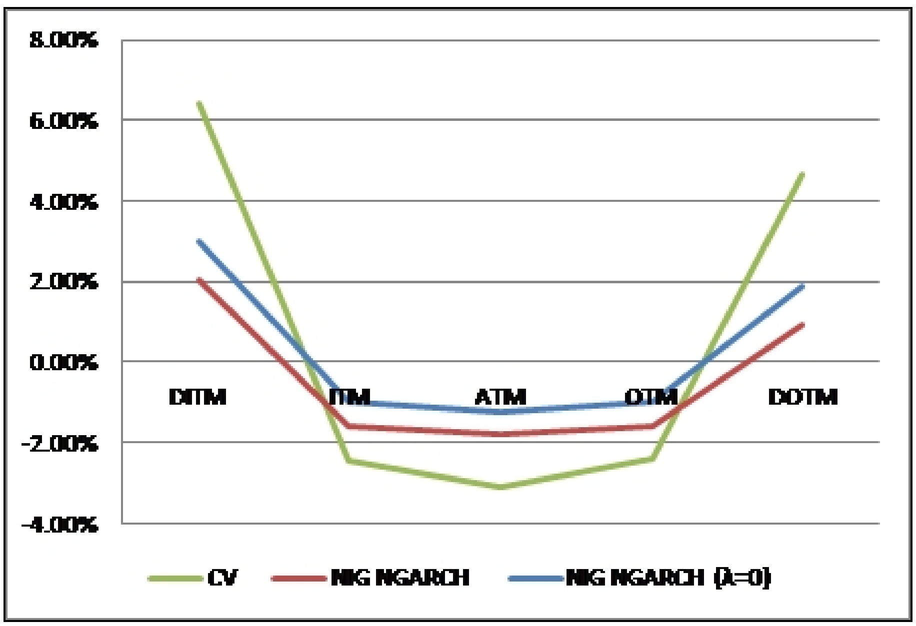

Figure 5: This figure plots the overall, across the 30 stocks, difference between the ISDs implied from the actual prices and from the price estimates from the CV model, the NIG NGARCH model, and the NIG NGARCH model with $\lambda = 0$ for each moneyness category.

Table 1: Constituents of the Dow Jones Industrial Index

Security	Ticker	OptionMetric ID	CRSP Permno	CUSIP	Period	# observations
3M CO	MMM	107616	22592	88579Y10	19460114-20071231	15796
ALCOA INC	AA	101204	24643	01381710	19510611-20071231	14278
AMERICAN EXPRESS CO	AXP	101375	59176	02581610	19721214-20071231	8843
AMERICAN INTL GROUP INC	AIG	101397	66800	02687410	19721214-20071231	8842
AT&T INC	T	109775	66093	00206R10	19840216-20071231	6025
BANK OF AMERICA CORPORATION	BAC	101966	59408	06050510	19721214-20071231	8842
BOEING CO	BA	102265	19561	09702310	19340905-20071231	19214
CATERPILLAR INC DEL	CAT	102796	18542	14912310	19291202-20071231	20617
CHEVRON TEXACO CORP	CVX	102968	14541	16676410	19251231-20071231	21796
CITIGROUP INC	C	103049	70519	17296710	19861029-20071231	5341
COCA COLA CO	KO	103125	11308	19121610	19251231-20071231	21802
DU PONT E I DE NEMOURS & CO	DD	103969	11703	26353410	19251231-20071231	21793
EXXON MOBIL CORP	XOM	104533	11850	30231G10	19251231-20071231	21835
GENERAL ELECTRIC CO	GE	105169	12060	36960410	19251231-20071231	21774
GENERAL MTRS CORP	GM	105175	12079	37044210	19260102-20071231	21803
HEWLETT PACKARD CO	HPQ	105700	27828	42823610	19610317-20071231	11777
HOME DEPOT INC	HD	105759	66181	43707610	19810922-20071231	6631
INTEL CORP	INTC	106203	59328	45814010	19721214-20071231	8842
INTERNATIONAL BUSINESS MACHS	IBM	106276	12490	45920010	19260102-20071231	21758
J.P. MORGAN CHASE & CO	JPM	102936	47896	46625H10	19690305-20071231	9800
JOHNSON & JOHNSON	JNJ	106566	22111	47816010	19440925-20071231	16181
MCDONALDS CORP	MCD	107318	43449	58013510	19660705-20071231	10443
MERCK & CO INC	MRK	107430	22752	58933110	19460516-20071231	15713
MICROSOFT CORP	MSFT	107525	10107	59491810	19860313-20071231	5501
PFIZER INC	PFE	108948	21936	71708110	19440117-20071231	16414
PROCTER & GAMBLE CO	PG	109224	18163	74271810	19290812-20071231	20708
UNITED TECHNOLOGIES CORP	UTX	111459	17830	91301710	19290411-20071231	20793
VERIZON COMMUNICATIONS	VZ	111668	65875	92343V10	19840216-20071231	6022
WAL MART STORES INC	WMT	111860	55976	93114210	19721120-20071231	8860
WALT DISNEY CO	DIS	103879	26403	25468710	19571112-20071231	12637

Notes: This table shows the constituents of the Dow Jones Industrial Average as of February 1, 2008.

Table 2: Schwartz Information Criteria values

Stock	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
AA	4.2561	4.1168	4.1126	4.0642	4.0627	4.0553	4.0542	4.0587	4.0574	4.0630	4.0616	4.0539	4.0528	4.0570	4.0558
AIG	3.9029	3.7085	3.6954	3.6510	3.6446	3.6391	3.6337	3.6434	3.6374	3.6502	3.6439	3.6387	3.6333	3.6427	3.6368
AXP	4.3167	4.0612	4.0517	4.0188	4.0134	4.0102	4.0057	4.0132	4.0083	4.0168	4.0117	4.0088	4.0044	4.0114	4.0066
BA	4.0872	3.9588	3.9482	3.8865	3.8816	3.8726	3.8687	3.8791	3.8746	3.8854	3.8809	3.8720	3.8683	3.8783	3.8741
BAC	4.0805	3.8449	3.8239	3.7635	3.7546	3.7510	3.7435	3.7562	3.7479	3.7635	3.7545	3.7508	3.7433	3.7561	3.7478
C	4.3483	4.1047	4.0961	4.0446	4.0391	4.0333	4.0278	4.0375	4.0318	4.0431	4.0376	4.0324	4.0269	4.0363	4.0306
CAT	4.1772	4.0995	4.0916	4.0018	3.9986	3.9880	3.9854	3.9954	3.9923	4.0009	3.9979	3.9876	3.9851	3.9947	3.9919
CVX	3.6659	3.5505	3.5437	3.5260	3.5221	3.5198	3.5169	3.5216	3.5183	3.5260	3.5221	3.5198	3.5168	3.5216	3.5183
DD	3.8955	3.7437	3.7367	3.7003	3.6972	3.6911	3.6891	3.6946	3.6920	3.6992	3.6963	3.6904	3.6885	3.6933	3.6910
DIS	4.2238	4.0030	3.9953	3.9259	3.9219	3.9093	3.9058	3.9167	3.9130	3.9247	3.9210	3.9084	3.9051	3.9157	3.9122
GE	3.8252	3.5589	3.5483	3.5354	3.5284	3.5279	3.5221	3.5301	3.5238	3.5342	3.5276	3.5273	3.5217	3.5291	3.5231
GM	4.2781	4.1552	4.1446	4.0951	4.0908	4.0863	4.0831	4.0899	4.0861	4.0929	4.0887	4.0844	4.0813	4.0871	4.0835
HD	4.4395	4.2361	4.2196	4.1707	4.1624	4.1579	4.1507	4.1630	4.1550	4.1696	4.1615	4.1573	4.1502	4.1622	4.1544
HPQ	4.6634	4.5309	4.5227	4.4303	4.4272	4.4120	4.4095	4.4217	4.4188	4.4300	4.4271	4.4120	4.4095	4.4217	4.4188
IBM	4.0780	3.8528	3.8294	3.7505	3.7428	3.7314	3.7258	3.7418	3.7346	3.7505	3.7428	3.7314	3.7258	3.7418	3.7346
INTC	4.8618	4.6851	4.6787	4.6368	4.6342	4.6202	4.6185	4.6265	4.6245	4.6366	4.6340	4.6198	4.6181	4.6263	4.6242
JNJ	3.7178	3.5159	3.5077	3.4740	3.4687	3.4657	3.4608	3.4686	3.4635	3.4735	3.4683	3.4654	3.4606	3.4682	3.4632
JPM	4.3946	4.1177	4.1036	4.0368	4.0298	4.0290	4.0225	4.0321	4.0253	4.0365	4.0295	4.0290	4.0225	4.0321	4.0253
KO	3.8339	3.5745	3.5669	3.5204	3.5161	3.5060	3.5024	3.5117	3.5077	3.5190	3.5149	3.5051	3.5017	3.5104	3.5067
MCD	3.9025	3.7706	3.7665	3.7334	3.7308	3.7238	3.7218	3.7273	3.7251	3.7324	3.7301	3.7232	3.7214	3.7266	3.7246
MMM	3.6793	3.5204	3.5117	3.3983	3.3966	3.3834	3.3826	3.3927	3.3913	3.3973	3.3960	3.3833	3.3826	3.3924	3.3912
MRK	3.9388	3.9028	3.8832	3.7674	3.7615	3.7475	3.7425	3.7572	3.7514	3.7671	3.7614	3.7475	3.7425	3.7571	3.7514
MSFT	4.5322	4.3083	4.3070	4.2324	4.2317	4.2187	4.2180	4.2248	4.2241	4.2306	4.2299	4.2177	4.2170	4.2233	4.2227
PFE	4.0429	3.9047	3.9022	3.8539	3.8516	3.8418	3.8396	3.8465	3.8443	3.8537	3.8515	3.8418	3.8396	3.8465	3.8442
PG	3.8322	3.5244	3.5050	3.4232	3.4186	3.4088	3.4054	3.4153	3.4112	3.4227	3.4183	3.4086	3.4053	3.4150	3.4111
T	3.9193	3.6533	3.6508	3.6112	3.6088	3.6061	3.6037	3.6078	3.6054	3.6103	3.6082	3.6059	3.6036	3.6074	3.6052
UTX	3.9382	3.7577	3.7316	3.6763	3.6665	3.6629	3.6552	3.6677	3.6590	3.6750	3.6658	3.6625	3.6551	3.6671	3.6588
VZ	3.8158	3.5922	3.5882	3.5488	3.5465	3.5410	3.5392	3.5439	3.5418	3.5475	3.5456	3.5400	3.5384	3.5426	3.5409
WMT	4.1079	3.9104	3.9076	3.8839	3.8823	3.8785	3.8772	3.8801	3.8787	3.8830	3.8816	3.8778	3.8767	3.8793	3.8780
XOM	3.6346	3.4340	3.4284	3.4055	3.4023	3.3968	3.3945	3.3994	3.3968	3.4053	3.4017	3.3966	3.3939	3.3992	3.3962

Notes: This table reports the Swartz Information Criteria, or SIC, values for the various models used for each of the stocks. Estimation is performed with the quasi-maximum likelihood method using data from 1986 through 2007. The 15 models are respectively: (1) CV, (2) GARCH, and (3) NGARCH with normal errors, (4) GARCH and (5) NGARCH with symmetric GED errors, (6) GARCH and (7) NGARCH with symmetric NIG errors, (8) GARCH and (9) NGARCH with symmetric VG errors, (10) GARCH and (11) NGARCH with skewed GED errors, (12) GARCH and (13) NGARCH with skewed NIG errors, (14) GARCH and (15) NGARCH with skewed VG errors.

Table 3: Estimation Results for NIG NGARCH models

Stock	λ	se(λ)	β	se(β)	α	se(α)	γ	se(γ)	a	se(a)	b	se(b)	Q(20)	$Q^2(20)$	ARCH5
AA	0.0234	(0.013)	0.9489	(0.011)	0.0396	(0.007)	-0.2610	(0.108)	2.0591	(0.276)	0.1631	(0.075)	[0.001]	[0.912]	[0.699]
AIG	0.0301	(0.013)	0.9168	(0.012)	0.0639	(0.009)	-0.4159	(0.079)	2.0494	(0.256)	0.0805	(0.063)	[0.001]	[0.952]	[0.982]
AXP	0.0335	(0.013)	0.9326	(0.013)	0.0539	(0.012)	-0.4195	(0.118)	2.3247	(0.295)	0.1743	(0.076)	[0.326]	[0.001]	[0.000]
BA	0.0245	(0.013)	0.9348	(0.023)	0.0428	(0.016)	-0.4819	(0.130)	1.6863	(0.194)	0.0707	(0.054)	[0.725]	[0.269]	[0.116]
BAC	0.0331	(0.012)	0.9210	(0.026)	0.0587	(0.024)	-0.4931	(0.163)	1.8067	(0.229)	-0.0600	(0.051)	[0.057]	[0.895]	[0.610]
C	0.0393	(0.013)	0.9384	(0.027)	0.0495	(0.031)	-0.4424	(0.305)	2.0299	(0.267)	0.1217	(0.065)	[0.301]	[0.626]	[0.171]
CAT	0.0274	(0.013)	0.9535	(0.014)	0.0295	(0.008)	-0.5066	(0.139)	1.3461	(0.138)	0.0467	(0.042)	[0.010]	[0.335]	[0.050]
CVX	0.0312	(0.013)	0.9167	(0.013)	0.0552	(0.007)	-0.3841	(0.100)	3.2629	(0.515)	-0.0604	(0.106)	[0.212]	[0.050]	[0.730]
DD	0.0211	(0.013)	0.9472	(0.014)	0.0398	(0.010)	-0.3588	(0.113)	2.0781	(0.240)	0.1000	(0.065)	[0.699]	[0.411]	[0.101]
DIS	0.0286	(0.013)	0.9210	(0.026)	0.0585	(0.019)	-0.3735	(0.104)	1.6967	(0.200)	0.0909	(0.059)	[0.329]	[0.821]	[0.279]
GE	0.0361	(0.012)	0.9392	(0.011)	0.0443	(0.009)	-0.5153	(0.103)	3.1067	(0.425)	0.1396	(0.102)	[0.272]	[0.026]	[0.002]
GM	0.0092	(0.013)	0.9295	(0.015)	0.0488	(0.012)	-0.4102	(0.140)	1.7652	(0.201)	0.1556	(0.057)	[0.156]	[0.400]	[0.153]
HD	0.0428	(0.012)	0.9353	(0.012)	0.0430	(0.008)	-0.5935	(0.098)	1.9385	(0.244)	0.0877	(0.062)	[0.040]	[0.996]	[0.841]
HPQ	0.0249	(0.014)	0.9677	(0.007)	0.0230	(0.009)	-0.5329	(0.287)	1.3874	(0.149)	-0.0089	(0.046)	[0.536]	[0.969]	[0.841]
IBM	0.0074	(0.013)	0.9415	(0.018)	0.0416	(0.014)	-0.5243	(0.116)	1.3866	(0.140)	0.0061	(0.042)	[0.838]	[0.911]	[0.643]
INTC	0.0353	(0.013)	0.9514	(0.012)	0.0389	(0.008)	-0.3051	(0.100)	2.2140	(0.260)	-0.0990	(0.072)	[0.004]	[0.774]	[0.155]
JNJ	0.0403	(0.013)	0.9342	(0.013)	0.0521	(0.010)	-0.4324	(0.089)	2.2478	(0.259)	0.0631	(0.066)	[0.005]	[0.001]	[0.000]
JPM	0.0244	(0.013)	0.9334	(0.014)	0.0501	(0.015)	-0.4935	(0.165)	1.8208	(0.248)	0.0105	(0.053)	[0.105]	[0.987]	[0.682]
KO	0.0417	(0.013)	0.9408	(0.011)	0.0482	(0.009)	-0.3801	(0.089)	2.0036	(0.232)	0.1163	(0.067)	[0.575]	[0.011]	[0.001]
MCD	0.0296	(0.013)	0.9447	(0.009)	0.0391	(0.006)	-0.3535	(0.119)	2.1832	(0.252)	0.0950	(0.072)	[0.160]	[0.000]	[0.000]
MMM	0.0254	(0.014)	0.9628	(0.012)	0.0278	(0.007)	-0.3581	(0.173)	1.0761	(0.102)	0.0142	(0.033)	[0.754]	[0.837]	[0.278]
MRK	0.0300	(0.013)	0.9060	(0.020)	0.0464	(0.010)	-0.6221	(0.144)	1.4456	(0.204)	-0.0101	(0.048)	[0.072]	[1.000]	[0.999]
MSFT	0.0572	(0.014)	0.9352	(0.013)	0.0595	(0.011)	-0.1454	(0.072)	1.7349	(0.216)	0.1077	(0.059)	[0.742]	[0.998]	[0.998]
PFE	0.0258	(0.013)	0.9341	(0.014)	0.0507	(0.010)	-0.3168	(0.095)	2.1159	(0.266)	0.0011	(0.065)	[0.014]	[0.337]	[0.053]
PG	0.0395	(0.013)	0.9217	(0.013)	0.0601	(0.009)	-0.4071	(0.101)	1.5543	(0.183)	0.0176	(0.048)	[0.041]	[0.994]	[0.652]
T	0.0335	(0.013)	0.9052	(0.021)	0.0760	(0.016)	-0.2768	(0.082)	2.0927	(0.263)	0.0442	(0.062)	[0.014]	[0.000]	[0.000]
UTX	0.0325	(0.012)	0.9267	(0.014)	0.0439	(0.012)	-0.6756	(0.186)	1.9190	(0.282)	0.0438	(0.062)	[0.090]	[1.000]	[0.945]
VZ	0.0247	(0.013)	0.9317	(0.022)	0.0560	(0.017)	-0.2653	(0.092)	2.1726	(0.276)	0.1329	(0.072)	[0.033]	[0.001]	[0.000]
WMT	0.0308	(0.013)	0.9542	(0.008)	0.0401	(0.006)	-0.2383	(0.091)	2.6742	(0.341)	0.1354	(0.084)	[0.015]	[0.020]	[0.002]
XOM	0.0321	(0.013)	0.9125	(0.018)	0.0603	(0.010)	-0.4041	(0.109)	2.9320	(0.431)	-0.1665	(0.101)	[0.000]	[0.000]	[0.000]

Notes: This table reports Quasi Maximum Likelihood Estimates (QMLE) for the NIG NGARCH model using daily returns from 1986 through 2007 assuming a risk-free interest rate of 4.7% corresponding to the value on December 31, 2007. Robust standard errors are reported in parentheses next to each estimates. $Q(20)$ is the Ljung-Box portmanteau test for up to 20'th order serial correlation in the standardized residuals, whereas $Q^2(20)$ is for up to 20'th order serial correlation in the squared standardized residuals. Finally, ARCH5 denotes the ARCH test from Engle (1982). In square brackets below all test statistics p-values are reported.

Table 4: Number of options across maturity and moneyness

Stock	All	ST	MT	LT	VLT	DITM	ITM	ATM	OTM	DOTM
AA	2693	754	696	674	569	415	409	430	657	782
AIG	3412	869	770	920	853	476	529	555	835	1017
AXP	3763	1125	946	934	758	502	627	658	980	996
BA	4711	1084	1065	1329	1233	842	739	667	1038	1425
BAC	4448	1010	1034	1248	1156	650	694	820	1040	1244
C	5694	1308	1346	1621	1419	1165	854	840	1140	1695
CAT	3628	937	865	1004	822	574	623	565	871	995
CVX	3374	845	777	938	814	461	587	604	1002	720
DD	3170	820	819	799	732	389	554	582	881	764
DIS	3710	935	911	1005	859	652	610	559	811	1078
GE	6701	1479	1501	1912	1809	1515	1071	816	1365	1934
GM	5391	1240	1301	1528	1322	1097	738	647	1009	1900
HD	4919	1118	1135	1360	1306	930	732	737	1014	1506
HPQ	5016	1272	1183	1411	1150	1062	665	606	906	1777
IBM	8949	2178	2229	2381	2161	1866	1336	1040	1648	3059
INTC	8884	2045	2081	2312	2446	2548	1018	752	1175	3391
JNJ	4092	952	978	1068	1094	694	705	694	996	1003
JPM	4957	1186	1112	1450	1209	922	783	676	1087	1489
KO	4212	942	949	1210	1111	614	756	741	1062	1039
MCD	3248	776	789	909	774	509	551	527	857	804
MMM	3603	1059	968	874	702	497	623	688	1008	787
MRK	5133	1199	1248	1370	1316	929	850	769	1165	1420
MSFT	8900	2074	2074	2314	2438	2473	1147	851	1355	3074
PFE	6113	1310	1351	1760	1692	1291	932	814	1215	1861
PG	3893	987	937	1052	917	556	675	747	1031	884
T	2481	613	564	641	663	383	460	343	568	727
UTX	2479	742	624	610	503	300	425	520	680	554
VZ	3047	732	731	803	781	460	493	538	730	826
WMT	4930	1123	1144	1404	1259	853	835	709	1096	1437
XOM	4328	1045	1041	1139	1103	642	789	775	1115	1007
All	139879	33759	33169	37980	34971	26267	21810	20270	30337	41195

Notes: This table reports the number of options in the different maturity and moneyness categories. The different categories of maturity, T, are labelled as follows: short term (ST) has $T \leq 21$, middle term (MT) has $21 < T \leq 63$. long term (LT) has $63 < T \leq 126$, and very long term (VLT) has $126 \leq T$. Moneyness, Mon, is calculated as the ratio of the asset price to the strike price. The different categories of moneyness are labelled as follows for call options: deep in the money, (DITM) has $Mon > 1.1$, in the money (ITM) has $1.1 \geq Mon > 1.025$, at the money (ATM) has $1.025 \geq Mon > 0.975$, out of the money (OTM) has $0.975 \geq Mon > 0.9$, and deep out of the money (DOTM) has $0.9 \geq Mon$. For put options the (D)ITM and (D)OTM categories are reversed.

Table 5: Average price of options across maturity and moneyness

Stock	All	ST	MT	LT	VLT	DITM	ITM	ATM	OTM	DOTM
AA	2.519	2.167	2.388	2.584	3.068	7.164	3.392	2.127	1.454	0.707
AIG	4.519	3.831	4.058	4.848	5.280	14.900	6.416	3.728	2.197	1.011
AXP	4.307	3.428	3.810	4.788	5.637	12.565	6.161	3.828	2.339	1.229
BA	4.110	3.260	3.409	4.267	5.294	12.009	5.209	3.252	1.905	0.880
BAC	3.819	3.196	3.302	3.851	4.792	12.066	5.228	3.020	1.738	0.991
C	3.989	3.306	3.636	4.094	4.833	11.286	4.446	2.807	1.642	0.907
CAT	4.470	3.589	3.799	4.549	6.084	14.242	5.635	3.451	1.904	0.928
CVX	4.116	3.578	3.500	4.280	5.072	13.583	5.659	3.295	1.702	0.845
DD	3.017	2.374	2.621	3.099	4.090	10.020	4.331	2.389	1.445	0.789
DIS	2.737	2.135	2.366	2.861	3.642	7.453	3.526	2.301	1.394	0.675
GE	4.940	4.381	4.342	4.870	5.966	12.915	5.400	3.750	2.200	0.873
GM	3.949	3.356	3.471	3.864	5.075	10.921	4.825	3.101	2.021	0.897
HD	3.651	3.246	3.229	3.665	4.349	10.522	4.321	2.800	1.669	0.833
HPQ	4.880	4.275	4.005	5.067	6.220	12.117	5.978	3.847	3.102	1.403
IBM	9.274	7.454	8.038	9.916	11.677	27.336	10.236	6.596	3.908	1.637
INTC	7.374	5.887	5.899	7.522	9.733	17.421	7.493	5.756	3.736	1.409
JNJ	4.647	3.707	4.142	4.600	5.961	14.344	5.800	3.211	1.842	0.904
JPM	3.940	3.437	3.146	4.020	5.067	10.539	4.996	3.427	2.017	0.935
KO	3.499	2.860	3.079	3.492	4.407	11.423	4.537	2.563	1.491	0.780
MCD	2.481	2.000	2.049	2.580	3.287	7.462	3.259	1.852	1.194	0.578
MMM	5.643	4.727	5.040	5.918	7.512	19.091	7.656	4.184	2.194	1.247
MRK	5.015	3.843	4.310	5.378	6.372	14.756	5.944	3.832	2.293	0.959
MSFT	8.032	6.688	6.416	8.537	10.072	19.853	7.562	5.625	3.457	1.382
PFE	4.481	3.509	3.507	4.562	5.925	11.856	5.138	3.665	2.089	0.954
PG	4.863	4.460	3.979	5.074	5.956	16.108	6.301	3.769	1.980	0.977
T	2.459	2.369	2.021	2.422	2.950	7.614	3.052	1.874	1.140	0.674
UTX	4.440	3.930	4.070	4.400	5.700	15.215	6.333	3.522	1.939	1.085
VZ	2.930	2.406	2.143	3.244	3.836	9.288	3.871	2.179	1.340	0.722
WMT	3.685	2.981	3.103	3.787	4.726	10.710	4.641	2.802	1.637	0.955
XOM	3.704	3.332	3.361	3.589	4.499	12.095	4.981	2.684	1.431	0.657
All	4.848	4.014	4.121	4.984	6.194	14.313	5.670	3.518	2.109	1.047

Notes: This table reports the average price of options in the different maturity and moneyness categories. See the notes to Table 4 for the definition of the categories.

Table 6: Average ISD of options across maturity and moneyness

Stock	All	ST	MT	LT	VLT	DITM	ITM	ATM	OTM	DOTM
AA	33.04	35.15	33.11	32.21	31.23	36.48	30.61	30.76	31.55	35.13
AIG	28.34	30.88	29.00	27.57	26.10	33.99	25.76	24.53	25.80	31.54
AXP	32.70	34.50	32.26	32.80	30.51	36.35	30.15	29.45	30.32	37.11
BA	31.21	33.27	31.47	30.97	29.51	34.93	28.44	29.11	28.44	33.65
BAC	28.85	31.74	29.78	28.44	26.03	35.04	25.53	24.20	25.57	33.74
C	33.01	36.97	33.42	31.68	30.63	40.90	27.93	27.81	27.91	36.79
CAT	29.85	31.00	29.84	29.54	28.97	33.03	27.98	28.25	28.30	31.67
CVX	23.83	25.15	23.85	23.77	22.58	28.57	22.42	22.29	22.42	25.76
DD	27.25	28.31	27.27	26.77	26.60	32.42	25.60	24.04	25.34	30.70
DIS	32.90	35.36	32.58	32.02	31.68	37.67	30.09	28.76	29.65	36.42
GE	31.34	35.59	31.37	30.38	29.09	38.56	26.76	26.44	26.46	34.55
GM	40.88	40.74	41.82	40.64	40.34	46.14	34.01	31.09	33.24	48.13
HD	33.24	36.22	33.90	32.68	30.85	38.66	29.81	29.28	29.21	36.55
HPQ	41.17	44.72	41.92	40.38	37.59	45.13	37.32	36.10	37.86	43.86
IBM	33.70	37.11	33.96	32.98	30.96	38.93	29.58	29.04	29.41	36.66
INTC	43.19	48.26	42.30	42.47	40.60	46.81	38.45	37.27	38.32	45.19
JNJ	25.68	27.62	25.57	25.50	24.36	30.34	23.80	22.08	23.56	28.94
JPM	33.71	36.74	33.58	33.48	31.28	38.73	29.60	28.33	29.42	38.64
KO	26.04	28.01	26.47	25.62	24.55	31.12	24.08	22.08	23.84	30.04
MCD	28.84	30.50	28.98	28.58	27.41	33.76	27.03	25.33	27.06	31.54
MMM	25.58	27.05	25.20	25.08	24.60	30.74	23.15	23.35	23.78	29.24
MRK	28.83	30.66	28.95	28.40	27.57	32.61	26.63	25.84	26.67	31.42
MSFT	38.16	43.91	38.05	36.78	34.93	43.55	31.91	32.05	32.10	41.05
PFE	31.60	34.30	32.12	31.15	29.64	35.37	28.96	28.97	28.92	33.50
PG	25.81	28.57	25.15	25.35	24.18	34.28	22.94	22.76	23.10	29.30
T	31.68	36.46	30.42	30.58	29.66	40.07	26.91	26.60	26.83	37.01
UTX	28.03	29.68	28.33	27.34	26.16	34.70	25.39	25.18	25.84	32.46
VZ	28.92	31.56	28.09	29.19	27.03	35.08	25.90	24.06	25.63	33.95
WMT	30.12	32.58	30.70	29.49	28.18	34.38	26.81	27.00	27.11	33.56
XOM	24.02	25.86	24.02	23.52	22.92	28.99	22.51	21.87	22.51	26.02
All	32.12	34.82	32.18	31.53	30.20	38.35	28.22	27.18	27.96	36.19

Notes: This table reports the average ISD, implied standard deviation, in percentage terms of options in the different maturity and moneyness categories. See the notes to Table 4 for the definition of the categories.

Table 7: Dollar BIAS

Stock	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	Best	Worst
AA	0.022	-0.012	-0.034	-0.011	-0.001	-0.016	-0.014	-0.016	-0.012	-0.006	-0.018	-0.010	-0.022	-0.010	-0.023	5	3
AIG	-0.063	-0.141	-0.161	-0.104	-0.109	-0.099	-0.119	-0.102	-0.117	-0.099	-0.128	-0.093	-0.132	-0.096	-0.133	1	3
AXP	-0.178	-0.093	-0.109	-0.047	-0.034	-0.041	-0.047	-0.045	-0.048	-0.041	-0.072	-0.029	-0.061	-0.032	-0.064	12	1
BA	-0.056	-0.003	-0.021	-0.040	-0.013	-0.053	-0.035	-0.048	-0.033	-0.045	-0.055	-0.049	-0.054	-0.056	-0.056	2	15
BAC	-0.431	-0.297	-0.327	-0.217	-0.224	-0.202	-0.243	-0.209	-0.243	-0.213	-0.256	-0.200	-0.242	-0.206	-0.247	12	1
C	-0.411	-0.182	-0.240	-0.148	-0.163	-0.143	-0.177	-0.145	-0.175	-0.146	-0.203	-0.135	-0.191	-0.136	-0.192	12	1
CAT	-0.346	-0.328	-0.350	-0.204	-0.188	-0.187	-0.195	-0.197	-0.193	-0.197	-0.225	-0.182	-0.213	-0.192	-0.215	12	3
CVX	-0.173	-0.115	-0.150	-0.103	-0.114	-0.105	-0.125	-0.104	-0.124	-0.100	-0.126	-0.102	-0.128	-0.101	-0.128	10	1
DD	-0.065	-0.084	-0.095	-0.075	-0.069	-0.078	-0.085	-0.078	-0.082	-0.073	-0.088	-0.075	-0.093	-0.075	-0.093	1	3
DIS	-0.088	-0.087	-0.110	-0.068	-0.068	-0.071	-0.078	-0.071	-0.077	-0.064	-0.089	-0.063	-0.088	-0.063	-0.090	12	3
GE	0.313	0.120	0.079	0.130	0.117	0.129	0.108	0.127	0.109	0.140	0.109	0.135	0.103	0.136	0.102	3	1
GM	0.252	0.214	0.197	0.213	0.215	0.206	0.202	0.208	0.207	0.215	0.195	0.208	0.183	0.210	0.185	13	1
HD	-0.327	-0.208	-0.363	-0.205	-0.281	-0.211	-0.289	-0.207	-0.286	-0.197	-0.307	-0.203	-0.305	-0.199	-0.304	10	3
HPQ	0.227	0.147	0.089	0.013	0.015	-0.055	-0.053	-0.027	-0.015	0.016	0.012	-0.057	-0.049	-0.024	-0.019	11	1
IBM	0.263	0.080	0.058	0.055	0.166	0.044	0.155	0.038	0.151	0.060	0.141	0.050	0.137	0.043	0.138	8	1
INTC	-0.273	-0.295	-0.351	-0.296	-0.334	-0.315	-0.362	-0.309	-0.353	-0.299	-0.331	-0.321	-0.347	-0.313	-0.342	1	7
JNJ	-0.177	-0.114	-0.173	-0.093	-0.144	-0.089	-0.149	-0.091	-0.147	-0.090	-0.145	-0.088	-0.147	-0.088	-0.148	12	1
JPM	-0.326	-0.186	-0.246	-0.152	-0.132	-0.147	-0.159	-0.150	-0.158	-0.150	-0.162	-0.147	-0.159	-0.150	-0.160	5	1
KO	-0.210	-0.126	-0.177	-0.088	-0.136	-0.084	-0.142	-0.085	-0.140	-0.081	-0.154	-0.076	-0.155	-0.076	-0.153	12	1
MCD	0.016	0.028	0.015	0.027	0.029	0.023	0.019	0.025	0.022	0.029	0.019	0.025	0.016	0.027	0.017	3	5
MMM	-0.047	-0.029	-0.059	0.044	0.021	0.053	0.022	0.046	0.008	0.047	-0.004	0.056	0.019	0.049	0.003	15	3
MRK	0.163	0.060	0.013	0.062	0.047	0.056	0.035	0.057	0.038	0.068	0.030	0.062	0.026	0.064	0.026	3	1
MSFT	-0.343	-0.313	-0.404	-0.272	-0.332	-0.271	-0.336	-0.274	-0.339	-0.253	-0.337	-0.260	-0.337	-0.259	-0.341	10	3
PFE	0.208	0.137	0.102	0.095	0.084	0.062	0.046	0.071	0.057	0.107	0.080	0.071	0.045	0.081	0.054	13	1
PG	-0.387	-0.213	-0.396	-0.229	-0.287	-0.249	-0.311	-0.236	-0.300	-0.220	-0.305	-0.242	-0.316	-0.228	-0.311	2	3
T	0.141	0.105	0.092	0.118	0.115	0.117	0.103	0.116	0.104	0.119	0.104	0.119	0.100	0.118	0.100	3	1
UTX	-0.222	-0.182	-0.229	-0.147	-0.111	-0.145	-0.149	-0.148	-0.139	-0.141	-0.164	-0.139	-0.162	-0.139	-0.161	5	3
VZ	0.083	0.085	0.070	0.086	0.098	0.074	0.075	0.079	0.082	0.089	0.073	0.079	0.065	0.083	0.069	13	5
WMT	-0.192	-0.035	-0.095	-0.020	-0.062	-0.019	-0.068	-0.019	-0.068	-0.018	-0.071	-0.017	-0.070	-0.017	-0.072	12	1
XOM	-0.078	-0.037	-0.065	-0.035	-0.049	-0.042	-0.061	-0.040	-0.060	-0.033	-0.054	-0.040	-0.061	-0.038	-0.060	10	1
All	-0.085	-0.074	-0.121	-0.064	-0.072	-0.070	-0.088	-0.069	-0.085	-0.059	-0.090	-0.066	-0.094	-0.064	-0.094	10	3

Notes: This table reports the dollar BIAS for the various models used for each of the stocks. The 15 models are respectively: (1) CV, (2) GARCH, and (3) NGARCH with normal errors, (4) GARCH and (5) NGARCH with symmetric GED errors, (6) GARCH and (7) NGARCH with symmetric NIG errors, (8) GARCH and (9) NGARCH with symmetric VG errors, (10) GARCH and (11) NGARCH with skewed GED errors, (12) GARCH and (13) NGARCH with skewed NIG errors, (14) GARCH and (15) NGARCH with skewed VG errors. The last row reports the aggregate results for all 30 stocks and the two last columns reports the best and worst performing model number.

Table 8: Dollar RMSE

Stock	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	Best	Worst
AA	0.465	0.272	0.264	0.250	0.243	0.242	0.232	0.243	0.233	0.259	0.251	0.253	0.244	0.254	0.245	7	1
AIG	0.979	0.612	0.605	0.593	0.569	0.583	0.560	0.587	0.562	0.595	0.576	0.586	0.566	0.590	0.569	7	1
AXP	1.070	0.703	0.676	0.603	0.603	0.553	0.546	0.571	0.564	0.610	0.590	0.568	0.549	0.584	0.564	7	1
BA	0.669	0.435	0.392	0.399	0.381	0.404	0.394	0.395	0.382	0.396	0.382	0.406	0.395	0.399	0.384	5	1
BAC	1.186	0.961	0.946	0.822	0.839	0.787	0.817	0.802	0.828	0.828	0.848	0.786	0.809	0.804	0.824	12	1
C	0.997	0.587	0.628	0.525	0.545	0.511	0.531	0.513	0.533	0.530	0.560	0.517	0.541	0.520	0.545	6	1
CAT	0.772	0.742	0.756	0.525	0.512	0.508	0.504	0.520	0.512	0.527	0.544	0.508	0.520	0.520	0.531	7	1
CVX	0.651	0.437	0.424	0.431	0.411	0.429	0.416	0.430	0.415	0.431	0.414	0.429	0.417	0.430	0.416	5	1
DD	0.645	0.379	0.383	0.344	0.349	0.330	0.337	0.335	0.341	0.347	0.356	0.334	0.344	0.339	0.349	6	1
DIS	0.637	0.587	0.590	0.564	0.558	0.554	0.554	0.559	0.557	0.560	0.565	0.549	0.557	0.553	0.560	12	1
GE	1.045	0.569	0.537	0.573	0.567	0.571	0.559	0.568	0.559	0.589	0.564	0.580	0.555	0.581	0.553	3	1
GM	0.699	0.604	0.562	0.593	0.562	0.582	0.546	0.585	0.552	0.598	0.553	0.587	0.538	0.591	0.542	13	1
HD	0.794	0.488	0.616	0.485	0.543	0.493	0.553	0.489	0.548	0.486	0.565	0.494	0.567	0.490	0.563	4	1
HPQ	1.180	0.887	0.766	0.655	0.632	0.610	0.596	0.626	0.610	0.659	0.634	0.608	0.596	0.623	0.603	13	1
IBM	1.492	1.118	1.009	0.991	0.979	0.958	0.957	0.985	0.964	0.995	0.967	0.965	0.953	0.990	0.959	13	1
INTC	0.899	0.745	0.791	0.699	0.748	0.689	0.759	0.694	0.756	0.701	0.746	0.693	0.743	0.696	0.745	6	1
JNJ	0.748	0.546	0.561	0.517	0.529	0.506	0.522	0.510	0.524	0.517	0.528	0.506	0.521	0.510	0.523	12	1
JPM	0.935	0.613	0.554	0.500	0.435	0.485	0.443	0.488	0.441	0.499	0.450	0.485	0.441	0.488	0.441	5	1
KO	0.679	0.487	0.492	0.425	0.442	0.402	0.433	0.409	0.434	0.428	0.450	0.406	0.439	0.413	0.441	6	1
MCD	0.379	0.266	0.259	0.260	0.259	0.254	0.255	0.256	0.255	0.260	0.256	0.255	0.254	0.256	0.254	13	1
MMM	1.004	0.830	0.764	0.659	0.642	0.643	0.619	0.649	0.625	0.662	0.643	0.647	0.623	0.652	0.629	7	1
MRK	0.652	0.527	0.501	0.526	0.514	0.525	0.512	0.525	0.511	0.535	0.507	0.534	0.506	0.534	0.505	3	1
MSFT	0.927	0.778	0.851	0.752	0.788	0.753	0.794	0.752	0.794	0.739	0.791	0.745	0.794	0.742	0.796	10	1
PFE	0.853	0.692	0.650	0.605	0.592	0.555	0.543	0.569	0.557	0.623	0.591	0.567	0.544	0.583	0.557	7	1
PG	1.114	0.872	0.922	0.779	0.781	0.788	0.799	0.786	0.790	0.780	0.797	0.789	0.804	0.788	0.801	4	1
T	0.638	0.477	0.472	0.477	0.475	0.471	0.462	0.472	0.464	0.478	0.469	0.473	0.461	0.474	0.463	13	1
UTX	1.098	0.851	0.813	0.782	0.712	0.769	0.721	0.777	0.719	0.783	0.732	0.773	0.726	0.780	0.728	5	1
VZ	0.624	0.418	0.405	0.381	0.389	0.353	0.352	0.364	0.364	0.387	0.376	0.364	0.353	0.374	0.363	7	1
WMT	0.907	0.448	0.460	0.426	0.444	0.418	0.440	0.419	0.439	0.429	0.445	0.421	0.441	0.422	0.440	6	1
XOM	0.459	0.353	0.339	0.319	0.310	0.306	0.299	0.310	0.302	0.320	0.308	0.308	0.297	0.312	0.301	13	1
All	0.917	0.676	0.664	0.607	0.608	0.592	0.599	0.599	0.602	0.610	0.610	0.595	0.599	0.602	0.602	6	1

Notes: This table reports the dollar RMSE for the various models used for each of the stocks. The 15 models are respectively: (1) CV, (2) GARCH, and (3) NGARCH with normal errors, (4) GARCH and (5) NGARCH with symmetric GED errors, (6) GARCH and (7) NGARCH with symmetric NIG errors, (8) GARCH and (9) NGARCH with symmetric VG errors, (10) GARCH and (11) NGARCH with skewed GED errors, (12) GARCH and (13) NGARCH with skewed NIG errors, (14) GARCH and (15) NGARCH with skewed VG errors. The last row reports the aggregate results for all 30 stocks and the two last columns reports the best and worst performing model number.

Table 9: ISD BIAS

Stock	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	Best	Worst
AA	1.26	0.26	-0.33	0.21	0.18	0.15	0.01	0.18	0.04	0.27	-0.10	0.18	-0.17	0.24	-0.17	7	1
AIG	1.19	-0.21	-0.73	-0.04	-0.32	-0.03	-0.44	-0.06	-0.42	0.00	-0.50	0.04	-0.59	0.03	-0.54	10	1
AXP	-1.47	-0.92	-1.27	-0.50	-0.56	-0.43	-0.66	-0.40	-0.68	-0.43	-0.90	-0.30	-0.76	-0.30	-0.78	12	1
BA	2.11	1.75	1.23	0.68	0.93	0.36	0.57	0.50	0.61	0.53	0.40	0.40	0.27	0.35	0.32	13	1
BAC	-2.00	-1.22	-1.85	-0.77	-1.01	-0.68	-1.28	-0.72	-1.24	-0.68	-1.32	-0.66	-1.25	-0.68	-1.29	12	1
C	-2.10	0.01	-1.26	0.18	-0.42	0.13	-0.72	0.19	-0.66	0.17	-0.99	0.22	-0.90	0.27	-0.89	2	1
CAT	-1.37	-1.58	-1.98	-1.05	-0.87	-1.01	-1.08	-1.05	-0.99	-0.93	-1.24	-1.00	-1.30	-1.00	-1.15	5	3
CVX	-0.52	-0.12	-0.59	-0.10	-0.33	-0.18	-0.48	-0.16	-0.43	-0.11	-0.44	-0.16	-0.55	-0.14	-0.44	4	3
DD	-0.05	-0.49	-0.72	-0.41	-0.38	-0.43	-0.63	-0.45	-0.57	-0.39	-0.64	-0.43	-0.71	-0.40	-0.74	1	15
DIS	1.50	0.57	-0.02	0.72	0.61	0.53	0.38	0.58	0.43	0.66	0.21	0.63	0.15	0.68	0.16	3	1
GE	5.78	2.62	1.38	2.57	1.77	2.50	1.63	2.53	1.68	2.66	1.70	2.54	1.55	2.55	1.57	3	1
GM	11.07	7.98	6.75	7.40	6.90	6.97	6.70	7.23	6.80	7.61	6.66	7.27	6.34	7.44	6.48	13	1
HD	-2.89	-2.00	-4.30	-2.12	-3.33	-2.24	-3.50	-2.17	-3.43	-2.05	-3.70	-2.21	-3.77	-2.08	-3.69	2	3
HPQ	2.42	1.00	0.29	-0.05	-0.13	-0.58	-0.79	-0.29	-0.39	0.04	-0.18	-0.57	-0.71	-0.29	-0.43	10	1
IBM	4.44	1.78	1.08	1.58	1.80	1.45	1.64	1.49	1.74	1.58	1.65	1.42	1.56	1.45	1.64	3	1
INTC	-0.17	-1.86	-2.81	-2.05	-2.72	-2.40	-3.10	-2.23	-3.01	-2.09	-2.72	-2.38	-2.89	-2.25	-2.80	1	7
JNJ	-0.26	0.14	-0.81	0.25	-0.58	0.24	-0.66	0.30	-0.65	0.28	-0.60	0.25	-0.65	0.30	-0.62	2	3
JPM	-1.43	-0.61	-1.67	-0.52	-0.56	-0.53	-0.86	-0.54	-0.88	-0.50	-0.92	-0.51	-0.87	-0.55	-0.91	10	3
KO	-1.48	-0.76	-1.49	-0.40	-1.00	-0.35	-1.14	-0.32	-1.11	-0.33	-1.29	-0.31	-1.29	-0.25	-1.23	14	3
MCD	1.98	1.66	1.19	1.55	1.38	1.41	1.17	1.51	1.22	1.55	1.15	1.42	1.09	1.54	1.14	13	1
MMM	0.88	0.57	0.15	1.23	0.79	1.17	0.79	1.28	0.74	1.24	0.63	1.22	0.78	1.27	0.69	3	8
MRK	2.39	0.85	0.10	0.57	0.25	0.47	0.12	0.52	0.19	0.62	0.10	0.49	0.04	0.55	0.09	13	1
MSFT	-0.58	-0.87	-2.21	-0.70	-1.59	-0.84	-1.69	-0.71	-1.70	-0.59	-1.78	-0.85	-1.75	-0.74	-1.73	1	3
PFE	2.37	1.19	0.47	0.85	0.36	0.61	0.07	0.69	0.17	0.96	0.32	0.70	0.02	0.76	0.10	13	1
PG	-1.35	-0.29	-2.12	-0.68	-1.30	-0.92	-1.52	-0.81	-1.41	-0.57	-1.43	-0.95	-1.63	-0.74	-1.49	2	3
T	4.57	2.50	2.20	2.56	2.50	2.48	2.09	2.55	2.21	2.59	2.26	2.51	2.06	2.55	2.20	13	1
UTX	0.31	-0.48	-1.23	-0.52	-0.40	-0.64	-0.80	-0.60	-0.69	-0.45	-0.87	-0.59	-0.94	-0.49	-0.86	1	3
VZ	3.00	2.06	1.74	2.06	2.08	1.84	1.73	1.96	1.86	2.02	1.70	1.88	1.56	1.96	1.65	13	1
WMT	-0.87	0.54	-0.46	0.63	-0.13	0.59	-0.26	0.58	-0.26	0.69	-0.22	0.58	-0.28	0.66	-0.27	5	1
XOM	0.37	0.36	-0.11	0.34	0.01	0.29	-0.11	0.33	-0.06	0.36	-0.04	0.31	-0.06	0.33	-0.08	5	1
All	1.10	0.49	-0.37	0.43	0.06	0.30	-0.16	0.37	-0.10	0.47	-0.15	0.33	-0.24	0.40	-0.19	5	1

Notes: This table reports the ISD BIAS for the various models used for each of the stocks. The 15 models are respectively: (1) CV, (2) GARCH, and (3) NGARCH with normal errors, (4) GARCH and (5) NGARCH with symmetric GED errors, (6) GARCH and (7) NGARCH with symmetric NIG errors, (8) GARCH and (9) NGARCH with symmetric VG errors, (10) GARCH and (11) NGARCH with skewed GED errors, (12) GARCH and (13) NGARCH with skewed NIG errors, (14) GARCH and (15) NGARCH with skewed VG errors. The last row reports the aggregate results for all 30 stocks and the two last columns reports the best and worst performing model number.

Table 10: ISD RMSE

Stock	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	Best	Worst
AA	9.68	6.10	5.20	5.74	4.59	5.74	4.84	5.95	4.74	5.74	4.86	5.48	4.87	5.86	4.88	5	1
AIG	11.47	7.14	6.32	6.74	6.27	6.65	6.04	6.60	6.07	6.75	6.17	6.73	5.74	6.75	6.09	13	1
AXP	12.03	7.50	6.82	6.71	6.40	6.44	6.03	6.91	6.22	6.86	6.37	6.72	6.33	6.84	6.48	7	1
BA	10.66	7.93	7.26	6.48	6.67	6.35	6.27	6.48	6.44	6.35	6.61	6.49	5.89	6.59	6.46	13	1
BAC	13.19	9.45	8.97	7.90	7.77	7.84	7.35	7.81	7.51	8.16	7.82	7.87	7.41	7.79	7.41	7	1
C	16.18	11.57	9.83	10.63	9.17	10.27	8.74	10.55	8.89	10.42	8.93	9.94	8.58	10.26	8.66	13	1
CAT	8.74	7.97	7.79	6.73	6.46	6.80	6.42	6.76	6.39	6.93	6.54	6.55	6.49	6.70	6.78	9	1
CVX	6.92	5.87	5.06	5.71	5.01	5.32	4.70	5.42	4.93	5.44	4.94	5.36	4.08	5.39	5.13	13	1
DD	8.89	5.60	5.47	5.28	5.47	5.17	4.90	5.06	5.02	5.30	5.40	5.04	5.02	5.31	4.93	7	1
DIS	11.91	8.55	7.88	8.07	7.50	7.69	7.26	7.82	7.47	7.76	7.46	7.76	7.21	7.96	7.34	13	1
GE	15.62	10.91	9.03	10.35	9.17	10.24	8.91	10.37	9.10	10.35	9.19	10.14	8.70	10.15	8.84	13	1
GM	25.07	19.60	16.13	17.96	16.15	16.83	16.16	17.78	16.23	18.75	16.22	18.11	15.80	18.45	16.23	13	1
HD	13.55	9.60	9.78	8.88	8.77	8.84	8.36	8.87	8.72	8.74	8.77	8.47	8.10	8.71	8.53	13	1
HPQ	15.36	10.03	9.13	8.91	8.28	8.73	7.84	9.09	8.22	9.21	8.35	8.78	8.03	9.00	8.14	7	1
IBM	14.77	10.66	9.35	9.79	8.89	9.14	8.18	9.58	8.91	9.60	8.94	8.96	8.29	9.33	8.74	7	1
INTC	17.80	13.28	12.76	12.29	11.94	11.79	11.20	12.10	11.55	12.22	11.78	11.94	11.38	12.12	11.72	7	1
JNJ	9.90	7.93	6.89	7.52	6.68	7.26	6.48	7.57	6.48	7.53	6.59	7.27	6.49	7.49	6.57	7	1
JPM	15.22	9.12	7.23	7.82	6.65	7.63	6.79	7.67	6.52	7.83	6.60	7.70	6.78	7.60	6.52	9	1
KO	9.97	7.08	6.39	6.25	6.31	6.03	5.74	6.27	5.89	6.13	5.90	5.90	5.58	6.15	5.92	13	1
MCD	10.74	8.95	6.79	8.67	6.35	8.42	6.14	8.70	6.24	8.64	6.11	8.33	6.03	8.64	6.22	13	1
MMM	9.48	7.51	6.87	7.21	6.60	6.58	6.11	7.33	6.58	7.21	6.53	6.75	6.20	7.22	6.48	7	1
MRK	10.30	8.28	7.51	7.59	6.72	7.76	7.09	7.85	7.29	7.77	6.72	7.75	7.03	7.69	7.20	11	1
MSFT	18.36	14.67	12.81	13.71	12.20	13.03	11.79	13.60	11.94	13.48	11.46	12.35	11.43	12.87	11.88	13	1
PFE	11.45	9.29	7.94	8.46	7.32	8.25	7.31	8.38	7.45	8.63	7.36	8.30	7.15	8.39	7.24	13	1
PG	11.81	10.72	9.77	9.50	8.75	8.84	8.64	8.88	8.73	9.58	8.72	8.42	8.19	8.87	8.75	13	1
T	15.59	9.83	9.47	9.42	9.65	9.16	8.54	9.48	9.21	9.64	9.49	9.16	8.55	9.39	9.41	7	1
UTX	11.27	9.13	8.15	8.80	7.37	8.66	7.54	8.73	7.50	8.82	7.51	8.54	7.53	8.87	7.64	5	1
VZ	13.33	8.15	7.90	7.84	7.53	7.34	6.95	7.71	7.34	7.68	7.43	7.32	6.83	7.45	7.18	13	1
WMT	11.92	7.35	6.18	7.07	6.04	6.79	5.67	6.82	5.70	7.14	6.04	6.73	5.69	6.98	5.94	7	1
XOM	7.69	5.59	4.82	5.34	4.47	5.24	4.12	5.39	4.53	5.33	4.49	5.30	4.57	5.28	4.49	7	1
All	13.91	10.25	9.08	9.42	8.60	9.06	8.28	9.34	8.48	9.45	8.50	9.05	8.19	9.27	8.46	13	1

Notes: This table reports the ISD RMSE for the various models used for each of the stocks. The 15 models are respectively: (1) CV, (2) GARCH, and (3) NGARCH with normal errors, (4) GARCH and (5) NGARCH with symmetric GED errors, (6) GARCH and (7) NGARCH with symmetric NIG errors, (8) GARCH and (9) NGARCH with symmetric VG errors, (10) GARCH and (11) NGARCH with skewed GED errors, (12) GARCH and (13) NGARCH with skewed NIG errors, (14) GARCH and (15) NGARCH with skewed VG errors. The last row reports the aggregate results for all 30 stocks and the two last columns reports the best and worst performing model number.

Table 11: MCS using dollar errors

Stock	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	#
AA					*		*		*							3
AIG		*		*	*	*	*	*	*	*	*	*	*	*	*	13
AXP						*	*					*	*			4
BA			*		*		*		*		*		*		*	7
BAC				*	*	*	*	*	*	*	*	*	*	*	*	12
C				*	*	*	*	*	*	*	*	*	*	*	*	12
CAT						*	*	*	*			*	*			6
CVX					*		*		*		*		*		*	6
DD				*	*	*	*	*	*	*	*	*	*	*	*	12
DIS						*	*		*			*	*	*	*	7
GE		*	*	*	*	*	*	*	*	*	*	*	*	*	*	14
GM							*		*				*		*	4
HD		*		*		*		*		*						5
HPQ					*		*		*		*		*		*	6
IBM			*	*	*	*	*	*	*	*	*	*	*	*	*	13
INTC	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	15
JNJ	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	15
JPM					*		*		*		*		*		*	6
KO			*	*	*	*	*	*	*	*	*	*	*	*	*	13
MCD			*		*	*	*	*	*	*	*	*	*	*	*	12
MMM				*	*	*	*	*	*	*	*	*	*	*	*	12
MRK		*	*	*	*	*	*	*	*	*	*	*	*	*	*	14
MSFT				*		*		*		*		*		*		6
PFE						*	*	*	*			*	*	*	*	8
PG	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	15
T					*	*	*	*	*		*	*	*	*	*	10
UTX							*						*			2
VZ						*	*						*			3
WMT		*	*	*	*	*	*	*	*	*	*	*	*	*	*	14
XOM							*						*			2
#	3	8	10	15	20	22	28	19	24	16	19	20	27	18	22	271

Notes: This table reports the MCS using dollar errors. The MCS was constructed using daily RMSE as the loss function, the MaxT test statistic, and using a significance level of 10%. The 15 models are respectively: (1) CV, (2) GARCH, and (3) NGARCH with normal errors, (4) GARCH and (5) NGARCH with symmetric GED errors, (6) GARCH and (7) NGARCH with symmetric NIG errors, (8) GARCH and (9) NGARCH with symmetric VG errors, (10) GARCH and (11) NGARCH with skewed GED errors, (12) GARCH and (13) NGARCH with skewed NIG errors, (14) GARCH and (15) NGARCH with skewed VG errors. The last row reports the number of times a model is in a MCS and the last column reports the number of models in the MCS for each stock.

Table 12: MCS using ISD errors

Stock	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	#
AA					*		*		*		*		*			5
AIG					*		*		*		*		*		*	6
AXP							*		*							2
BA													*			1
BAC						*	*		*			*	*		*	6
C					*		*		*		*		*		*	6
CAT							*		*			*	*			4
CVX			*		*		*		*		*		*		*	7
DD			*	*	*	*	*	*	*	*		*	*	*	*	12
DIS					*		*						*		*	4
GE			*		*		*		*		*		*		*	7
GM													*			1
HD		*	*	*	*	*	*	*	*	*	*	*	*	*	*	14
HPQ							*						*			2
IBM							*						*			2
INTC				*	*	*	*	*	*	*	*	*	*	*	*	12
JNJ			*		*		*		*		*		*		*	7
JPM			*		*		*		*		*		*		*	7
KO				*	*	*	*	*	*	*	*	*	*	*	*	12
MCD			*		*		*		*		*		*		*	7
MMM					*	*	*						*		*	5
MRK				*	*		*		*	*	*	*	*		*	9
MSFT							*				*		*			3
PFE					*		*		*		*		*		*	6
PG						*	*	*			*	*	*	*	*	8
T				*	*	*	*		*	*	*	*	*	*	*	11
UTX							*		*				*		*	4
VZ						*	*						*		*	4
WMT							*		*				*			3
XOM					*		*		*		*		*		*	6
#	0	1	7	6	18	9	28	5	21	6	17	9	29	6	21	183

Notes: This table reports the MCS using ISD errors. The MCS was constructed using daily RMSE as the loss function, the MaxT test statistic, and using a significance level of 10%. The 15 models are respectively: (1) CV, (2) GARCH, and (3) NGARCH with normal errors, (4) GARCH and (5) NGARCH with symmetric GED errors, (6) GARCH and (7) NGARCH with symmetric NIG errors, (8) GARCH and (9) NGARCH with symmetric VG errors, (10) GARCH and (11) NGARCH with skewed GED errors, (12) GARCH and (13) NGARCH with skewed NIG errors, (14) GARCH and (15) NGARCH with skewed VG errors. The last row reports the number of times a model is in a MCS and the last column reports the number of models in the MCS for each stock.

Table 13: Overall statistics for the MCS's using ISD errors across various dimensions

Panel A: Across option type

Subset	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	#	Best	Worst
All	0	1	7	6	18	9	28	5	21	6	17	9	29	6	21	183	13	1
Call	0	2	4	3	13	8	26	5	18	4	13	8	29	5	16	154	13	1
Put	0	5	15	11	25	13	30	10	26	7	24	12	26	10	24	238	7	1

Panel B: Across maturity

Subset	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	#	Best	Worst
ST	1	2	10	6	18	7	25	4	18	5	17	9	25	7	20	174	7,13	1
MT	0	2	16	4	22	7	28	5	25	5	19	7	24	5	21	190	7	1
LT	1	3	13	8	19	11	28	10	26	6	19	11	24	9	21	209	7	1
VLT	2	7	16	12	22	17	29	15	28	11	22	17	28	14	27	267	7	1

Panel C: Across moneyness

Subset	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	#	Best	Worst
DITM	0	8	18	10	21	10	25	7	23	10	23	12	30	10	24	231	13	1
ITM	1	8	13	15	24	21	28	17	26	16	22	21	28	19	23	282	7,13	1
ATM	1	10	13	18	19	23	24	19	23	18	18	23	24	21	21	275	7,13	1
OTM	1	6	11	11	21	18	28	16	26	10	15	16	24	14	21	238	7	1
DOTM	1	3	5	4	14	8	29	5	17	4	11	7	23	5	11	147	7	1

Notes: This table reports overall statistics for the MCS using ISD errors across option type (call or put), maturity, and moneyness. The individual MCS's were constructed using daily RMSE as the loss function, the MaxT test statistic, and using a significance level of 10%. The 15 models are respectively: (1) CV, (2) GARCH, and (3) NGARCH with normal innovations, (4) GARCH and (5) NGARCH with symmetric GED innovations, (6) GARCH and (7) NGARCH with symmetric NIG innovations, (8) GARCH and (9) NGARCH with symmetric VG innovations, (10) GARCH and (11) NGARCH with skewed GED innovations, (12) GARCH and (13) NGARCH with skewed NIG innovations, (14) GARCH and (15) NGARCH with skewed VG innovations. The last three columns report the total number of models in the MCS and the modess which are most frequently and least frequently in the MCS.

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