

Option pricing with non-Gaussian scaling and infinite-state switching volatility

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Abstract: Volatility clustering, long-range dependence, and non-Gaussian scaling are stylized facts of financial assets dynamics. They are ignored in the Black & Scholes framework, but have a relevant impact on the pricing of options written on financial assets. Using a recent model for market dynamics which adequately captures the above stylized facts, we derive closed form equations for option pricing, obtaining the Black & Scholes as a special case. By applying our pricing equations to a major equity index option dataset, we show that inclusion of stylized features in financial modeling moves derivative prices about 30% closer to the market values without the need of calibrating models parameters on available derivative prices.

Keywords: option pricing; anomalous scaling; Markov switching; GARCH

JEL Classifications: C58; G13; C22; C51; C52; C53

1 Introduction

Dynamical properties and stylized facts of financial time series have raised considerable interest in both theoretical and applied econometrics. Within these fields, one topic widely discussed is related to the memory properties observed over return sequences, in particular regarding their absolute value (volatility). A variety of techniques have been developed to include realistic volatility dynamic features into a continuous time model, thus improving the geometric Brownian motion assumption underlying the classic Black-Scholes (BS) model. We mention, among many others, the stochastic volatility, see, e.g., Fouque et al. (2000) and therein cited references, the and GARCH-based approach of Heston (1993), and Heston and Nandi (2000). In what follows, volatility memory properties, and in particular the long-memory behaviour, are taken into account on the basis of the “scaling

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symmetry” concept, that has a long tradition in statistical mechanics and in the physics of complex systems. Our main purpose is to discuss the impact of memory and scaling properties on the price of financial derivatives, and to compare them with those coming from the BS framework.

Long-memory behaviour has been often associated with the evaluation of the Hurst exponent, H , introduced in the seminal work of Hurst (1951). The Hurst exponent links the time series fluctuations with the time scale over which they are observed. Indeed, in the presence of a simple scaling symmetry for a stochastic process X_t ($t = 1, 2, \dots$) supposed to generate the time series of interest, the q -th order moment satisfies $\mathbb{E} [|\sum_{t=1}^{\tau} X_t|^q] \sim A_q \tau^{qH}$, where τ defines the time scale at which the terms of the series are aggregated and A_q is an amplitude. This follows from the fact that the probability density function of $X_1 + X_2 + \dots + X_{\tau}$ satisfies the scaling identity, $\tau^H g_{\tau}(\tau^H x) = g(x)$, where $g(\cdot)$ is the scaling function and H is also called scaling exponent. Well-studied forms of scaling were first observed in the study of critical phenomena, as in a critical magnetic system, see (see, e.g., Sethna et al. (2001), and therein cited references, or disordered systems, see Bouchaud and Georges (1990). Indeed, if the elements of a time series are extracted independently from a Gaussian probability density function, the Hurst exponent H has a value equal to $1/2$. In several empirical studies, deviations from this reference behaviour have been observed, and are referred to as forms of “anomalous scaling”. These deviations are generally considered a consequence of long-memory effects.¹ It is important to point out that anomalous scaling conditions can also arise in cases in which the scaling exponent is equal to $1/2$, whenever g is not Gaussian. Finally, a more general form of anomalous scaling called “multiscaling” is associated with those cases in which the scaling exponent depends on the moment order q . If multiscaling is present, the scaling or Hurst exponent H can be expressed as a function of the moment order, leading to $H = H(q)$. Non-Gaussian scaling plays a central role in the present study, where an interesting case is made for the existence of multiscaling associated with long-memory behaviour of financial data.

A seminal contribution linking scaling properties to the financial framework was made

¹However, we point out that, strictly speaking, an anomalous Hurst exponent is not necessarily a consequence to the existence of long-memory, Cont (2005).

by Mandelbrot (1963). Further studies appeared only at the beginning of the '90s, mainly starting with the newly available high frequency data on currencies. We cite, among others, Muller et al. (1990), Dacorogna et al. (1993, 2001), and Guillaume et al. (1997). Subsequently, additional works analysed the scaling properties of financial assets other than currencies such as bonds (Ballocci et al. 1999) and equities (Di Matteo et al. 2005). Finally, scaling properties of financial data have been also analysed from an econo-physics point of view (see Mantegna and Stanley 1995, Ghashghaie et al. 1996, and Stanley and Plerou 2001), establishing a connection with the physics of critical phenomena.

The presence of non-Gaussian or anomalous scaling in financial log-return time series introduces a relevant challenge for practitioners, in particular when their purpose is the determination of a derivative contract price. As a matter of fact, the dynamics of underlying prices assumed in the BS framework is well known to be not consistent with the scaling properties of equity indices. This is a source of derivative pricing inefficiencies.

Rather than relying on concepts like implied volatility to correct the BS framework, our aim here is an evaluation of the effects on pricing of a substantial improvement of the model describing the dynamics of the underlying asset, while maintaining a link with the BS formalism. The main contribution of the present paper is the derivation of closed-form formulae for option pricing and associated hedging strategy, based on an equivalent martingale measure. This is obtained by means of a model recently introduced in statistical mechanics by Zamparo et al. (2013) whose advantage is to be consistent with the observed features of financial data, thus including non-Gaussian scaling behaviour. The general results provided here include as a special case the BS pricing formula. Although we rely on a Monte Carlo computation to evaluate probabilities related to the underlying dynamics, these formulae define *a priori* the option price and the associated strategy, conditioned on the previously observed values of the underlying asset's returns. Also, we differ from the stochastic volatility pricing approaches (see, e.g., Fouque et al. 2000, or Heston, 1993) since our formulae are closed in the sense that the pricing parameters are directly inferred from the underlying model dynamics and do not need any calibration with respect to known derivatives' market prices. Indeed, an empirical application shows

that compared with BS the proposed approach determines a price sensibly closer to the market one. We postpone to future works the derivation of Greeks and the use of our pricing approach within option trading strategies.

The paper proceeds as follows: Section 2 introduces the stochastic process for the underlying risky asset; Section 3 reports the novel approach for option pricing based on the model presented in Section 2; an empirical analysis is outlined in Section 4 and Section 5 concludes. Proofs are reported in the Appendix.

2 Non-Gaussian scaling in financial data

We consider the dynamics of a financial asset or index whose value at time t is denoted by S_t , $t = 0, 1, 2, \dots$, while its log-returns are given as $X_t = \log(S_t) - \log(S_{t-1})$. The existence of non-Gaussian scaling properties may be associated with different effects, including various kind of data seasonality, see Dacorogna et al. (1993), among others, or long-range dependencies. The latter have been extensively studied in statistics (Beran, 1994), econometrics (Robinson, 2003), and finance by the pioneering work of Lo (1991). For financial time series, and for time scales ranging from minutes to months, significant deviations from Gaussianity of the scaling function g have been observed; see Cont (2001), among others. Moreover, whereas a scaling exponent $H \simeq 1/2$ is observed for $q \lesssim 3$, multiscaling behaviour with q -dependent $H(q) < 1/2$ is often observed for higher-order moments (see, e.g., Di Matteo et al., 2005).

Following the original suggestion by Baldovin and Stella (2007), Zamparo et al. (2013) assume the anomalous scaling symmetry of the density for the aggregated returns. Taking this as a guiding criterion, they propose stochastic processes whose realizations are able to replicate the long-range dependence and non-Gaussianity typical of a financial time series. At the same time, the use of scaling symmetry leads to processes which are relatively easy to manipulate for both calibration purposes and analytical calculations. High frequency models based on the same criterion were already proposed in Baldovin et al. (2011) and adopted for trading strategies in Baldovin et al. (2014).

While referring to the original publication (Zamparo et al. 2013) for motivations

and details of the model construction, we give here the basic definitions of the process used then in a derivative pricing framework. In the proposed structure, two independent stochastic components affect the asset returns' dynamical evolution. The first one, is a fully *endogenous* process called Y_t , dependent on the past asset history through an autoregressive scheme of order M . Once the memory range M is established,² the conditional probability density function of Y_t only depends on the previous M values of Y_t , as can be deduced by the following definitions for its joint probability density f_t^Y :

$$f_t^Y(y_1, \dots, y_t) \equiv \varphi_{1,t}(y_1, \dots, y_t) \quad (1)$$

if $t = 1, 2, \dots, M + 1$, and

$$f_t^Y(y_1, \dots, y_t) \equiv \frac{\varphi_{t-M,t}(y_{t-M}, \dots, y_t)}{\varphi_{t-M,t-1}(y_{t-M}, \dots, y_{t-1})} f_t^Y(y_1, \dots, y_{t-1}) \quad (2)$$

if $t > M + 1$. The probability densities φ_t (for simplicity, we now suppress the first index) are assumed to be Gaussian mixtures:

$$\varphi_t(y_1, \dots, y_t) \equiv \int_0^\infty \left(\prod_{i=1}^t \mathcal{N}_\sigma(y_i) \right) \rho(\sigma) d\sigma, \quad (3)$$

where \mathcal{N}_σ is a Gaussian with volatility σ and $\rho(\sigma) \geq 0$, with $\int_0^{+\infty} \rho(\sigma) d\sigma = 1$. The φ_t defined in (3) allows recovering proper empirical scaling properties while fat tailed densities for ρ lead to fat tailed marginal distributions for the Y_t (Zampano et al. 2013). Notably, the process defined in this way is similar to an ARCH process of order M , with the difference that Y_t is in general heterodistributed in place of just heteroskedastic. Indeed, not only the variance, as in ordinary ARCH schemes, but also the form of the conditional PDF of Y_t depends on the previous M values y_{t-1}, \dots, y_{t-M} . Specific choices for the density ρ give the advantage of enabling the explicit integration over σ . This is what happens, for instance, when choosing σ^2 to be distributed according to an inverse-

²The memory range M can be fixed according to the data frequency, or with respect the objective of the researcher. With daily data, one might take $M = 21$, that is one month, given it is a sufficient range to approximate a truly long-memory process as shown in Corsi (2009). Alternatively, one could set $M = 60$, close to three months, to provide a better approximation.

Gamma density. The density $\rho(\sigma)$ is then associated with a “shape parameter” α and a “scale parameter” β , according to

$$\rho_{\alpha,\beta}(\sigma) = \frac{2^{1-\frac{\alpha}{2}}}{\Gamma(\frac{\alpha}{2})} \frac{\beta^\alpha}{\sigma^{\alpha+1}} e^{-\frac{\beta^2}{2\sigma^2}}. \quad (4)$$

Upon explicit integration over σ , the endogenous component becomes in this case a genuine ARCH process (see Zamparo et al., 2013) described by

$$Y_t = \begin{cases} \beta \cdot Z_1 & \text{if } t = 1; \\ \sqrt{\beta^2 + \sum_{n=1}^{\min\{t-1, M\}} Y_{t-n}^2} \cdot Z_t & \text{if } t > 1, \end{cases} \quad (5)$$

where the return residual process $\{Z_t\}_{t=1}^\infty$ is given as a sequence of independent Student’s t-distributed variables:

$$f_t^Z(z_1, \dots, z_t) = \prod_{n=1}^t \frac{\Gamma(\frac{\alpha_n+1}{2})}{\sqrt{\pi} \Gamma(\frac{\alpha_n}{2})} (1 + z_n^2)^{-\frac{\alpha_n+1}{2}}, \quad (6)$$

with $\alpha_n \equiv \alpha + \min\{n - 1, M\}$.³ Below, we will assume the previous form for $\rho(\sigma)$, since a number of analytical results can be obtained in closed form, see Zamparo et al. (2013). For any memory order M , the endogenous component Y_t is thus specified by two parameters only: α , determining the form of the distributions; β identifying the scale of the process. The parsimonious number of parameters, independent of the memory order, is a further advantage coming from the implementation of the scaling symmetry.

The second component describing the model is partly *exogenous* and partly *endogenous* and is introduced as a modulation of the process Y_t :

$$X_t = a_{I_t} Y_t \quad (7)$$

³Zamparo et al. (2013) also show that $\{Y_t\}_{t=1}^\infty$ is a strictly stationary process. For a general overview of covariance and strict stationarity in GARCH processes, see Francq and Zakoian (2010).

where the component a_{I_t} is defined as

$$a_{I_t} \equiv \sqrt{I_t^{2D} - (I_t - 1)^{2D}}, \quad (8)$$

with D a suitable parameter. The process $\{I_t\}_{t=1}^{\infty}$ is a Markov chain in \mathbb{N}^+ , defined by

$$\pi(i) \equiv \mathbb{P}[I_1 = i] \equiv \nu(1 - \nu)^{i-1} \quad (9)$$

and

$$W(i, j) \equiv \mathbb{P}[I_{t+1} = i | I_t = j] \equiv \nu\delta_{i-1} + (1 - \nu)\delta_{i-j+1}, \quad (10)$$

δ_{i-j} being the Kronecker delta. Thus, the definition of this latter component involves two additional parameters: $0 < \nu \leq 1$ and $D > 0$. The quantity ν^{-1} is the average interval between two random external inputs, where each input event restarts from 1 the sequence of integers I_t , thus re-setting a_{I_t} to 1 (for this reason we will call “restarts” these inputs which could be either endogenous or exogenous). The exponent D in (8) regulates how fast the restart is absorbed by market dynamics. In particular, $0 < D < 1/2$ corresponds to the case in which the restart produces a volatility burst due to some external input that then decays in time. The component a_{I_t} determines the generalized Hurst exponent $H(q)$ associated with the model, which is influenced by both D and ν , and conveys realistic time properties to the volatility autocorrelation function. Since the process a_{I_t} multiplies Y_t , it can be regarded as a Markov process switching the value of the volatility. In such a way, the combination of the two components becomes a Markov-Switching ARCH (SWARCH) process. Differently from the proposal of Hamilton and Susmel (1994), the process I_t assumes values in \mathbb{N}^+ and implies that the switching process is endowed with an infinite number of states.

One can prove that the composed process $X_t = a_{I_t}Y_t$ is stationary, ergodic, and displays realistic multiscaling and volatility autocorrelations if properly calibrated on reasonably long daily returns series (Zamparo et al. 2013). The estimation of model parameters is performed by matching various moments of the model’s distributions. The model parameters are 5 in total, $(D, \nu, \alpha, \beta, M)$. Since M represents a lower limit for

the range up to which memory effects are supposed to be properly taken into account by the model, one can fix this parameter in relation with the time scale relevant for the application of interest. For instance, in the present work we consider $M = 21$, corresponding to a month of market activity, and coherently with the common practice adopted for modeling realized volatility sequences, see Corsi (2009).

3 Pricing with non-Gaussian scaling

One of the basic features of the BS model (Black and Scholes, 1973; Merton, 1973; see also Hull, 2000, and references therein) is that it derives a closed formula for the value of, say, a European call option C depending only on two free parameters: the risk-free interest rate r and the volatility of the underlying asset σ_{BS} . In principle, these parameters can be identified *a priori* on the basis of historical data. However, in view of the unrealistic assumption of memoryless Gaussian returns, financial practitioners are forced to correct the BS option value at different strike prices with appropriately chosen different values of σ_{BS} . This allows compensating for volatility changes and for the so-called “smile effect” observed in the implicit volatility of the real-market option value. From a logical perspective, however, a model for determining “derivative prices” should not rely on “market derivative prices”, the latter being what determines the implicit volatility. Instead, derivative prices should be identified by a proper rational price (obtained, e.g., through an equivalent martingale measure) and an efficient hedging strategy associated with the stochastic dynamics of the underlying asset (i.e., with the “physical probability”).

Many models have been proposed to overcome the BS limitations. Among others, we cite Heston (1993), Heston and Nandi (2000), Borland and Bouchaud (2004) and Christoffersen et al. (2006). On the one hand, approaches like those using continuous-time stochastic-volatility models are capable of defining *a priori* formulae for option prices and associated hedging strategies that reproduce the volatility smile. However, they still need to be calibrated on some real-market derivative prices in order to determine the price of other ones. On the other hand, pricing methods relying entirely on the underlying asset’s dynamics typically do not provide explicit formulae. As a consequence, they require the

use of Monte Carlo approaches that simulate many possible asset's trajectories to identify efficient hedging strategies and the derivative prices (see Bouchaud and Potters, 2003).

In view of the fact that the model for the underlying log-returns presented in the previous section generalizes Gaussian dynamics, we wish here to follow a different approach, which aims at deriving closed expressions for derivative prices and associated hedging strategies generalizing those of BS to this more complex situation. If, consistently with the spirit of our model, one assumes that the dynamical evolution of the primary asset's returns could be described as a mixture of Gaussian processes, a natural way of pricing an option and finding a hedging strategy is by averaging the BS formula through the Gaussian mixture density (see, e.g., Peirano and Challet, 2012). Our basic idea is then to find the Gaussian mixture density that most effectively reproduces the underlying asset's dynamics, given the historical conditions observed at the moment the derivative contract is written. Additional effort must then be made in order to properly take into account time restarts that may occur either before the contract stipulation or between the writing and the maturity of the contract. Through this approach we will prove that, indeed, we are defining an equivalent martingale price. In section 4 we will then show that for S&P500 options, prices calculated on the basis of the anomalous scaling dynamics are closer to market prices than BS ones by about 30% on average (see table 4 in section 4). We stress that such an evaluation is performed by comparing models performances on a common playground, without thus correcting the BS volatility across option maturity and/or strike prices. Adjustments on the BS inputs would favour the BS model being closer to the observed prices, thus producing a biased evaluation of the impact of non-Gaussian scaling on the option prices. An assessment of the efficacy of the hedging strategy is instead left to future work.

3.1 Closed-form option pricing formulae

We first point out that, in accordance with the model outlined in Section 2 for the underlying asset dynamics, our derivation of option prices assumes discrete time. The market includes a riskless bond B_t evolving at rate $r > 0$ according to $B_t = (1 + r)^t$,

and a stock S_t described through its returns X_t and mean return rate μ , such that $S_t = S_0 \exp\left[\mu t + \sum_{j=1}^t X_j\right]$, where S_0 is the asset value at time $t = 0$. We denote by \mathbb{P} the “physical probability measure” associated with the returns X_t , as described in section 2, and by \mathcal{F}_t the σ -algebra generated by X_1, \dots, X_t , with $\mathcal{F}_0 \equiv \{\emptyset, \Omega\}$. $\{S_t\}_{t=0}^T$ is adapted to the filtration $\{\mathcal{F}_t\}_{t=0}^T$. The market is assumed free of arbitrage, liquid, with no transaction costs, no interest spread, no dividends, and with unlimited short selling for an unlimited period of time.

Notice that by choosing $\rho(\sigma) = \delta(\sigma - \sigma_{BS})$ and $a_{I_t} = 1$ for all I_t (e.g., with $D = 1/2$), our model degenerates into a discrete-time version of the geometric Brownian motion for S_t , without memory effects or volatility bursts. Our basic pricing strategy is then to define a general equivalent martingale measure which reproduces (in discrete time) the BS formula in the above degenerate conditions. We aim first at obtaining equivalent martingale measures for general (arbitrary) choices of the parameters σ and a_{i_t} , that will thus be valid even if they become random variables. In the next subsections, we will identify the most appropriate distributions for σ and i_t conditioned to the past dynamics of X_t .

Let f_{t_0, t_1}^I be the joint density of I_t in the range $[t_0, t_1]$ and $\bar{\rho}$ the volatility density conditional to some past values for X_t and I_t . The following Lemma introduces the martingale measures \mathbb{P}^* equivalent to \mathbb{P} used later for option pricing.

Lemma 1. *Consider the function*

$$h(x, \sigma, i_t) \equiv \frac{1}{\sqrt{2\pi} \sigma a_{i_t}} \exp\left[-\frac{1}{2} \left(\frac{x}{\sigma a_{i_t}} + \frac{\sigma a_{i_t}}{2} - \frac{\gamma}{\sigma a_{i_t}}\right)^2\right], \quad (11)$$

with $\gamma \equiv \ln(1 + r) - \mu$ and $a_{i_t} \equiv \sqrt{i_t^{2D} - (i_t - 1)^{2D}}$. Given $\sigma \in \mathbb{R}^+$, $i_t \in \mathbb{N}^+$ for $t = t_0, t_0 + 1, \dots, T$ the probability density function⁴

$$f_{t_0, T}^{*X}(x_{t_0}, \dots, x_T | \sigma; i_{t_0}, \dots, i_T) = \prod_{t=t_0}^T h(x_t, \sigma, i_t) \quad (12)$$

⁴ Since we need now to explicitly indicate the time partition to which a probability density function is referred to, we slightly change the notation with respect to Section 2. In the case of a conditional probability density function, we will explicitly indicate the conditioning values among the arguments after the usual vertical bar, |.

defines an equivalent martingale measure $\mathbb{P}_{\sigma; i_{t_0}, \dots, i_T}^*$.

More generally, for any given parameters distributions $\bar{\rho}$ and $f_{t_0-M, T}^I$, also the probability density function

$$f_{t_0, T}^{*X}(x_{t_0}, \dots, x_T | \bar{\rho}; f_{t_0-M, T}^I) = \sum_{i_{t_0-M}=1}^{\infty} \dots \sum_{i_T=1}^{\infty} \left[f_{t_0-M, T}^I(i_{t_0-M}, \dots, i_T) \cdot \int_0^{\infty} \left(\prod_{t=t_0}^T h(x_t, \sigma, i_t) \right) \bar{\rho}(\sigma | x_{t_0-M}, \dots, x_{t_0-1}; i_{t_0-M}, \dots, i_T) d\sigma \right] \quad (13)$$

defines an equivalent martingale measure $\mathbb{P}_{\bar{\rho}; f_{t_0-M, T}^I}^*$.

The price $C(K, t_0, T)$ at time $0 < t_0 < T$ of a European call option with maturity at time T and strike price K satisfies $\frac{C(K, t_0, T)}{(1+r)^{t_0}} = \mathbb{E}_{\mathbb{P}^*} \left[\frac{C}{(1+r)^T} \middle| \mathcal{F}_{t_0-1} \right]$, where $C = C(K, T, T)$ is the option pay-off at maturity (see, e.g., Föllmer et al., 2011). The conditional expectation is taken with respect to the σ -algebra \mathcal{F}_{t_0-1} since we assume that while computing the price $C(K, t_0, T)$, valid at time t_0 , we still do not know the value of the return X_{t_0} . The following theorem provides the option price.

Theorem 1. *Given the equivalent martingale measure $\mathbb{P}_{\sigma; i_{t_0}, \dots, i_T}^*$ defined in Lemma 1, the call price conditioned by the values σ and i_{t_0}, \dots, i_T is*

$$C(K, t_0, T | \sigma; i_{t_0}, \dots, i_T) = (1+r) [S_{t_0-1} N(d_+) - K(1+r)^{t_0-T-1} N(d_-)], \quad (14)$$

where $N(x)$ is the standard normal cumulative distribution function, and

$$d_{\pm} \equiv \frac{1}{\tilde{\sigma}} \left[\ln \frac{S_{t_0-1}}{K} + (T - t_0 + 1) \ln(1+r) \pm \frac{(\tilde{\sigma})^2}{2} \right], \quad (15)$$

$$\tilde{\sigma} \equiv \tilde{\sigma}(\sigma; i_{t_0}, \dots, i_T) \equiv \sigma \sqrt{a_{i_{t_0}}^2 + \dots + a_{i_T}^2}. \quad (16)$$

More generally, given the equivalent martingale measure $\mathbb{P}_{\bar{\rho}; f_{t_0-M, T}^I}^*$, defined in Lemma 1,

the call price is

$$C(K, t_0, T) = \sum_{i_{t_0-M}=1}^{\infty} \cdots \sum_{i_T=1}^{\infty} \left[f_{t_0-M, T}^I(i_{t_0-M}, \dots, i_T) \cdot \int_0^{\infty} \bar{\rho}(\sigma | x_{t_0-M}, \dots, x_{t_0-1}; i_{t_0-M}, \dots, i_T) C(K, t_0, T | \sigma; i_{t_0}, \dots, i_T) d\sigma \right]. \quad (17)$$

By assuming $\bar{\rho}(\sigma | x_{t_0-M}, \dots, x_{t_0-1}; i_{t_0-M}, \dots, i_T) = \delta(\sigma - \sigma_{BS})$ and $a_{i_t} = 1$ for any i_t , all equivalent martingale measures coincide with each other, (16) simplifies into $\tilde{\sigma} = \sigma_{BS} \sqrt{T - t_0 + 1}$, and the call price obtained in (17) equals the standard BS formula. Although not explicitly addressed in the present paper, we highlight that, by means of (14) and (17), one also obtains Delta-hedging formulas which generalize BS' one. Namely, $\Delta(K, t_0, T | \sigma; i_{t_0}, \dots, i_T) = (1 + r) N(d_+)$, and

$$\Delta(K, t_0, T) = \sum_{i_{t_0-M}=1}^{\infty} \cdots \sum_{i_T=1}^{\infty} \left[f_{t_0-M, T}^I(i_{t_0-M}, \dots, i_T) \cdot \int_0^{\infty} \bar{\rho}(\sigma | x_{t_0-M}, \dots, x_{t_0-1}; i_{t_0-M}, \dots, i_T) \Delta(K, t_0, T | \sigma; i_{t_0}, \dots, i_T) d\sigma \right]. \quad (18)$$

So far, $f_{t_0-M, T}^I(i_{t_0-M}, \dots, i_T)$ and $\bar{\rho}(\sigma | x_{t_0-M}, \dots, x_{t_0-1}; i_{t_0-M}, \dots, i_T)$ are generic distributions for the parameters i_t and σ . In the next subsections, we will link these parameters to the dynamics characterizing the evolution of X_t . This will also motivate the dependence of the distribution of σ on the x_t 's for $t = t_0 - M, \dots, t_0 - 1$ and on the i_t 's for $t = t_0 - M, \dots, T$. Moreover, we will propose for $\bar{\rho}$ a Gaussian mixture density representing both the “state of the market” summarized in the M returns previous to the derivative contract pricing day, and the possible future evolutions of the market up to the maturity time. Since our model contains the hidden component I_t , in order to calculate $\bar{\rho}$ it is also needed to include a dependence on the random time i_t both before the contract pricing day and between the pricing day and the maturity of the contract. The density $f_{t_0-M, T}^I$ will then identify the probability of the random time string i_{t_0-M}, \dots, i_T . Those two elements are fundamental for the evaluation of (17), our main result for derivative pricing. The evaluation of (17) will be discussed in a following subsection (3.4).

3.2 Identification of $\bar{\rho}$

Within this subsection, the sequence i_{t_0-M}, \dots, i_T is assumed to be given. At the time t_0 at which we wish to price a European option expiring at time T , the “state of the market” for the underlying asset is characterized by the historical values $x_{t_0-M}, \dots, x_{t_0}$. Indeed, since $X_t = Y_t a_{I_t}$, the assumed knowledge of $i_{t_0-M}, \dots, i_{t_0}$ means that we can identify also $y_{t_0-M}, \dots, y_{t_0}$ as $y_t = x_t/a_{i_t}$. We aim at finding an approximation for the probability density function $f_{t_0,T}^X(x_{t_0}, \dots, x_T | x_{t_0-1}, \dots, x_{t_0-M}; i_{t_0-M}, \dots, i_T)$, so that the pricing scheme in Section 3.1 could be applied. We propose to approximate $f_{t_0,T}^X$ as a Gaussian mixture $g_{t_0,T}^X$ with mixing density $\bar{\rho}$:

$$\begin{aligned} & g_{t_0,T}^X(x_{t_0}, \dots, x_T | x_{t_0-1}, \dots, x_{t_0-M}; i_{t_0-M}, \dots, i_T) = \\ & = \int_0^\infty \bar{\rho} \left(\sigma \left| \frac{x_{t_0-1}}{a_{i_{t_0-1}}}, \dots, \frac{x_{t_0-M}}{a_{i_{t_0-M}}}; i_{t_0}, \dots, i_T \right. \right) \left[\prod_{t=t_0}^T \frac{1}{a_{i_t}} \mathcal{N}_\sigma \left(\frac{x_t}{a_{i_t}} \right) \right] d\sigma. \end{aligned} \quad (19)$$

In such a way, the returns’ dynamic can be viewed as a superposition of Gaussian processes with a fixed (although stochastic) volatility σ . Consistently, the mixture density $\bar{\rho}$ so identified enters in (17) to determine the option price. The approximation is realized by matching the expected fluctuation of the return from t_0 to T calculated through $f_{t_0,T}^X$ with that obtained using $g_{t_0,T}^X$.

Theorem 2. *Consider the cumulated return from t_0 to T , $R \equiv X_{t_0} + \dots + X_T$. If*

$$\bar{\rho} \left(\sigma \left| \frac{x_{t_0-1}}{a_{i_{t_0-1}}}, \dots, \frac{x_{t_0-M}}{a_{i_{t_0-M}}}; i_{t_0}, \dots, i_T \right. \right) \equiv \frac{\sum_{t=t_0}^T a_{i_t}^2 \hat{\rho}_{t,t} \left(\sigma \left| \frac{x_{t_0-1}}{a_{i_{t_0-1}}}, \dots, \frac{x_{t_0-M}}{a_{i_{t_0-M}}} \right. \right)}{\sum_{t=t_0}^T a^2(i_t)}, \quad (20)$$

with

$$\tilde{\rho}_{t,t}(\sigma_t | y_{t-1}, \dots, y_{t-M}) \equiv \frac{\rho(\sigma_t) \prod_{j=t-M}^{t-1} \mathcal{N}_{\sigma_t}(y_j)}{\int_0^\infty d\sigma'_t \rho(\sigma'_t) \prod_{j'=t-M}^{t-1} \mathcal{N}_{\sigma'_t}(y_{j'})}, \quad (21)$$

$$\hat{\rho}_{t,t}(\sigma | y_{t_0-1}, \dots, y_{t_0-M}) = \int \prod_{j=t_0}^{t-1} \tilde{\rho}_{t,t}(\sigma | y_{t-1}, \dots, y_{t-M}) f_{j,j}^Y(y_j | y_{j-1}, \dots, y_{j-M}) dy_j, \quad (22)$$

then the expected value of R^2 coincides for $f_{t_0,T}^X$ and $g_{t_0,T}^X$: $\mathbb{E}_{f_{t_0,T}^X} [R^2] = \mathbb{E}_{g_{t_0,T}^X} [R^2]$.

As shown in Fig. 1, the distribution $\bar{\rho}$ is peaked around the present value of the volatility if the maturity T is very close to t_0 , whereas it becomes $\bar{\rho}(\sigma) \simeq \rho(\sigma)$ if $T \gg t_0$. For $\rho(\sigma) = \delta(\sigma - \sigma_{BS})$, $\bar{\rho}$ also degenerates to a delta, $\bar{\rho}(\sigma) = \delta(\sigma - \sigma_{BS})$. In practice, $\bar{\rho}$ can be evaluated by simulating the process $\{X_t\}_{t=t_0}^T$ conditionally to M past values $x_{t_0-M}, \dots, x_{t_0-1}$ and given i_{t_0-M}, \dots, i_T . In the Appendix we give an explicit expression for $\hat{\rho}_{t,t}$ when ρ is parametrized as in (4). For the empirical application in Section 4, for each couple (t_0, T) , the distribution $\bar{\rho}$ has been evaluated averaging over 100 different simulated realizations.⁵

3.3 Identification of $f_{t_0-M,T}^I$

Here we specify a numerical scheme which enables the extraction of the random time string i_{t_0-M}, \dots, i_T and of their associated probability $f_{t_0-M,T}^I$, according to the model's dynamic and the historical information available at time t_0 . This is instrumental to the evaluation of the option price as discussed in the following subsection. Given that the process I_t is not directly identifiable, and given its Markovian nature, we have that the probability of the string i_{t_0-M}, \dots, i_T depends on the whole historical time series x_1, \dots, x_{t_0-1} . This prevents the direct evaluation/estimation of the density. To solve this problem we propose a Monte Carlo procedure which relies on local information only, within a window whose size is taken to be $2\tau + 1$, to facilitate notations. Numerical constraints limit the value of τ to some units, as specified in what follows. More precisely, we present a numerical method to calculate the probability $f_{t_0-M,T}^I(i_{t_0-M}, \dots, i_T | x_{t_0-M-\tau}, \dots, x_{t_0-1})$.

It is convenient to distinguish between the distribution f_{t_0-M,t_0-1}^I of the stochastic variables I_t before the pricing time t_0 and the distribution $f_{t_0,T}^I$ of I_t from t_0 to T . Since the random time process is a Markov chain, we have

$$\begin{aligned} & f_{t_0-M,T}^I(i_{t_0-M}, \dots, i_T | x_{t_0-M-\tau}, \dots, x_{t_0-1}) \\ &= f_{t_0-M,t_0-1}^I(i_{t_0-M}, \dots, i_{t_0-1} | x_{t_0-M-\tau}, \dots, x_{t_0-1}) f_{t_0,T}^I(i_{t_0}, \dots, i_T | i_{t_0-1}). \end{aligned} \quad (23)$$

⁵We verified by simulations that 100 realizations are sufficient to obtain convergence of the distribution.

Before t_0 , one can exploit the local information contained in the historical returns. In details, we suggest considering

$$\begin{aligned}
& f_{t_0-M, t_0-1}^I(i_{t_0-M}, \dots, i_{t_0-1} | x_{t_0-M-\tau}, \dots, x_{t_0-1}) \simeq \\
& \simeq f_{t_0-M, t_0-M}^I(i_{t_0-M} | x_{t_0-M-\tau}, \dots, x_{t_0-M+\tau}) \cdot \\
& \quad \cdot \prod_{t=t_0-M+1}^{t_0-1} f_{t,t}^I(i_t | i_{\max\{t-\tau, t_0-M\}}, \dots, i_{t-1}; x_{t-\tau}, \dots, x_{\min\{t+\tau, t_0-1\}}) , \tag{24}
\end{aligned}$$

where the approximation comes from the fact that on the r.h.s. of the equation only local information is considered. The appendix shows explicit expressions for the r.h.s. of (24); using these expressions, a Monte Carlo procedure can extract the string $i_{t_0-M}, \dots, i_{t_0-1}$ according to our approximation of the probability f_{t_0-M, t_0-1}^I .

From t_0 to T , according to (10) we simply have

$$f_{t_0, T}^I(i_{t_0}, \dots, i_T | i_{t_0-1}) = \prod_{t=t_0}^T W(i_t, i_{t-1}) . \tag{25}$$

3.4 The evaluation of the option price

Since we have now specified $\bar{\rho}$ in (20), and $f_{t_0-M, T}^I$ in (23), (24), and (25), the option price can be computed according to (17), which however contains multiple series with infinite terms. To evaluate these series with respect to the past of t_0 , we propose the use of a Monte Carlo method. We suggest calculating the option price as the weighted average on a number of histories $i_{t_0-M}, \dots, i_{t_0-1}$ extracted with probability f_{t_0-M, t_0-1}^I . In addition, to reduce the computational complexity, in the range from t_0 to T , we restrict the sums in (17) on all possible realizations i_{t_0}, \dots, i_T with at most two restarts occurring in the interval $[t_0, T]$. Despite the apparent strong assumption, we highlight that this corresponds to a second order approximation of the option price with respect to ν , which is indeed a small parameter. In addition, unreported tests with a third order approximation in ν (at most three restarts in $[t_0, T]$) provided negligible changes.

Numerical tests suggest that a local window with $\tau = 3$ in (24) is enough to implement an appropriate Monte Carlo sampling. In the empirical application outlined in Section

4, the Monte Carlo scheme has been realized by sampling N_{MC} Monte Carlo realizations, with $N_{MC} \simeq 20$ since f_{t_0-M, t_0-1}^I is sharply peaked.⁶ Given a Monte Carlo realization $\{i_{t_0-M}^{(n)}, \dots, i_{t_0-1}^{(n)}\}$ with $n = 1, \dots, N_{MC}$, and given the random time sequence i_{t_0}, \dots, i_T , we can indicate the associated option price $C^{(n)}$ as

$$\begin{aligned} C^{(n)}(K, t_0, T | i_{t_0-M}^{(n)}, \dots, i_T^{(n)}; i_{t_0}, \dots, i_T) = \\ = \int_0^\infty \bar{\rho} \left(\sigma \left| \frac{x_{t_0-1}}{a_{i_{t_0-1}}^{(n)}}, \dots, \frac{x_{t_0-M}}{a_{i_{t_0-M}}^{(n)}}; i_{t_0}, \dots, i_T \right. \right) C(K, t_0, T | \sigma; i_{t_0}, \dots, i_T) d\sigma. \end{aligned} \quad (26)$$

Therefore, we denote with $C^{(n,0)}$ the option price in the above expression when no restarts occur between t_0 and T , while $C^{(n,1,j)}$ is the option price in the above expression when only a single restart occurs between t_0 and T at time $t = j$. Finally, $C^{(n,2,j,j')}$ is the option price in the above expression when only two restarts occur between t_0 and T at time $t = j$ and $t = j'$. Using those three elements, the final explicit expression for the option price becomes

$$\begin{aligned} C(K, t_0, T) = \frac{1}{A N_{MC}} \sum_{n=1}^{N_{MC}} \left[(1 - \nu)^{T-t_0+1} C^{(n,0)}(K, t_0, T) + \right. \\ \left. + \nu(1 - \nu)^{T-t_0} \sum_{j=t_0}^T C_{t_0, T}^{(n,1,j)}(K) + \nu^2(1 - \nu)^{T-t_0-1} \sum_{j=t_0}^{T-1} \sum_{j'=j+1}^T C_{t_0, T}^{(n,2,j,j')}(K) \right], \end{aligned} \quad (27)$$

where A is the normalization constant

$$A = (1 - \nu)^{T-t_0+1} + \sum_{j=t_0}^T \nu(1 - \nu)^{T-t_0} + \sum_{j=t_0}^{T-1} \sum_{j'=j+1}^T \nu^2(1 - \nu)^{T-t_0-1}. \quad (28)$$

In (27), the probability of the random time sequence past to t_0 , f_{t_0-M, t_0-1}^I , has been replaced by a sum over the Monte Carlo realizations, since the $i_t^{(n)}$'s are extracted according to f_{t_0-M, t_0-1}^I , whereas the probability of the random time sequence beyond t_0 , $f_{t_0, T}^I$, has been explicitly calculated at second order in ν .

Summarizing, the numerical evaluation of the option price includes the following steps:

(i) Given the historical information, extract the past random time sequence $i_t^{(n)}$'s through

⁶Higher values of N_{MC} do not sensibly affect the option prices.

the Monte Carlo algorithm; (ii) Consider then a possible future random time sequence with zero, one or at most two restarts between t_0 and T ; (iii) Evaluate \bar{p} as described in subsection 3.2; (iv) Calculate a partial option price using (26); (v) Take the average across sequences described in (i) and (ii) using, (27). In terms of CPU time-consumption, points (i) and (iii) are the bottlenecks in the implementation of this algorithm, and are independent of the strike price K .

We close this section, by noting that the stochastic process previously introduced and the associated option pricing approach allow generating asset returns and option prices characterized by a volatility smile effect, as we will show in the next section.

4 Empirical application

4.1 Options database

We now compare the pricing approach previously introduced and the standard BS model with market prices for options on the S&P500 index as recovered from Datastream. We consider European call options with maturity between June 2007 and May 2013, and for those contracts we download the prices available from January 2007 up to May 2012.⁷ The S&P500 index options have already been used in several studies dealing with option pricing, see Bakshi et al. (1997), Ait-Sahalia and Lo (1998), Dumas et al. (1998), Chernov and Ghysels (2000), Heston and Nandi (2000) and Christoffersen et al. (2006), among others. Similarly to Christoffersen et al. (2006), we evaluate the pricing performances both in-sample and out-of-sample.⁸ We fix the in-sample to the range starting in January 2007 and ending at December 2010. The remainder period, January 2011 to May 2012, is used as out-of-sample. The Appendix reports additional details on the database and the filters applied to the option prices, following Bakshi et al. (1997), Dumas et al. (1998), Ait-Sahalia and Lo (1998), Bakshi et al. (2000), Christoffersen and Jacobs (2004) and Christoffersen et al. (2006). Table (1) reports the number of option contracts, the

⁷We consider options with maturity in the twelve months following the reference download date, the 31 May 2012.

⁸The present paper reports out-of-sample pricing results only. In-sample results are available from the authors upon request.

average option price, and the average implied volatility from the BS model, distinguishing on the basis of the moneyness (computed as the ratio between the equity index level and the option strike price) and time to maturity. Excluding the extreme moneyness classes (below 0.5 and above 2.5), we observe the presence of a volatility smile effect, with implied volatility differing across strike prices, and characterized by some asymmetry. In fact, call options highly in-the-money have higher implied volatility compared to out-of-the money call options. Notably, the options' implied volatility is extremely high, in many cases well above 100%. This is related to the peculiar features of the time range analysed in the current paper, which is characterised by very high volatility.⁹

In comparing our approach to the BS model, option prices are filtered from the dividends effects, as in Bakshi et al. (1997), Ait-Sahalia and Lo (1998) and Christoffersen et al. (2006). In addition, the risk-free rate is proxied by a set of interbank rates, at 1, 3, 6 and 12 months, recovered from Thomson Datastream, and matched with the options maturity; see the Appendix for details.

4.2 Scaling and persistence in the S&P500 index

The pricing of call options starts from the estimation of the model outlined in section 2. We use a time-series length of five years to determine the model parameters (D, ν, α, β) , and, for computational simplicity, we impose a grid over the model parameters with precision $5 \cdot 10^{-3}$ for D , $1 \cdot 10^{-4}$ for ν and 0.5 for α .¹⁰

For the in-sample period, the years 2007-2010, we estimate the model parameters using the S&P500 index in the range 2006-2010 (five years). As previously mentioned, we set $M = 21$ and the estimated parameters are $(D, \nu, \alpha) = (0.225, 2 \cdot 10^{-4}, 4.0)$. The in-sample parameter D shows evidence of some long-range persistence in the second order moment of the daily S&P500 returns. In addition, the shape parameters of the volatility density are quite high. Finally, the parameter ν suggests that the average time between two restarts, creating a regime change, is equal to about 5000 days.¹¹ The scale parameter

⁹Similar evidences are provided for the in-sample period.

¹⁰Parameters have been estimated with a minimum-distance-type estimator, see Zamparò et al. (2013), for additional details.

¹¹We also estimated the model with $M = 63$ obtaining $(D, \nu, \alpha) = (0.150, 8 \cdot 10^{-4}, 5.0)$. This suggests

of the volatility density, β , plays a role similar to the volatility parameter σ_{BS} in the BS model. In view of a fair comparison with this benchmark model, we estimate these two parameters on the basis of the same sample data. In preliminary evaluations, we have verified that the use of the above in-sample interval, 2006-2010, to determine σ_{BS} in the BS formula gives very poor results in comparison with the market option prices. For this reason, β and σ_{BS} have been both estimated in an out-of-sample framework, using the historical data of one year previous to the pricing day. Using common convention, the volatility σ_{BS} of the BS model is defined as the returns' standard deviation. The last plot of Figure 2 compares the historical evolution of the β (for $M = 21$) and of the BS volatility. We note that the two quantities share a common pattern, a somewhat expected result given the two parameters are evaluated over the same sample. In turn, this highlights that the two models will provide option prices derived from a common playground. This would have not been the case, for instance, if the BS prices were derived by changing the underlying volatility according to the option time to maturity and moneyness. As a consequence, the differences observed in the option prices reported below are due to the different dynamic behaviour of the underlying models.

For the out-of-sample evaluation, we estimate the model parameters D , ν and α using the five years data prior to the pricing day.¹² As a result, we obtain a sequence of parameters values. The parameter evolution is reported in the first to third plots of Figure 2, while some descriptive quantities are included in Table (2) (in all cases we consider $M = 21$). We observe that the memory parameter D has a decreasing pattern, suggesting a reduction of the persistence of the equity index. The parameter ν shows evidence of limited oscillations, influenced by the grid used in its evaluation (its value ranges from 0.0002 to 0.0004). Finally, the shape parameter α has a sharp increase in the last part of the sample.

an interval between regime changes equal to 1250 days. The parameter ν changes across values of M and this might be counter-intuitive as it represents a memory-independent part of the model. This is however an estimation/calibration issue. In fact, as in the estimation step we assume *a priori* the value of M , the estimation of all remaining parameters becomes in fact M -dependent. We nevertheless point out that the obtained values for ν are not much different, and the most relevant outcome is the evidence of having rare regime changes.

¹²The appropriate estimation of those parameters requires longer samples compared to the parameter β as discussed in Zamparo et. al (2013).

4.3 Pricing and non-Gaussian scaling

The pricing approach presented in this paper is contrasted to a more traditional BS pricing.

Table (3) reports the out-of-sample pricing outcomes expressed as root mean squared errors (RMSE) between the prices implied by the two models and the observed market prices. The Table shows a preference for the pricing consistent with the scaling property of the S&P500. The BS approach turns out to be preferred for higher levels of moneyness and shorter maturities. The pricing with anomalous scaling and switching volatility gives, overall, smaller pricing errors for moneyness levels up to 1.75, independently of the time to maturity, and for moneyness levels above 1.75, only for options with maturity in more than three months. If we focus solely on the moneyness, the introduction of scaling properties provides pricing errors smaller than those associated with the BS model for most moneyness levels. Differently, if we consider only the time to maturity, the BS pricing gives smaller pricing errors for maturities above three months. Finally, we observe that the largest differences across the two pricing approaches occur for moneyness levels below 1.5 independently of the time to maturity. In those cases, the pricing with anomalous scaling provides smaller RMSE with a sensibly larger frequency.

However, as one might expect, those results are given by a combination of cases where the preference for our approach is striking, with cases where the BS pricing is preferred, at least in some dates or for some maturities. We provide an example in Figures 3.¹³ where we report the mean squared error for options with a given maturity for different moneyness levels and different pricing days (the Wednesdays of several consecutive weeks). In many cases we observe that the BS model provides substantially greater pricing errors than those of the anomalous scaling-based prices. Pricing errors might be either increasing or decreasing when approaching time to maturity. Finally, the proposed model provides option prices consistent with a volatility smile effect, as shown for a specific cases in Figure 4.¹⁴

¹³Additional examples are available upon request.

¹⁴Additional examples are available upon request.

5 Conclusions

Self-similarity is a remarkable symmetry linking properties observed at different scales. Whenever a system is (at least approximately) self-similar, this symmetry may be exploited as a guiding line for an appropriate modelling of non-trivial behaviours (e.g., those induced by non-Gaussianity and long-range dependence).

We analysed a stochastic model recently introduced in physics (Zamparo et al., 2013) as a tool for modelling assets' dynamics on the basis of the anomalous scaling properties observed on financial returns. Thanks to the scaling symmetry, presence of exogenous and endogenous effects, few parameters, and analytical tractability, coexist within the model. We discussed the model properties, in particular with respect to an implementation that amounts to an infinite-state, Markov switching, auto-regressive model. We framed the model components in a financial perspective and described the estimation of its parameters.

Building on the model potential, we worked out novel closed-form pricing and associated hedging strategy formulae for a European call option. We provided details on the derivation of the pricing equation and of the associated relevant quantities.

Our work includes an empirical comparison of the proposed pricing approach with real market prices, together with benchmark comparisons with a more traditional BS pricing. We focused on European call options written on the S&P500 index, with maturity between 2007 and 2013. Results exhibit evidence that the novel derivative prices are closer to the market prices than BS ones.

Assessment of the efficacy of the proposed strategy, together with the development of specific Greeks for the aforementioned pricing approach, are left to future research work.

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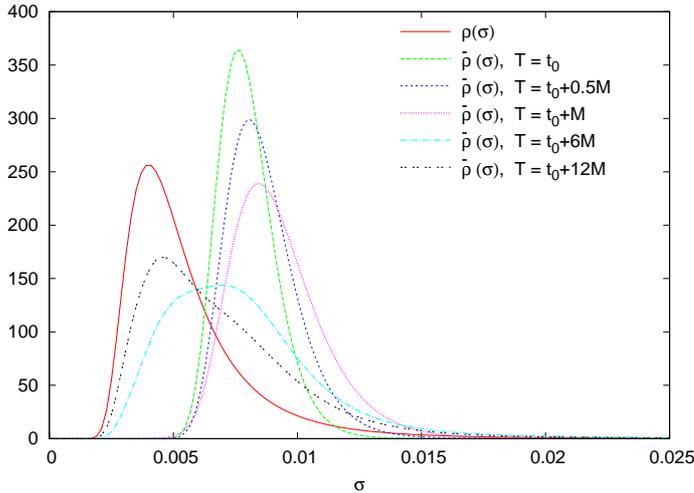


Figure 1: Behaviour of $\bar{\rho}(\sigma)$ at different maturities T . t_0 is 2 March 2007. Parameters used are $M = 21$, $D = 1/2$, $\alpha = 4$ and $\beta = 0.01$. For each T , the distribution $\bar{\rho}$ has been calculated averaging over 100 different numerical realizations of the process.

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Appendix

Proof of Lemma 1.

For all the measures \mathbb{P}^* introduced in Lemma 1 and for $t_0 \leq t \leq T$, it is straightforward to see that $\mathbb{E}_{\mathbb{P}^*} \left[\frac{S_t}{(1+r)^t} \middle| \mathcal{F}_{t-1} \right] = \frac{S_{t-1}}{(1+r)^{t-1}}$. \square

Table 1: Out-of-sample database description over different levels of moneyness (on rows) and days to maturity (DTM, on columns): number of contracts (upper panel); average CALL option price (central panel); average Black-Scholes implied volatility (lower panel).

DTM (days)	< 21	21 – 63	63 – 126	126 – 252	All
Moneyiness					
Number of contracts					
0.50	2	11	30	117	160
0.50 – 0.75	28	155	494	925	1602
0.75 – 1.00	2044	5561	2603	2538	12746
1.00 – 1.25	3146	6437	2094	1886	13563
1.25 – 1.50	2164	3987	1139	1160	8450
1.50 – 1.75	1133	1938	725	799	4595
1.75 – 2.00	459	738	436	548	2181
2.00 – 2.25	144	319	291	386	1140
2.25 – 2.50	76	167	192	289	724
> 2.50	396	876	898	1326	3496
All	9592	20189	8902	9974	48657
Average option price					
< 0.50	0.05	0.09	0.29	0.35	0.32
0.50 – 0.75	0.25	0.24	0.41	0.65	0.53
0.75 – 1.00	4.36	9.30	14.81	28.20	13.39
1.00 – 1.25	133.46	138.46	144.14	172.24	142.87
1.25 – 1.50	342.31	339.55	335.12	342.80	340.11
1.50 – 1.75	487.86	481.70	478.94	478.28	482.19
1.75 – 2.00	603.35	598.90	586.95	578.33	592.28
2.00 – 2.25	685.49	682.29	672.24	654.81	670.82
2.25 – 2.50	748.82	744.33	731.36	707.02	726.47
> 2.50	962.03	958.83	929.54	899.65	929.22
All	264.37	240.44	280.41	315.20	267.79
Average implied volatility					
< 0.50		0.581	0.447	0.337	0.380
0.50 – 0.75	0.675	0.317	0.256	0.188	0.227
0.75 – 1.00	0.186	0.173	0.171	0.177	0.175
1.00 – 1.25	0.300	0.257	0.247	0.246	0.265
1.25 – 1.50	0.498	0.353	0.313	0.301	0.383
1.50 – 1.75	0.646	0.422	0.330	0.316	0.456
1.75 – 2.00	0.745	0.492	0.347	0.304	0.493
2.00 – 2.25	0.813	0.493	0.356	0.302	0.459
2.25 – 2.50	0.904	0.542	0.389	0.315	0.475
> 2.50	1.430	0.790	0.508	0.329	0.650
All	0.448	0.307	0.285	0.256	0.326

Table 2: Estimated parameters for the out-of-sample analysis. β and σ_{BS} have been calibrated using the returns of one year previous to the pricing day, while D , ν and α have been calibrated using the returns of five years previous to the pricing day and $M = 21$.

	D	ν	α	β	σ_{BS}
mean	0.224	0.0002	5.50	0.241	0.221
st. dev.	0.033	0.0001	1.75	0.108	0.101
min.	0.155	0.0002	3.50	0.108	0.096
max.	0.295	0.0004	9.00	0.490	0.440
median	0.230	0.0002	4.50	0.207	0.187

Table 3: Out-of-sample pricing root mean squared errors between the option prices derived from the two alternative pricing approaches (the one described in the present paper and the traditional Black-Scholes) and the option prices observed in the market over different levels of moneyness, reported over rows, and different days to maturity (DTM), reported over columns.

DTM (days)	< 21	21 – 63	63 – 126	126 – 252	Total
Moneyness					
Pricing with anomalous scaling and switching volatility					
< 0.50	0.0500	0.1091	0.3736	0.4276	0.4009
0.50 – 0.75	0.4204	0.5869	0.8635	2.7064	2.1203
0.75 – 1.00	3.9723	4.5316	7.1004	14.5335	7.9903
1.00 – 1.25	4.5711	9.2425	16.3600	33.7892	15.6675
1.25 – 1.50	1.8501	4.0428	7.8244	22.3663	9.2474
1.50 – 1.75	1.4836	3.2287	7.6356	17.2082	8.1012
1.75 – 2.00	1.5083	2.9552	8.2243	13.9656	8.1217
2.00 – 2.25	1.5855	2.7726	8.4971	12.8151	8.7467
2.25 – 2.50	1.6387	2.7528	8.9124	11.5236	8.7236
> 2.50	1.7663	2.9877	4.4880	6.0581	4.6566
All	3.3978	6.1656	9.9871	19.4427	10.6670
Pricing with Black-Scholes					
< 0.50	0.0500	0.1158	0.3898	0.4810	0.4457
0.50 – 0.75	0.4328	0.3490	0.5561	1.9711	1.5342
0.75 – 1.00	4.8791	7.9976	9.0545	12.4562	8.9085
1.00 – 1.25	5.5124	10.0431	13.9941	24.8824	13.0862
1.25 – 1.50	1.8571	4.3065	8.4834	22.1285	9.3035
1.50 – 1.75	1.4775	3.2480	7.7517	17.6818	8.2966
1.75 – 2.00	1.5057	2.9546	8.2606	14.1985	8.2296
2.00 – 2.25	1.5842	2.7720	8.5098	12.9228	8.8033
2.25 – 2.50	1.6384	2.7522	8.9198	11.5729	8.7516
> 2.50	1.7661	2.9875	4.4889	6.0673	4.6614
Total	4.0462	7.4394	9.6756	16.2858	9.8836

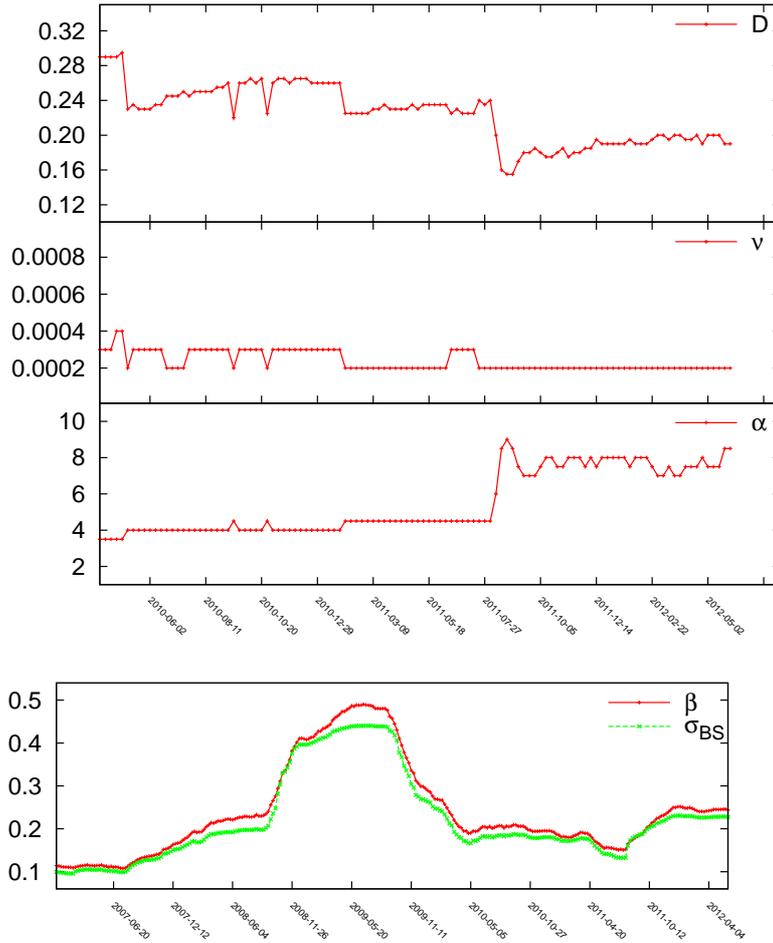


Figure 2: Estimated parameters for the out-of-sample analysis; β and σ_{BS} have been calibrated using the returns of one year previous to the pricing day, while D , ν and α have been calibrated using the returns of five years previous to the pricing day. D (a), ν (b), α (c), β and σ_{BS} (d).

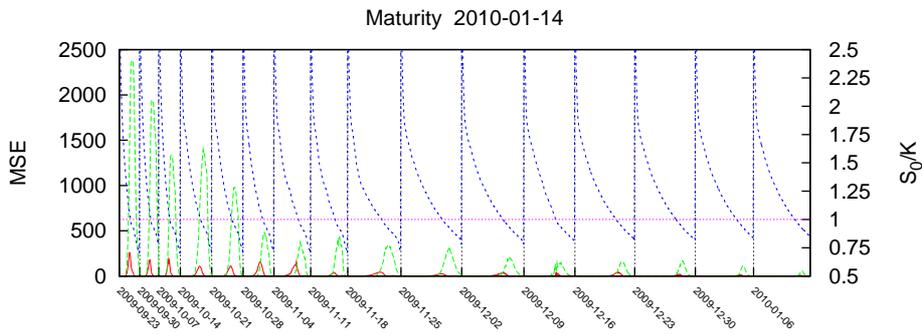


Figure 3: Mean squared pricing errors for options with maturity 14 January 2010, across different moneyness levels (blue line - right vertical axis) and pricing days (horizontal axis). Black-Scholes (B&S - green line - left axis) pricing errors compared to pricing errors from the model with anomalous scaling and switching volatility (ASP - red line - left axis).

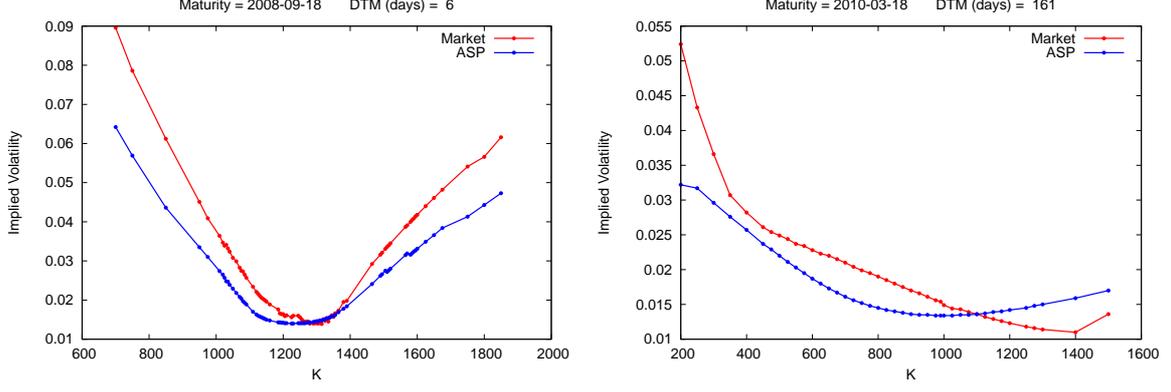


Figure 4: Implied volatilities associated with option prices determined in presence of anomalous scaling (blue) and empirical smile effect (red) on two different options and days to maturity.

Proof of Theorem 1.

Using the equivalent martingale measure $\mathbb{P}^*_{\sigma; i_{t_0}, \dots, i_T}$, we have

$$\begin{aligned} C(K, t_0, T | \sigma; i_{t_0}, \dots, i_T) &= (1+r)^{t_0-T} \mathbb{E}_{\mathbb{P}^*_{\sigma; i_{t_0}, \dots, i_T}} [\max\{S_T - K, 0\} | \mathcal{F}_{t_0-1}] = \\ &= (1+r)^{t_0-T} \int_{-\infty}^{+\infty} \max\{S_T - K, 0\} \left(\prod_{t=t_0}^T h(x_t, \sigma, i_t) \right) dx_{t_0} \dots dx_T. \end{aligned} \quad (29)$$

Since $S_T = S_{t_0-1} \exp \left[\mu(T - t_0 + 1) + \sum_{t=t_0}^T X_t \right]$, making the change of variables $\lambda_t \equiv x_t - \gamma$ we obtain

$$\begin{aligned} C(K, t_0, T | \sigma; i_{t_0}, \dots, i_T) &= (1+r) \int_{-\infty}^{+\infty} \max \left\{ S_{t_0-1} e^{\sum_{t=t_0}^T \lambda_t} - K(1+r)^{t_0-T-1}, 0 \right\} \\ &\quad \left(\prod_{t=t_0}^T \frac{1}{\sqrt{2\pi}\sigma a_{i_t}} \exp \left[-\frac{1}{2} \left(\frac{\lambda_t}{\sigma a_{i_t}} + \frac{\sigma a_{i_t}}{2} \right)^2 \right] \right) d\lambda_{t_0} \dots d\lambda_T = \\ &= (1+r) \int_{-\infty}^{+\infty} \max \left\{ S_{t_0-1} e^\lambda - K(1+r)^{t_0-T-1}, 0 \right\} \frac{1}{\sqrt{2\pi}\tilde{\sigma}} \exp \left[-\frac{1}{2} \left(\frac{\lambda}{\tilde{\sigma}} + \frac{\tilde{\sigma}}{2} \right)^2 \right] d\lambda, \end{aligned} \quad (30)$$

where for the last equality we have used the closeness of the Gaussian under aggregation with $\lambda \equiv \sum_{t=t_0}^T \lambda_t$. Following now standard steps as in the BS derivation, we end up with (14).

Taking the expectation over the distributions of σ and i_{t_0}, \dots, i_T , (17) derives then from (14). \square

Proof of Theorem 2.

We have

$$\begin{aligned} f_{t_0, T}^X(x_{t_0}, \dots, x_T | x_{t_0-1}, \dots, x_{t_0-M}; i_{t_0-M}, \dots, i_T) &= \\ \prod_{t=t_0}^T f_{t, t}^X(x_t | x_{t-1}, \dots, x_{t_0-M}; i_{t_0-M}, \dots, i_T). \end{aligned} \quad (31)$$

Using $X_t = a_{i_t} Y_t$ and conditionally to the sequence i_{t_0-M}, \dots, i_T , for $t_0 \leq t \leq T$ we can write

$$\begin{aligned} f_{t,t}^X(x_t | x_{t-1}, \dots, x_{t_0-M}; i_{t_0-M}, \dots, i_T) &= \frac{1}{a_{i_t}} f_{t,t}^Y \left(\frac{x_t}{a_{i_t}} \mid \frac{x_{t-1}}{a_{i_{t-1}}}, \dots, \frac{x_{t_0-M}}{a_{i_{t_0-M}}} \right) \\ &= \frac{1}{a_{i_t}} f_{t,t}^Y \left(\frac{x_t}{a_{i_t}} \mid \frac{x_{t-1}}{a_{i_{t-1}}}, \dots, \frac{x_{t-M}}{a_{i_{t-M}}} \right), \end{aligned} \quad (32)$$

where we have used the fact that Y_t depends on the previous M values only. Assuming, for simplicity of notation that $t_0 \geq M$, setting $y = x/a$ and exploiting (2) and (3) we get

$$f_{t,t}^Y(y_t | y_{t-1}, \dots, y_{t-M}) = \int_0^\infty \hat{\rho}_{t,t}(\sigma_t | y_{t-1}, \dots, y_{t-M}) \mathcal{N}_{\sigma_t}(y_t) d\sigma_t, \quad (33)$$

with $\hat{\rho}_{t,t}(\sigma_t | y_{t-1}, \dots, y_{t-M})$ given by (21). Putting together, we obtain

$$\begin{aligned} f_{t_0,T}^X(x_{t_0}, \dots, x_T | x_{t_0-1}, \dots, x_{t_0-M}; i_{t_0-M}, \dots, i_T) &= \\ &= \prod_{t=t_0}^T \frac{1}{a_{i_t}} \int_0^\infty \hat{\rho}_{t,t} \left(\sigma_t \mid \frac{x_{t-1}}{a_{i_{t-1}}}, \dots, \frac{x_{t-M}}{a_{i_{t-M}}} \right) \mathcal{N}_{\sigma_t} \left(\frac{x_t}{a_{i_t}} \right) d\sigma_t. \end{aligned} \quad (34)$$

Notice that (34) is exact but has the disadvantage that $\hat{\rho}_{t,t}$ is a conditional density for a ‘‘dynamical stochastic volatility’’ σ_t that also depends on the endogenous values $y_t = x_t/a_{i_t}$ future to t_0 and is not then identified by historical data only. Using the fact that $\frac{1}{a_{i_t}} \mathcal{N}_{\sigma_t} \left(\frac{x_t}{a_{i_t}} \right) = \mathcal{N}_{a_{i_t}\sigma_t}(x_t)$ and the parity of $f_{t_0,T}^X$ with respect to all its arguments, we have

$$\begin{aligned} \langle R^2 \rangle_{f_{t_0,T}^X} &= \int dx_{t_0} \dots dx_T (x_{t_0} + \dots + x_T)^2 \cdot \\ &\quad \cdot \prod_{t=t_0}^T \int_0^\infty \hat{\rho}_{t,t} \left(\sigma_t \mid \frac{x_{t-1}}{a_{i_{t-1}}}, \dots, \frac{x_{t-M}}{a_{i_{t-M}}} \right) \mathcal{N}_{a_{i_t}\sigma_t}(x_t) d\sigma_t = \\ &= \int dx_{t_0} \dots dx_T (x_{t_0}^2 + \dots + x_T^2) \cdot \\ &\quad \cdot \prod_{t=t_0}^T \int_0^\infty \hat{\rho}_{t,t} \left(\sigma_t \mid \frac{x_{t-1}}{a_{i_{t-1}}}, \dots, \frac{x_{t-M}}{a_{i_{t-M}}} \right) \mathcal{N}_{a_{i_t}\sigma_t}(x_t) d\sigma_t = \\ &= \sum_{t=t_0}^T dx_t x_t^2 \int_0^\infty \hat{\rho}_{t,t} \left(\sigma_t \mid \frac{x_{t_0-1}}{a_{i_{t_0-1}}}, \dots, \frac{x_{t_0-M}}{a_{i_{t_0-M}}} \right) \mathcal{N}_{a_{i_t}\sigma_t}(x_t) d\sigma_j = \\ &= \sum_{t=t_0}^T a_{i_t}^2 \langle \sigma^2 \rangle_{\hat{\rho}_{t,t}} \end{aligned} \quad (35)$$

where we use the facts that

$$\begin{aligned} \hat{\rho}_{t,t}(\sigma_t | y_{t_0-1}, \dots, y_{t_0-M}) &= \\ &= \int \hat{\rho}_{t,t}(\sigma_t | y_{t-1}, \dots, y_{t-M}) \left[\prod_{\substack{j=t_0 \\ j \neq t}}^T \hat{\rho}_{j,j}(\sigma_j | y_{j-1}, \dots, y_{j-M}) \mathcal{N}_{\sigma_j}(y_j) dx_j \right], \end{aligned} \quad (36)$$

$$\int_{-\infty}^\infty z^2 \mathcal{N}(z) dz = 1 \quad (37)$$

and

$$\langle \sigma^2 \rangle_{\hat{\rho}_{t,t}} \equiv \int_0^\infty \sigma_t^2 \hat{\rho}_{t,t} \left(\sigma_t \mid \frac{x_{t_0-1}}{a_{i_{t_0-1}}}, \dots, \frac{x_{t_0-M}}{a_{i_{t_0-M}}} \right) d\sigma_t. \quad (38)$$

On the other hand:

$$\begin{aligned}
\langle R^2 \rangle_{g_{i_0, T}^X} &= \int dx_{t_0} \dots dx_T (x_{t_0} + \dots + x_T)^2 \cdot \\
&= \int_0^\infty \bar{\rho} \left(\sigma \left| \frac{x_{t_0-1}}{a_{i_{t_0-1}}}, \dots, \frac{x_{t_0-M}}{a_{i_{t_0-M}}}; i_{t_0}, \dots, i_T \right. \right) \left[\prod_{t=t_0}^T \frac{1}{a_{i_t}} \mathcal{N}_\sigma \left(\frac{x_t}{a_{i_t}} \right) \right] d\sigma = \\
&= \int_0^\infty \bar{\rho} \left(\sigma \left| \frac{x_{t_0-1}}{a_{i_{t_0-1}}}, \dots, \frac{x_{t_0-M}}{a_{i_{t_0-M}}}; i_{t_0}, \dots, i_T \right. \right) \left[\sum_{t=t_0}^T \int x_t^2 \mathcal{N}_{a_{i_t} \sigma}(x_t) dx_t \right] d\sigma = \\
&= \langle \sigma^2 \rangle_{\bar{\rho}} \sum_{t=t_0}^T a_{i_t}^2, \tag{39}
\end{aligned}$$

where

$$\langle \sigma^2 \rangle_{\bar{\rho}} \equiv \int_0^\infty \sigma^2 \bar{\rho} \left(\sigma \left| \frac{x_{t_0-1}}{a_{i_{t_0-1}}}, \dots, \frac{x_{t_0-M}}{a_{i_{t_0-M}}}; i_{t_0}, \dots, i_T \right. \right) d\sigma. \tag{40}$$

By direct inspection, we thus see that $\langle R^2 \rangle_{f_{i_0, T}^X} = \langle R^2 \rangle_{g_{i_0, T}^X}$. \square

An explicit expression for $\hat{\rho}_{t,t}$

By choosing the density $\rho(\sigma)$ to be an inverse-Gamma distribution, (4), it is possible to analytically solve (3) and (21). Indeed, with an inverse-Gamma distribution for $\rho(\sigma)$, (3) becomes

$$\varphi_t(y_1, \dots, y_t) = \frac{\beta^\alpha \Gamma(\frac{\alpha+t}{2})}{\pi^{\frac{t}{2}} \Gamma(\frac{\alpha}{2})} [\beta^2 + y_1^2 + \dots + y_t^2]^{-\frac{\alpha+t}{2}}, \tag{41}$$

and (33) casts into

$$f_{t,t}^Y(y_t | y_{t-1}, \dots, y_{t-M}) = \frac{\Gamma(\frac{\alpha+M+1}{2})}{\sqrt{\pi} \Gamma(\frac{\alpha+M}{2})} \frac{[\beta^2 + y_{t-M}^2 + \dots + y_t^2]^{-\frac{\alpha+M+1}{2}}}{[\beta^2 + y_{t-M}^2 + \dots + y_{t-1}^2]^{-\frac{\alpha+M}{2}}} \tag{42}$$

and finally (21) now reads

$$\hat{\rho}_{t,t}(\sigma_t | y_{t-1}, \dots, y_{t-M}) = \frac{2 e^{-\frac{\beta^2 + y_{t-M}^2 + \dots + y_{t-1}^2}{2\sigma_t^2}}}{2^{\frac{\alpha+M}{2}} \sigma_t^{\alpha+M+1} \Gamma(\frac{\alpha+M}{2})} [\beta^2 + y_{t-M}^2 + \dots + y_{t-1}^2]^{\frac{\alpha+M}{2}}. \tag{43}$$

An explicit expression for f_{t_0-M, t_0-1}^I

In order to write explicitly the r.h.s. of (24), let us start with the model's probability density function of t return variables X_1, \dots, X_t for $t \leq M+1$ (see Zamparo et al., 2013, for details):

$$f_{1,t}^X(x_1, \dots, x_t) = \sum_{i_1=1}^\infty \dots \sum_{i_t=1}^\infty f_{1,t}^{X,I}(i_1, \dots, i_t; x_1, \dots, x_t), \tag{44}$$

where

$$f_{1,t}^{X,I}(i_1, \dots, i_t; x_1, \dots, x_t) \equiv \frac{W(i_t, i_{t-1}) \dots W(i_2, i_1) \pi(i_1)}{a_{i_1} \dots a_{i_t}} \varphi_t \left(\frac{x_1}{a_{i_1}}, \dots, \frac{x_t}{a_{i_t}} \right). \tag{45}$$

With a slightly more complex notation, let us also define:

$$f_{1,t; t_1, t_2}^{X,I}(i_{t_1}, \dots, i_{t_2}; x_1, \dots, x_t) \equiv \sum_{i_1=1}^\infty \dots \sum_{i_{t_1-1}=1}^\infty \sum_{i_{t_2+1}=1}^\infty \dots \sum_{i_t=1}^\infty f_{1,t}^{X,I}(i_1, \dots, i_t; x_1, \dots, x_t), \tag{46}$$

where $1 \leq t_1 \leq t_2 \leq t$.

We can thus specify the factors in the r.h.s. of (24) as

$$\begin{aligned} & f_{t_0-M, t_0-M}^I(i_{t_0-M} | x_{t_0-M-\tau}, \dots, x_{t_0-M+\tau}) = \\ & = \frac{f_{t_0-M-\tau, t_0-M+\tau; t_0-M, t_0-M}^{X,I}(i_{t_0-M}; x_{t_0-M-\tau}, \dots, x_{t_0-M+\tau})}{f_{t_0-M-\tau, t_0-M+\tau}^X(x_{t_0-M-\tau}, \dots, x_{t_0-M+\tau})} \end{aligned} \quad (47)$$

and

$$\begin{aligned} & f_{t,t}^I(i_t | i_{t-1}; x_{t-\tau}, \dots, x_{\min\{t+\tau, t_0-1\}}) = \\ & = \frac{f_{t-\tau, \min\{t+\tau, t_0+1\}; \max\{t-\tau, t_0-M\}, t}^{X,I}(i_{\max\{t-\tau, t_0-M\}}, \dots, i_t; x_{t-\tau}, \dots, x_{\min\{t+\tau, t_0-1\}})}{f_{t-\tau, \min\{t+\tau, t_0+1\}; \max\{t-\tau, t_0-M\}, t-1}^{X,I}(i_{\max\{t-\tau, t_0-M\}}, \dots, i_{t-1}; x_{t-\tau}, \dots, x_{\min\{t+\tau, t_0-1\}})}. \end{aligned} \quad (48)$$

Option database filters and data management

Similarly to Dumas et al. (1998), Christoffersen and Jacobs (2004), and Christoffersen et al. (2006), we focus on the Wednesday prices to reduce the computational burden associated with the pricing of several options with different maturities and strike prices. We then apply to the raw Wednesday data filters similar to those proposed by Bakshi et al. (1997): we discard the last week of trading for each option contract to limit the effects associated with option expiration; we drop prices below a threshold set at 0.125 US dollars, to avoid effects associated with price discreteness; we control for prices not satisfying the arbitrage restriction in equation (15) in Bakshi et al. (1997). Similar filters have been applied in previous studies (Ait-Sahalia and Lo, 1998, Bakshi et al., 2000, and Christoffersen et al., 2006, among others). Finally, for each Wednesday, we consider options with maturities in maximum one year.

In performing the option pricing exercise, we consider S&P500 index levels recorded at 3 p.m. US Central Time (Chicago time), to maintain the temporal alignment with the option prices (we consider the closing price recorded at the close of the option trading, at 3 p.m. Chicago time). Moreover, we follow Bakshi et al. (1997), Ait-Sahalia and Lo (1998) and Christoffersen et al. (2006), and account for the effects of dividends paid by the stocks included in the index. To perform the pricing, we remove from the current index level the future dividends which are expected to be paid during the life of the option. We evaluate the dividends following Ait-Sahalia and Lo (1998), starting from the relation between the index price and its future value:

$$F_{t,\tau} = S_t e^{(r_{t,\tau} - d_{t,\tau})\tau},$$

where $F_{t,\tau}$ is the Future price with maturity in τ periods, $r_{t,\tau}$ is the constant risk-free interest rate from t to $t + \tau$ and $d_{t,\tau}$ is the constant, and unknown, divided rate expected from t to $t + \tau$. We determine the Future price from the put-call parity

$$P(K, t, \tau, r_{t,\tau}) + K e^{-r_{t,\tau}\tau} = C(K, t, \tau, r_{t,\tau}) + S_t e^{-d_{t,\tau}\tau} \quad (49)$$

$$= C(K, t, \tau, r_{t,\tau}) + F_{t,\tau} e^{-r_{t,\tau}\tau}. \quad (50)$$

Note that the discounted Future price equals the Index level discounted from future dividends. The dividend yield might be recovered using the actual equity index level. In computing the dividend discounted index, (50) must be evaluated using reliable option prices with, obviously, the same strike price and the same maturity. We select, for each point in time (each Wednesday) and each maturity, the pair of put and call options which are closer to at-the-money (with the strike closest to the equity index level). The interest rates are obtained from Thomson Datastream. We download the interbank rates at 1, 3, 6 and 12 months. For options expiring in less than 41 (open market) days, we use as risk-free the one month interbank rate. The three months rate was used for values of τ between 41 and 82 days, while the six months rate was considered for options expiring in more than 82 days but less than 183 days. Finally, the 12 months rate was used for options expiring in more than 183 days. After this procedure, for each point in our sample and each maturity we obtain a set of discounted index levels which are then used in the pricing, together with the set of risk-free rates and the option prices previous described.