Delpini, Danilo; Bormetti, Giacomo

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Quaderni di Dipartimento

A Minimal Model of Financial Stylized Facts

Danilo Delpini
(Università di Pavia)

Giacomo Bormetti
(Scuola Normale Superiore di Pisa)

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Dipartimento di economia politica
e metodi quantitativi
Università degli studi di Pavia
Via San Felice, 5
I-27100 Pavia

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A minimal model of financial stylized facts

Danilo Delpini1,2,3,* and Giacomo Bormetti4,2,†

1Dipartimento di Economia Politica e Metodi Quantitativi, Università degli Studi di Pavia
2INFN - Sezione di Pavia, via Bassi 6, Pavia, 27100, Italy
3CeRS - IUS, V.le Lango Ticino Sforza 56, Pavia, 27100, Italy
4Scuola Normale Superiore, Piazza dei Cavalieri 7, Pisa, 56123, Italy

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I. INTRODUCTION

A large number of empirical studies has shown that financial time series exhibit statistical features strongly departing from the Gaussian behavior, and characterized by the non trivial scaling of higher order correlations between returns at different times, pointing toward the existence of a secondary stochastic process, as fundamental as that of the price, governing the volatility of returns, see for instance [1, 2]. More precisely, the emergence of fat tails, multifractality, the correlation between returns and volatilities, and the persistence of the volatility autocorrelation are all universal evidences, shared among different markets in different times. Effective mechanisms allowing to reproduce many of these stylized facts, where the stochastic nature of the volatility plays a central role, include ARCH-GARCH processes [3, 4], multifractal cascades [5] and continuous time stochastic volatility models [6]. Focusing on the latter approach, in this work we aim at reproducing many of the above mentioned facts.

The structure of the paper is the following. After introducing a general class of stochastic models driving the evolution of the volatility, in Section II we concentrate on a linear one able to reproduce an Inverse Gamma stationary distribution for the high frequency volatility. We detail the derivation of the moments of the return distribution, revealing the role of the Inverse Gamma law in the emergence of fat tails, and of the relevant correlation functions. We also propose a systematic methodology for estimating the model parameters, and we apply it to the time series of the daily returns of the Standard & Poor 500 index. The relevant conclusions, along with possible perspectives, will be summarized in Section VII.

II. THE MODEL

We consider a model where the asset price

\[ S_t = S_0 \exp(\mu t + X_t) \]

is a function of the stochastic centred log-return \( X_t \) and \( \mu \) is a constant drift coefficient. We assume that \( X_t \) can be modeled with the following stochastic differential equation (SDE)

\[ dX_t = \sigma_t \, dW_{1,t}, \quad (1) \]

where \( \sigma_t \) is the instantaneous volatility of the price. Since \( X_0 = 0 \), from the above assumption we have that \( \langle X_t \rangle = 0 \) and \( \langle \ln(S_t/S_0) \rangle = \mu t \) for all \( t \). In the context of stochastic volatility models (SVMs) the instantaneous volatility is assumed to be a function of an underlying driving process \( Y_t \), i.e. \( \sigma_t = \sigma(Y_t) \). Typically, the dynamics chosen for \( Y_t \) corresponds to a particular case of the following general multiplicative diffusion process

\[ dY_t = (aY_t + b) \, dt + \sqrt{cY_t^2 + dY_t} + e \, dW_{2,t}, \quad (2) \]

with suitable constraints on the parameters, in order to ensure the well definiteness of the process. Moreover, the two standard Wiener processes \( W_{1,2} \) are possibly correlated

\[ \langle dW_{1,t} \, dW_{2,t} \rangle = \rho \delta(t_1 - t_2) \, dt, \quad (3) \]

with \( \rho \in [-1, 1] \), which is necessary to account for skewness effects and for the return-volatility correlation. For instance, in the Stein-Stein model [7, 8] the volatility is linear, \( \sigma_t \propto Y_t \), and \( Y_t \) follows a mean reverting

* Electronic address: danilo.delpini@pv.infn.it
† Electronic address: giacomo.bormetti@sns.it
Ornstein-Uhlenbeck dynamics corresponding to $a < 0$, $b > 0$, $c = d = 0$. Under the same $Y$ dynamics but with $\sigma_t \propto \exp(Y_t)$ we obtain the exponential Ornstein-Uhlenbeck model [9, 10]. In the Heston model [11] $\sigma_t = \sqrt{y_t}$ and $Y_t$ evolves according to a Cox-Ingersoll-Ross dynamics, stemming from (2) by taking $a < 0$, $b > 0$ with $c = e = 0$. Finally, in the Hull-White model the volatility has the same functional dependence as in Heston, but $Y_t$ has a Log-Normal (non mean reverting) dynamics corresponding to $a > 0$ and $b = d = e = 0$.

In the Econophysics literature several studies have been devoted to assess the statistical properties of the volatility (see for instance Chapter 7 in [2] and [12]), especially its distribution, and it has been recognized that the instantaneous volatility, measured by suitable proxies, distributes in good agreement with a Log-Normal distribution [13, 14], while the Inverse Gamma was introduced in the context of an ARCH-like evolution of the variance in [15].

Here we afford the statistical characterization of the simplest linear SVM able to account for this stylized fact about the volatility. The process (2) has been extensively studied and characterized in [16] where exact solutions for the moments of the associated PDF have been obtained allowing to study its relaxation modes toward a stationary distribution, if any. In particular, when $a < 0$ and $d = e = 0$, with $c > 0$, the process (2) has indeed an Inverse Gamma stationary distribution, whose support is $[0, +\infty)$ as long as $b > 0$. Thereby we consider the following SVM

$$\begin{align*}
dX_t &= \sqrt{\sigma_t} Y_t dW_{1,t}, \quad X_0 = 0 \\
dY_t &= (a Y_t + b) dt + \sqrt{c} Y_t dW_{2,t}, \quad Y_{t_0} = y_{t_0},
\end{align*}$$

(4)

where $t_0 \leq 0$, $y_{t_0}$ may be a fixed constant or randomly sampled, and the factor $\sqrt{c}$ in the expression of the instantaneous volatility has been added for later convenience. As explained in [16] the stationary PDF of $\sigma_t$ is

$$\Pi_{st}(\sigma) = \frac{\lambda^{\nu}}{\Gamma(\nu)} \exp(-\lambda/\sigma) \frac{\sigma^\nu}{\sigma^{\nu+1}},$$

(5)

where the shape parameter $\nu$ and the scale parameter $\lambda$ are given by

$$\nu = 1 - \frac{2a}{c} \quad \text{and} \quad \lambda = \frac{2b}{\sqrt{c}}.$$ 

(6)

### III. Emergence of Fat Tails

A major point to be discussed before presenting a detailed derivation of our results is the different role played by the initial time conditions for the $X$ and $Y$ processes. Since $X_t$ represents the detrended logarithmic increment of the price over the time lag $t$, it can be directly measured from real time series, and in a natural way we can assume as starting point for this process the spot time $t = 0$. On the other hand, the secondary process can not be observed directly but some of its statistical properties have been measured by means of suitable proxies. In particular, for intra-day frequencies there is no clear evidence of mean reversion, that is the high frequency volatility is very close to its asymptotic value [17, 18]. In order to capture this evidence, we assume that $Y$, driving the return process from 0 to $t$, had started at the time $t_0 < 0$ in the past and we will perform the limit $t_0 \to -\infty$ at the end. The assumption of stationarity for the $\sigma_t$ process in (1) allows also to consider the returns $dX_t$ as identically distributed and uncorrelated, even though not independent variables, by virtue of the i.i.d. property of the Wiener increments.

The structure of the model (4) allows to compute the moments of the PDF of $X_t$ at all times $t$ recursively. Application of the Itô Lemma to the function $X^n_t$ readily provides

$$\langle X^n_t \rangle = \frac{1}{2} n(n-1) c \int_0^t \langle X^{n-2}_s Y^2_s \rangle \, ds,$$

and the same Lemma proves that the correlation functions between $X$ and $Y$ satisfy the following differential equation

$$\frac{d}{dt} \langle X^n_t Y^q_t \rangle = F_q \langle X^n_t Y^q_t \rangle + A_q \langle X^n_t Y^{q-1}_t \rangle + c \rho p q \langle X^{n-1}_t Y^{q+1}_t \rangle + \frac{1}{2} p(p-1)c \langle X^{n-2}_t Y^{q+2}_t \rangle,$$

(7)

where we defined $F_k = k(a + (k-1)c)/2$, $A_k = kb$ for every $k \in \mathbb{N}$, and $p, q \in \mathbb{N}$. The previous equation is a linear ordinary differential equation (ODE) for every $p$ and $q$, which can be solved recursively starting from the lowest order of $p$ and $q$ [19], and whose solution involves integration of the moments $\langle Y^n_t \rangle \equiv \mu_n(t; t_0)$ of the $Y$ process. For every $n$ and every time $t$ the latter can be expressed as a linear superposition of exponential functions

$$\mu_n(t; t_0) = \sum_{j=0}^{n} K_j^{(n)} \exp [F_j (t - t_0)].$$

(8)

The explicit expressions of the coefficients in the above expansion can be computed as explained in [16], and it turns out that $K_j^{(n)}$ involves the values $\mu_k(t_0; t_0)$ for $k = 1, \ldots, j$, while $K_j^{(n)}$ does not. This implies that whenever the constants $F_j$ are all negative, the only term
surviving in the limit \( t_0 \to -\infty \) is \( K_0^{(n)} \) and the process looses every information about the distribution of \( y_{(t)} \). It is worth noticing that, even though the moments \( \mu_n(t; t_0) \) are homogeneous functions of time, when \( t_0 \) is finite this is not true for the solution of Eq. (7) which is obtained by integration from 0 to \( t \), with boundary condition \( (X^p_{0})_0 = 0 \) for every \( p > 0 \) [20].

From the analysis of Eq. (7) it is not difficult to verify that the moments of \( X \) can be expressed always as a superposition of exponential functions of the starting time of the volatility as follows

\[
(X^p_{t}) = \sum_{j=0}^{n} H_j^{(n)}(t) \exp(-F_j t_0). \tag{9}
\]

The coefficients \( H_j^{(n)} \) depend on the time lag \( t \) and, more precisely, by virtue of the linearity of the ODEs (7), they correspond to a combination of exponential terms weighted by polinomial functions of \( t \). In Appendix A we report the explicit expressions of the coefficients \( H_j^{(n)}(t) \) for the cases \( n = 2 \) and \( n = 3 \), from which it can be readily verified that the skewness of the PDF converge to zero asymptotically for \( t \to +\infty \). A messy calculation would show that an analogous behavior holds for kurtosis. Thus the scaling of the lowest order moments is in full agreement with the one of the empirical distributions over long time horizons [1, 2]. When \( t \) is finite the coefficients \( H_j^{(n)}(t) \) are finite quantities themselves, and all the relevant information about the behavior of \( (X^p_{t}) \) in the stationary limit of \( Y \) is retained by the \( t_0 \)-exponential in Eq. (9).

Two cases are possible here: if all the \( F_j \) are negative \((j \neq 0), (X^p_{t}) \) is finite in the stationary limit \( t_0 \to -\infty \), otherwise it diverges [21] indicating the emergence of fat tails in the PDF of \( X_t \). The latter case applies when \( n > \nu = 1 - 2a/c \), as can be checked directly from the definition of \( F_n \). Since \( F_{n+1} > F_n \), when \( F_n > 0 \), the divergence of \( (X^p_{t}) \) implies the divergence of all the higher order moments [22]. The same condition is responsible for the divergence of the moments \( \mu_n(t) \) of the volatility for \( n > \nu \) (see Eq. (8)) in agreement with the fact that the stationary distribution of the volatility (5) is an Inverse Gamma distribution with shape parameter \( \nu \). Here we see at work a mechanism in which the power law tail of the stationary distribution of the volatility induces, for every time lag \( t \), fat tails in the return distribution, whose scaling for large \( |x| \) is compatible with a power law assumption

\[
p(x) \xrightarrow{x \to \pm \infty} \frac{1}{|x|^{1+\beta}}.
\]

This is in agreement with empirical studies about the distribution of high frequency returns over daily or intra-day time scales [1, 2, 23–25], and from the previous considerations we are able to constraint the tail index in the following range

\[
n^* < \beta \leq n^* + 1, \tag{10}\]

Empirically, for arbitrary \( t \), \( \mathcal{L}(\tau; t) \) is found to be exponentially decaying for positive \( \tau \) and approximately zero otherwise, meaning that a correlation exists between past returns and the volatility in the future and not vice versa. Empirical analysis shows that it is a short range correlation; more precisely, the decay time of \( \mathcal{L}(\tau; t) \) is found to be of approximately 69 days for U.S. stocks and even smaller, about 10 days, for indexes [2].

The numerator (11) can be rewritten as

\[
\langle dX_t dX_{t+\tau}^2 \rangle = c^{3/2} \langle \zeta_t Y_{t+\tau}^2 \rangle dt^2,
\]

expressing the Wiener increment as \( \zeta_t dt \), where \( \zeta_t \) is a Gaussian noise with zero mean and \( 1/dt \) variance.
Novikov theorem [26, 27] allows to compute the expectation involving \( \zeta_{1,t} \), giving us

\[
\langle dX_t \, dX^2_{t+\tau} \rangle = 2\rho \, c^2 \, H(\tau) \exp(at) \, \langle Y_t^2 \, Y_{t+\tau} \exp[\sqrt{t} \, \Delta W_2(\tau)] \rangle,
\]

where we defined \( \Delta W(t) \equiv \int_t^{t+\tau} dW_s \), we took into account the correlation structure (3) and we used the following expression of the functional derivative of \( Y \)

\[
\frac{\delta Y_{t+\tau}}{\delta \zeta_{1,t}} = \frac{\rho}{\sqrt{\Delta H(\tau) \exp(a \tau)}} \, Y_t \exp[\sqrt{\Delta W_2(\tau)}],
\]

with the Heaviside step function \( H(\tau) \) defined as zero if \( \tau \leq 0 \) and one otherwise. The expectation \( f(\tau; t, Y) \equiv \langle Y_t^2 \, Y_{t+\tau} \exp[\sqrt{t} \, \Delta W_2(\tau)] \rangle \) satisfies an integral Volterra equation of the second kind, whose derivation is detailed in Appendix B, and the final expression of the leverage correlation reads

\[
\mathcal{L}(\tau; t) = \frac{2 \rho H(\tau)}{\mu_2(t) \mu_3(t)} \left\{ \frac{b}{a+c} \mu_2(t) \right\} \times \exp \left[ \left( 2a + \frac{3}{2} c \right) \tau - \frac{b}{a+c} \mu_2(t) \exp \left( \frac{a+c}{2} \tau \right) \right],
\]

which inherits the explicit dependence on \( t \) from the moments of \( Y \). In order to compare the previous expression with real data, following the discussion at the beginning of Section III, we take the limit \( t_0 \to -\infty \), so that we can replace \( \mu_2(t) \) and \( \mu_3(t) \) with their asymptotic values, whose general expression, valid for \( n < \nu \), is

\[
\mu_{n,ss} = K_0^{(n)} = \prod_{k=1}^{n} (-1)^k \frac{A_k}{F_k}.
\]

Substitution in Eq. (12) reveals that the first term vanishes, and the leverage correlation reduces to

\[
\mathcal{L}(\tau) = -\rho H(\tau) \frac{a(2a + c)}{b(a + c)} \exp \left( -\frac{\tau}{\tau_L} \right),
\]

where the leverage decay time reads

\[
\tau_L = \frac{2}{2 |a| - c}.
\]

So, the model correctly forecasts the exponential decay of \( \mathcal{L}(\tau) \) and its vanishing for negative correlation times.

V. VOLATILITY AUTOCORRELATION

The volatility autocorrelation provides an estimate of how much the volatility at time \( t + \tau \) depends on the value it had at time \( t \) and it is usually defined as

\[
A(\tau; t) = \frac{\langle dX_t^2 \, dX^2_{t+\tau} \rangle - \langle dX_t^2 \rangle \, \langle dX^2_{t+\tau} \rangle}{\sqrt{\text{Var}[dX_t^2] \, \text{Var}[dX^2_{t+\tau}]}},
\]

It is a well known stylized fact [10, 28, 29] that \( A \) decays with multiple time scales and in particular, it shows a long range memory effect, vanishing over a time scale of the order of few years for stock indexes.

For the model under investigation, the volatility autocorrelation can be computed exactly too. Recalling again the Novikov theorem and the fact that \( \delta \, dW_{1,t}/\delta \zeta_{1,t} = 1 \), the correlation entering the numerator of (15) becomes

\[
\langle dX_t^2 \, dX^2_{t+\tau} \rangle = c^2 \langle Y_t^2 \, Y_{t+\tau} \rangle \, dt^2 + 2 \rho c^{5/2} H(\tau) \langle Y_t^2 \, Y_{t+\tau} \exp[\sqrt{t} \, \Delta W_2(\tau)] \rangle \, dW_{1,t} \, dt^2,
\]

but, due to the presence of \( dW_{1,t} \), the second term results to be of order \( O(dt^3) \) and therefore it can be discarded. The exact expression of the autocorrelation function \( \langle Y_t^2 \, Y_{t+\tau} \rangle \) can be obtained as explained in Appendix C, leaving us with

\[
A(\tau; t) = \frac{\exp(a \tau)}{3 \mu_4(t) - \mu_2(t)^2} \left\{ \frac{2b}{a+c} \left[ \mu_1(t) \mu_2(t) - \mu_3(t) \right] + \exp[(a+c)\tau] \left[ \mu_4(t) + \frac{2b}{a+c} \mu_3(t) - \mu_2(t) \left( \mu_2(t) + \frac{2b}{a+c} \mu_1(t) \right) \right] \right\},
\]

where the coefficients read

\[
D = \frac{(4a^2 - 2ac - 3c^2) \, (a + c)}{c^2},
\]

\[
N_1 = -\frac{(2a + 3c) \, (2a + c)}{c},
\]

\[
N_2 = a,
\]

and we also defined the two volatility autocorrelation
time scales as

\[ \tau_1^A = \frac{1}{|a|} \quad \text{and} \quad \tau_2^A = \frac{1}{2|a| - c}. \]

At this point it is crucial to notice that in deriving Eq. (14) and Eq. (16) we assumed implicitly that the moments of \( Y_t \) up to the order \( n = 4 \) do converge asymptotically. Recalling the expression of the shape parameter \( \nu \) in (6), we see this assumption imposes

\[ \frac{|a|}{c} > \frac{3}{2}, \quad (17) \]

which has to be interpreted as a consistency relation for the model. This constraint imposes the following strict ordering between the time scales of the model

\[ \tau_2^A < \tau_1^A < \tau^C, \quad \text{with} \quad \tau_1^A > \frac{2}{3}\tau^C. \quad (18) \]

where the second inequality for \( \tau_1^A \) follows from the convergence of third moment of \( Y_t \) which requires \( |a|/c > 1 \). This ordering predicts a volatility autocorrelation function which decays faster than the leverage correlation, but the lacking of a long range scale is shared with other linear models, such as the Stein-Stein one. It can be encompassed only at the cost of introducing a non linear volatility, as it is for the exponential Ornstein-Uhlenbeck model [10], or coupling a third stochastic equation driving the dynamics of the long run value of \( Y_t \) as in [28]. However, it is also known that for short \( \tau \) the empirical \( A \) decays with a time constant of the same order of the leverage scale, and this evidence is correctly taken into account by the ordering in (18).

**VI. ESTIMATION OF PARAMETERS**

Now we provide a systematic methodology for estimating the model parameters, which are the constants \( a, b, c \) entering the dynamics of \( Y_t \), plus the correlation coefficient \( \rho \). We perform the estimation over the Standard & Poor 500 (S&P500) index daily returns from 1970 to 2010, approximating \( dX_t \) with \( \Delta X_t = X_{t+\Delta t} - X_t \)

\[ dX_t \approx \Delta X_t = \ln \left( \frac{S_{t+\Delta t}}{S_t} \right) - \left\langle \ln \left( \frac{S_{t+\Delta t}}{S_t} \right) \right\rangle, \]

where \( \Delta t = 1/250 \) yr (one trading day). Taking into account that \( dW_1 \) is independent of \( \sigma_t \) and that \( |\Delta W_1| \) is distributed accordingly to a Folded Normal law, the following relations hold for the model (4)

\[ A \equiv \frac{\langle |\Delta X| \rangle}{\langle |\Delta W_1| \rangle} = \sqrt{\frac{\pi}{2\Delta t}} \langle |\Delta X| \rangle = -\sqrt{c} \frac{b}{a} \]

\[ B \equiv \frac{\langle |\Delta X|^2 \rangle}{\langle |\Delta W_1|^2 \rangle} = \frac{\langle |\Delta X|^2 \rangle}{\Delta t} = c - \frac{2b^2}{(a + c)a} \]

\[ C \equiv \frac{\langle |\Delta X|^3 \rangle}{\langle |\Delta W_1|^3 \rangle} = \frac{\langle |\Delta X|^3 \rangle}{\langle |\Delta W_1|^3 \rangle} = \frac{\pi}{\langle |\Delta X|^3 \rangle} \quad \text{for the daily log-returns} \]

The constants \( A \) and \( B \) can be measured directly from the data, providing us an estimation of the ratio \( a/c \) through the relation

\[ D \equiv \frac{B}{2(A^2 - B)} = \frac{a}{c}. \]

The value of these quantities extracted from the series of the daily returns of the S&P500 index are reported in Table I. It is crucial to observe that the value obtained for the ratio \( |a|/c \) is compatible with the constraint (17), supporting the consistency of our model and the convergence of the volatility autocorrelation. Moreover, since we have \( n^* = 4 \), the relation (10) indicates the following range for the tail index of \( p(x) \)

\[ 4 < \beta \leq 5. \]

The leverage correlation (14) provides a way to obtain the two further relations needed to fix the four free parameters of the models. Indeed, a two parameters fit of the function \( \mathcal{L}(\tau) \) gives estimates for the time scale \( \tau^C \) and for the limit \( \tau \to 0^+ \)

\[ \mathcal{L}(0^+) = -\rho a(2a + c) \frac{b(a + c)}{b(a + c)}, \]

with the results reported in Table II and Fig. 2. In particular, the value obtained for the leverage time scale, \( \tau^C \approx 21 \) days, and for its amplitude \( \mathcal{L}(0^+) \) are consistent with those quoted in past analysis of different stock indexes such as the Dow Jones Industrial Average [8, 28], and confirm the short range nature of this effect.
Table II. Estimation of the leverage time scale and its limit for $\tau \rightarrow 0$, obtained from the fit of the empirical leverage correlation (11) for the daily log-returns of the S&P500 index, with the model predicted expression (14).

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Estimate from S&amp;P500</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\tau^L$</td>
<td>0.0864 yr</td>
</tr>
<tr>
<td>$\mathcal{L}(0^+)$</td>
<td>-30.9515</td>
</tr>
</tbody>
</table>

Table III. Model parameters estimated from the daily log-returns of the S&P500 index during 1970-2010 through the relations (19)-(22).

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Estimate from S&amp;P500</th>
</tr>
</thead>
<tbody>
<tr>
<td>$a$</td>
<td>$-16.0608$ yr$^{-1}$</td>
</tr>
<tr>
<td>$b$</td>
<td>0.8627 yr$^{-1}$</td>
</tr>
<tr>
<td>$c$</td>
<td>8.9749 yr$^{-1}$</td>
</tr>
<tr>
<td>$\rho$</td>
<td>$-0.5089$</td>
</tr>
</tbody>
</table>

At this point all the parameters can be recovered through the following relations:

\begin{align}
    c &= - \left[ \tau^L \left( D + \frac{1}{2} \right) \right]^{-1} \\
    a &= c D \\
    b &= - \frac{a + c}{\sqrt{c}} \frac{C}{B} \\
    \rho &= - \frac{b(a + c)}{a(2a + c)} \mathcal{L}(0^+) 
\end{align}

(19) \hspace{2cm} (20) \hspace{2cm} (21) \hspace{2cm} (22)

The final results, reported in Table III, show a negative correlation coefficient, in agreement with the known leftward asymmetry of daily return distributions. Moreover, our calibration provides for the relaxation time of the volatility process a finite value $\tau^\sigma = -1/a \approx 15$ days, implying that, from a practical point of view, the limit $t_0 \rightarrow -\infty$ is equivalent to $t_0 \ll -\tau^\sigma$. The fitted values of $\tau^L$ and $\mathcal{L}(0^+)$ provides a good description of real data, as shown in Fig. 2; on the other hand, Fig. 3 shows that the theoretical volatility autocorrelation for the estimated values of the parameters, Eq. (16), does not capture the long range persistence of the empirical volatility, as expected from the constraints (18), while it describes correctly the exponential decay for small values of $\tau$.

Finally, it is important to compare the return PDF predicted by the model with the data sample from which the model parameters were estimated. Since we model the return dynamics for increasing $t$, it is even more important to assess to which extent the diffusion process (4) is able to capture the scaling properties of the empirical distribution over different time horizons. At this aim, with the parameters fixed from the daily S&P500 series, we reconstruct the theoretical PDFs simulating the process at different time scales, $t = 1, 3, 7, 14$ days, and we compare them with the corresponding empirical distributions obtained aggregating the daily returns. This comparison is shown in Fig. 4 and Fig. 5. The daily distribution is very well reproduced by the theoretical PDF, which is able to fully capture the leptokurtic nature of the daily data. The plots also confirm that the diffusive dynamics (4), once the parameters have been fixed at the daily scale, follows closely the evolution of the empirical curves for larger $t$. In particular, it captures the progressive convergence in the central region to a distribution with vanishing skewness and kurtosis.

VII. CONCLUSIONS

In this work, we have introduced a class of SVMs where the volatility is driven by the general process with multiplicative noise analyzed in detail in [16]. More specifi-
Figure 4. (Color online) Linear plot showing the comparison between the return PDFs predicted by the model (lines) and the data for the S&P500 index, for different time scales.

Figure 5. (Color online) In log-linear scale, return probabilities for the model (lines) vs S&P500 returns (points). Curves have been shifted for sake of readability.

Numerically, we focused on the set of parameters resulting in an Inverse Gamma stationary distribution for the \( \sigma_t \) process. This choice was motivated by empirical analysis discussed in the literature [2, 12] concerning the statistical properties of volatility proxies in high frequency data. We provided an analytical characterization of the moments of the return distribution, revealing the role played by the power law behavior of the Inverse Gamma in the emergence of fat tails. Nevertheless, even though the highest order moments of \( X \) diverge for every time lag, the analytical expressions we obtained reveal the vanishing of both the skewness and the kurtosis, in agreement with the Normality of returns for long horizons. As far as the correlation functions are concerned, our model correctly predicts zero autocorrelation for the returns, and the short range exponential decay of the leverage and of the volatility autocorrelation. The persistence of the latter over longer horizons is not captured, and in this perspective we would like to explore the possibility of coupling a third SDE in the same spirit of [28]. Moreover, we expect that relaxing the time homogeneity of the processes, as done in [16], we may induce time scalings more general than the exponential one. A further perspective would be to explore possible ways to characterize analytically the PDF associated to the process (4) or its characteristic function. This task requires to solve the Fokker-Planck equation for the PDF or its equivalent version in the Fourier space, analogously to what has been done in [30] for the Heston case. Such a result would also allow for an application of the model in the context of market risk evaluation, possibly exploiting efficient Fourier methodologies such as those proposed in [31, 32].

Appendix A: Coefficients of \( \langle X_t^2 \rangle \) and \( \langle X_t^3 \rangle \)

Here we report the explicit expressions of the coefficients \( H_j^{(n)}(t) \) entering the expansion (9) of the moments of \( X_t \) for the cases \( n = 2 \) and \( n = 3 \). They were used to plot the analytical curves in Fig. 1.

\[
H_0^{(2)}(t) = c K_0^{(2)} t
\]
\[
H_0^{(3)}(t) = 3 \rho c^2 \left[ \frac{t}{F_2} \left[ A_2 \frac{K_0^{(2)}}{F_1} - 2 K_0^{(3)} \right] + 2 K_0^{(3)} \frac{\exp (F_2 t) - 1}{F_2^2} \right]
\]
\[
H_1^{(2)}(t) = c K_1^{(2)} \frac{\exp (F_1 t) - 1}{F_1}
\]
\[
H_1^{(3)}(t) = 3 \rho c^2 \left[ \frac{1}{F_2 - F_1} \left[ A_2 \frac{K_1^{(2)}}{F_2 - F_1} + 2 K_1^{(3)} \right] - \frac{\exp (F_2 t) - 1}{F_2} \right]
\]
\[
H_2^{(2)}(t) = c K_2^{(2)} \frac{\exp (F_2 t) - 1}{F_2}
\]
\[
H_2^{(3)}(t) = 6 \rho c^2 \frac{K_3^{(3)}}{F_3 - F_2} \left[ \frac{\exp (F_3 t) - 1}{F_3} - \frac{\exp (F_2 t) - 1}{F_2} \right]
\]

where the coefficients \( K_j^{(2)} \) and \( K_j^{(3)} \), entering the expansion (8) of the moments of \( Y_t \), read

\[
K_0^{(2)} = \frac{A_2 A_1}{F_2 F_1},
\]
\[
K_1^{(2)} = - \frac{A_2}{F_2 - F_1} \left[ \mu_1 (t_0) + A_1 \right]
\]
\[
K_2^{(2)} = \mu_2 (t_0) + \frac{A_2}{F_2 - F_1} \left[ \mu_1 (t_0) + A_1 \right]
\]

\[
K_0^{(3)} = A_2 A_1 K_0^{(3)} + 2 A_2 K_1^{(3)} + 3 \rho c^2 \frac{K_3^{(3)}}{F_3 - F_2} \frac{\exp (F_3 t) - 1}{F_3} - \frac{\exp (F_2 t) - 1}{F_2}.
\]

\[
K_1^{(3)} = - \frac{A_2}{F_2 - F_1} \left[ \mu_1 (t_0) + A_1 \right]
\]
\[
K_2^{(3)} = \mu_2 (t_0) + \frac{A_2}{F_2 - F_1} \left[ \mu_1 (t_0) + A_1 \right]
\]
\]

\[
K^{(3)} \alpha = -A_3\alpha A_1 \frac{F_3 - F_1}{F_3 - F_1} \left[ \mu_1(t_0) + A_1 \right] \\
K^{(3)}_1 = A_3 A_2 \frac{F_3 - F_2}{F_3 - F_1} \left[ \mu_1(t_0) + A_1 \right] \\
K^{(3)}_2 = -A_3 \frac{F_3 - F_2}{F_3 - F_1} \left[ \mu_2(t_0) + A_1 \right] \\
K^{(3)}_3 = \mu_3(t_0) + A_3 \frac{F_3 - F_2}{F_3 - F_1} \left[ \mu_1(t_0) + A_1 \right].
\]

Appendix B: Derivation of Eq. (12)

After expressing \( Y_{t+\tau} \) in terms of its integral solution from \( t \) to \( t + \tau \), the function \( f(\tau, t; Y) \) can be rewritten in the form

\[
f(\tau, t; Y) = \left\{ \begin{array}{l}
Y^T \left( Y_1 + \int_{t}^{t+\tau} (aY_1 + b) ds \right) \exp \left[ \sqrt{\Delta} \Delta \cdot W_2(\tau) \right] \\
+ \sqrt{\tau} \int_{t}^{t+\tau} \left\{ Y^2 Y_1 \exp \left[ \sqrt{\Delta} \Delta \cdot W_2(\tau) \right] \right\} ds \\
+ \exp \left[ \sqrt{\Delta} \Delta \cdot W_2(\tau) \right] \left[ \mu_3(t) + b \mu_2(t) \right]
\end{array} \right.
\]

Taking into account that for \( t \leq s \leq t + \tau \) we can always split \( \Delta t W_2(\tau) \) as

\[
\Delta t W_2(\tau) = W_{2,t+\tau} - W_{2,t} = W_{2,t+\tau} - W_{2,s} + W_{2,s} - W_{2,t} = \Delta t W_2(t + \tau - s) + \Delta t W_2(s - t),
\]

the function \( f(\tau, t; Y) \) becomes

\[
f(\tau, t; Y) = \exp \left[ \sqrt{\Delta} \Delta \cdot W_2(\tau) \right] \left[ \mu_3(t) + b \mu_2(t) \right] \\
+ a \int_{0}^{\tau} \left\{ Y^2 Y_1 \exp \left[ \sqrt{\Delta} \Delta \cdot W_2(\tau) \right] \right\} ds \\
\times \exp \left[ \sqrt{\Delta} \Delta \cdot W_2(\tau) \right] dr' \\
+ \exp \left[ \sqrt{\Delta} \Delta \cdot W_2(\tau) \right] dr'.
\]

where we changed the variable of integrations to \( \tau' = s - t \). Since the process \( \sqrt{\Delta} \Delta \cdot W_2(\tau - \tau') \) is Normally distributed with zero mean and variance \( c(\tau - \tau') \), and recalling the expression of the Gaussian characteristic function, \( \phi_G \), we can write

\[
\exp \left[ \sqrt{\Delta} \Delta \cdot W_2(\tau - \tau') \right] = \phi_G(\omega)_{\omega = \sqrt{\tau} \cdot (\tau - \tau')},
\]

Application of the Novikov theorem also gives

\[
\exp \left[ \sqrt{\Delta} \Delta \cdot W_2(\tau - \tau') \right] = \frac{d \exp \left[ \sqrt{\Delta} \Delta \cdot W_2(\tau - \tau') ds \right]}{d \Delta \Delta W_2(t + \tau')} dr' \\
= \sqrt{\tau} \exp \left[ \frac{\phi_G(\omega)_{\omega = \sqrt{\tau} \cdot (\tau - \tau')}}{\tau} \right],
\]

where we expressed the Wiener variation in terms of a Gaussian white noise \( \xi_{2,t} \), as \( dW_{2,t} = \xi_{2,t} \, dt \). Replacing the previous expressions in Eq. (B1) we conclude that \( f(\tau, t; Y) \) has to satisfy

\[
f(\tau, t; Y) = (a + c) \int_{0}^{\tau} f(\tau', t; Y) \exp \left[ \frac{\phi_G(\omega)}{\tau} \right] \, d\tau' \\
= \exp \left[ \frac{\phi_G(\omega)}{\tau} \right] \left[ \mu_3(t) + b \mu_2(t) \right],
\]

which is a Volterra equation of the second kind, whose solution leads to Eq. (12).

Appendix C: Computation of \( \langle Y^2 \rangle \)

With reference to the model (4), the cross correlation \( \langle Y^m Y^n \rangle \) can be computed exactly. Provided to express \( Y_{t+\tau} \) as integral solution from \( t \) to \( t + \tau \)

\[
Y_{t+\tau} = Y_t + \int_{t}^{t+\tau} F_n Y_{n+1} + A_n Y_{n+1} \, ds + \int_{t}^{t+\tau} dW_{2,s} 
\]

it is straightforward to check that \( \langle Y^m Y^n \rangle \) satisfies the following equation

\[
\frac{d}{d\tau} \langle Y^m Y^n \rangle = F_n \langle Y^m Y^n \rangle + A_n \langle Y^{m-1} Y^n \rangle, \quad \text{(C1)}
\]

which is an ODE provided that the correlation \( \langle Y^m Y^n \rangle \) has been computed at the lower order \( n - 1 \). In particular, for the case \( m = n = 2 \), we need the following correlation

\[
\langle Y^2 \rangle = \exp(\sigma \tau) \mu_2(t) - \frac{a}{a - b} \left( 1 - \exp(\sigma \tau) \right) \mu_2(t),
\]

whose substitution in Eq. (C1) provides the solution

\[
\langle Y^2 \rangle = \exp(F_2 \sigma \tau) \mu_2(t) + \frac{A_2}{a - F_2} \left[ \exp(\sigma \tau) - \exp(F_2 \sigma \tau) \right] \mu_2(t)
\]

\[
= \frac{a}{a - F_2} \left( \exp\left(\frac{\sigma \tau}{2} \right) - 1 \right) - \frac{A_2}{a - F_2} \left[ \exp(\sigma \tau) - \exp(F_2 \sigma \tau) \right] \mu_2(t).
\]

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[19] Note1, it is worth mentioning that a similar equation holds for the more general dynamics (3), after defining the volatility as $\sigma_t = \sqrt{c Y_{t-}^2 + d Y_t + \varepsilon}$.

[20] Note2, from now on we will drop the dependence on $t_0$ from the moments $\mu_n$.

[21] Note3, since $F_j \neq F_k$ for every $j, k > 1$ with $j \neq k$, no cancellation of the divergent terms can take place in the limit $t_0 \rightarrow -\infty$.

[22] Note4, the case $\rho = 0$ represents an exception since, due to symmetry arguments, all the odd moments vanish identically.


