The VIX Future in Bergomi Models

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QuantMinds 2019

Vienna, May 14, 2019

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Motivation		

- Volatility indices, such as the VIX index, are not only used as market-implied indicators of volatility.
- Futures and options on these indices are also widely used as risk-management tools to hedge the volatility exposure of options portfolios.
- Existence of a liquid market for these futures and options models that jointly calibrate to the prices of options the underlying asset and prices of volatility derivatives.
- Since VIX options started trading in 2006, many researchers and practitioners have tried to build a model that jointly and exactly calibrates to the prices of S&P 500 (SPX) options, VIX futures and VIX options.
- Very challenging problem, especially for short maturities.

Motivation		

- The very large negative skew of short-term SPX options, which in continuous models implies a very large volatility of volatility, seems inconsistent with the comparatively low levels of VIX implied volatilities.
- One should decrease the volatility of volatility to decrease the latter, but this would also decrease the former, which is already too small. See G. (2017, 2018).
- Objective: quantitatively describe the structural constraints that continuous stochastic volatility models jointly put on SPX and VIX derivatives.

Motivation		

- In particular, we focus on Bergomi models: one factor, two factors (+ skewed versions that calibrate to VIX smile).
- Popular variance curve models that can be used to price SPX and VIX derivatives.
- Bergomi-G. (2012) have already derived a general expansion of the smile in variance curve models at order two in vol-of-vol
- Objective: derive an expansion of the price of VIX futures in Bergomi models. Order 6.
- Precisely pinpoint the roles of vol-of-vol and mean-reversion.
- Understand the structural constraints that flexible continuous stochastic volatility models like Bergomi models jointly put on SPX and VIX derivatives.

One-factor Bergomi model		

One-factor Bergomi model



- ξ_t^u : instantaneous lognormal variance of the SPX S at time u > t seen from t.
- Forward instantaneous variances are driftless (Dupire, Bergomi).
- Second generation stochastic volatility models directly model the dynamics of $(\xi_t^u, t \in [0, u])$ under a risk-neutral measure. Only requirement: that these processes, indexed by u, be nonnegative and driftless (in t).
- One-factor Bergomi model: the simplest model on $(\xi_t^u, t \in [0, u])$. First suggested by Dupire (1993). Assumes that forward instantaneous variances are lognormal and all driven by a single standard one-dimensional Brownian motion Z, correlated with the Brownian motion W that drives the SPX dynamics:

$$\frac{d\xi_t^u}{\xi_t^u} = \omega e^{-k(u-t)} dZ_t, \qquad \frac{dS_t}{S_t} = (r_t - q_t) dt + \sqrt{\xi_t^t} dW_t, \qquad \omega, k > 0$$

• r_t , q_t : instantaneous interest rate and dividend yield, inclusive of repo.

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One-factor Bergomi model

$$\frac{d\xi_t^u}{\xi_t^u} = \omega e^{-k(u-t)} dZ_t, \qquad \frac{dS_t}{S_t} = (r_t - q_t) dt + \sqrt{\xi_t^t} dW_t, \qquad \omega, k > 0$$

 Time-homogeneous exponential kernel K(u - t) = ωe^{-k(u-t)} motivated by two objectives: (1) K decreasing function; (2) ξ^u_t admits a one-dimensional Markov representation:

$$\xi_t^u = \xi_0^u f^u(t, X_t)$$
 (1.1)

with a Markov process \boldsymbol{X} which does not depend on $\boldsymbol{u}.$

Indeed, (1.1) holds with

$$X_t := \int_0^t e^{-k(t-s)} dZ_s, \quad f^u(t,x) := \exp\left(\omega e^{-k(u-t)}x - \frac{\omega^2}{2}e^{-2k(u-t)}v_t\right),$$
$$v_t := \operatorname{Var}(X_t) = \frac{1 - e^{-2kt}}{2k}$$

where the Ornstein-Uhlenbeck process X follows the Markov dynamics:

$$dX_t = -kX_t \, dt + dZ_t, \qquad X_0 = 0 \tag{1.2}$$

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One-factor Bergomi model

$$\begin{aligned} \xi_t^u &= \xi_0^u f^u(t, X_t) \\ dX_t &= -kX_t \, dt + dZ_t, \qquad X_0 = 0 \\ \sigma_t^2 &:= \xi_t^t = \xi_0^t \exp\left(\omega X_t - \frac{\omega^2}{2} \operatorname{Var}(X_t)\right) \end{aligned}$$

- k: parameter of mean-reversion of the instantaneous volatility.
- ω : instantaneous (lognormal) volatility of the instantaneous variance; $\omega/2$: instantaneous (lognormal) volatility of the instantaneous volatility σ_t . ω referred to as **vol-of-vol**.
- Initial condition ξ_0^u computed from market prices VS(T) of variances swaps on the SPX: $\xi_0^u = \frac{d}{du}(uVS(u))$. Assumed strictly positive and bounded.
- Markov representation is very convenient. Will be instrumental in our derivation of an expansion of the price of VIX futures in small vol-of-vol.
- In particular, our technique of proof does not apply to the rough Bergomi models (see pricing methods in Jacquier, Martini, Muguruza, On VIX Futures in the Rough Bergomi Model, 2017).

One-factor Bergomi model		

- Let $T \ge 0$. By definition, the (idealized) VIX at time T is the implied volatility of a 30-day log-contract on the SPX index starting at T.
- For continuous models on the SPX such as the one-factor Bergomi model, this translates into

$$\operatorname{VIX}_{T}^{2} = \mathbb{E}\left[\frac{1}{\tau}\int_{T}^{T+\tau}\sigma_{u}^{2} du \middle| \mathcal{F}_{T}\right] = \frac{1}{\tau}\int_{T}^{T+\tau} \mathbb{E}\left[\sigma_{u}^{2}\middle| \mathcal{F}_{T}\right] du = \frac{1}{\tau}\int_{T}^{T+\tau}\xi_{T}^{u} du$$

• $\tau = \frac{30}{365}$ (30 days)

• \mathcal{F}_t : information available at time t, in this case the filtration generated by the Brownian motions W and Z

For any continuous model on the SPX:

$$\operatorname{VIX}_T^2 = \frac{1}{\tau} \int_T^{T+\tau} \xi_T^u \, du$$

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One-factor Bergomi model		

$$\Xi_n := \frac{1}{\tau} \int_T^{T+\tau} \xi_0^u e^{-nk(u-T)} du > 0, \qquad I_n := \frac{\Xi_n}{\Xi_0}, \qquad n \in \mathbb{N}$$
$$I(x) := \frac{1-e^{-x}}{x}, \quad x > 0, \qquad I(0) := 1.$$

- When the initial term-structure of forward instantaneous variances $u \mapsto \xi_0^u$ is flat at level ξ , $\Xi_n = \xi I(nk\tau)$ and $I_n = I(nk\tau)$ are known in closed form.
- Otherwise, the computation of I_n requires a one-dimensional quadrature. Note: $v_t = tI(2kt)$.





Proposition

In the one-factor Bergomi model, the price of a VIX future satisfies

$$\mathbb{E}[\text{VIX}_T] = \sqrt{\Xi_0} \left\{ 1 + \alpha_2 \omega^2 v_T + \alpha_4 (\omega^2 v_T)^2 + \alpha_6 (\omega^2 v_T)^3 \right\} + O(\omega^7)$$

where
$$v_T = \frac{1-e^{-2kT}}{2k}$$
 and
 $\alpha_2 = -\frac{1}{8}I_1^2,$
 $\alpha_4 = -\frac{1}{16}I_2^2 + \frac{3}{16}I_1^2I_2 - \frac{15}{128}I_1^4,$
 $\alpha_6 = -\frac{1}{48}I_3^2 + \frac{1}{16}I_2^3 + \frac{3}{16}I_1I_2I_3 - \frac{75}{128}I_1^2I_2^2 - \frac{5}{32}I_1^3I_3 + \frac{105}{128}I_1^4I_2 - \frac{315}{1024}I_1^6.$

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Proposition (cont'd)

In particular, this expansion provides a closed form expression of the prices of VIX futures in the one-factor Bergomi model at order 6 in small vol-of-vol when $u \mapsto \xi_0^u$ is flat at level ξ :

$$\mathbb{E}[\mathrm{VIX}_T] = \sqrt{\xi} \left\{ 1 + \alpha_2(k\tau)\omega^2 v_T + \alpha_4(k\tau)(\omega^2 v_T)^2 + \alpha_6(k\tau)(\omega^2 v_T)^3 \right\} + O(\omega^7)$$

where the functions $\alpha_i(\cdot)$ are defined by:

$$\begin{aligned} \alpha_2(x) &= -\frac{1}{8}I(x)^2, \\ \alpha_4(x) &= -\frac{1}{16}I(2x)^2 + \frac{3}{16}I(x)^2I(2x) - \frac{15}{128}I(x)^4, \\ \alpha_6(x) &= -\frac{1}{48}I(3x)^2 + \frac{1}{16}I(2x)^3 + \frac{3}{16}I(x)I(2x)I(3x) \\ &\quad -\frac{75}{128}I(x)^2I(2x)^2 - \frac{5}{32}I(x)^3I(3x) + \frac{105}{128}I(x)^4I(2x) - \frac{315}{1024}I(x)^6. \end{aligned}$$

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Remark

In the case where ω_u is maturity-dependent, we can still expand in small vol-of-vol by multiplying ω_u by a dimensionless parameter ε (that can later be taken equal to one) and expand in powers of ε . Then the expansion still holds by replacing ω by ε and with

$$\Xi_n := \frac{1}{\tau} \int_T^{T+\tau} \xi_0^u \omega_u^n e^{-nk(u-T)} du, \qquad I_n := \frac{\Xi_n}{\Xi_0}, \qquad n \in \mathbb{N}.$$



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Remark

In the case where the mean reversion k(t) is time-dependent,

$$dX_t = -\frac{\mathbf{k}(t)}{X_t} \, dt + dZ_t,$$

the expansion still holds with

$$\begin{aligned} \Xi_n &:= \quad \frac{1}{\tau} \int_T^{T+\tau} \xi_0^u e^{-n(K(u) - K(T))} du, \qquad I_n := \frac{\Xi_n}{\Xi_0}, \\ v_t &:= \quad e^{-2K(t)} \int_0^T e^{2K(s)} ds \end{aligned}$$

where

$$K(t) := \int_0^t k(s) \, ds.$$

Of course one can mix maturity-dependent ω_u with time-dependent k(t).

Remark

In the case where both k(t) and $\omega(t)$ are time-dependent,

$$dX_t = -k(t)X_t \, dt + \boldsymbol{\omega}(t) \, dZ_t,$$

we can still expand in small vol-of-vol by multiplying $\omega(t)$ by a dimensionless parameter ε (that can later be taken equal to one) and expand in powers of ε . Then the expansion still holds by replacing ω by ε and with

$$\begin{aligned} \Xi_n &:= \quad \frac{1}{\tau} \int_T^{T+\tau} \xi_0^u e^{-n(K(u) - K(T))} du, \qquad I_n := \frac{\Xi_n}{\Xi_0}, \\ v_t &:= \quad e^{-2K(t)} \int_0^T \omega(s)^2 e^{2K(s)} ds. \end{aligned}$$

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Remark

One can easily mix maturity-dependent ω_u with time-dependent $\omega(t)$ (and time-dependent k(t)) if they are in **product form:** $\omega_u(t) = \omega_u \omega(t)$. Then, as above, we can expand in powers of ε and the expansion still holds by replacing ω by ε and with

$$\begin{split} \Xi_n &:= \quad \frac{1}{\tau} \int_T^{T+\tau} \xi_0^u \omega_u^n e^{-n(K(u) - K(T))} du, \qquad I_n := \frac{\Xi_n}{\Xi_0} \\ v_t &:= \quad e^{-2K(t)} \int_0^T \omega(s)^2 e^{2K(s)} ds. \end{split}$$



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$$\mathbb{E}[\text{VIX}_T] = \sqrt{\Xi_0} \left\{ 1 + \alpha_2 \omega^2 v_T + \alpha_4 (\omega^2 v_T)^2 + \alpha_6 (\omega^2 v_T)^3 \right\} + O(\omega^7)$$

- The formula is essentially an expansion in powers of $\omega^2 v_T$, suggesting that the expansion is accurate not only for small ω , but also for small $\omega^2 v_T$.
- Let us define $\nu := \frac{\omega}{\sqrt{2k}}$. As $\operatorname{Var}(\omega X_t) = \omega^2 v_t = \nu^2 (1 e^{-2kt})$, ν is the long term standard deviation of ωX_t .
- \blacksquare Since $\omega^2 v_T \leq \nu^2$ and $\omega^2 v_T = \omega^2 T I(2kT) \leq \omega^2 T$, we have

$$0 \le \omega^2 v_T \le \min(\nu^2, \omega^2 T).$$

- In particular we expect the expansion to be accurate when ν is small enough or when $\omega\sqrt{T}$ is small enough.
- ν small enough: mean-reversion large enough to mitigate vol-of-vol.
- Both ν and $\omega\sqrt{T}$ are dimensionless quantities, while ω has the dimension of a volatility, i.e., time^{-1/2}.
- We expect the expansion to be accurate when the vol ω is small enough compared to the vols $\sqrt{2k}$ or $1/\sqrt{T}$.

$$\mathbb{E}[\text{VIX}_T] = \sqrt{\xi} \left\{ 1 + \alpha_2(k\tau)\omega^2 v_T + \alpha_4(k\tau)(\omega^2 v_T)^2 + \alpha_6(k\tau)(\omega^2 v_T)^3 \right\} + O(\omega^7)$$

- How small should ω be, compared to $\sqrt{2k}$ or $1/\sqrt{T}$?
- Dependence of the formula on ξ is trivial: simply proportional to $\sqrt{\xi}$.
- After dividing by $\sqrt{\xi}$, each term in the expansion is of the form $\alpha_{2i}(k\tau)(\omega^2 v_T)^i$, where $\alpha_{2i}(k\tau)$ depends only on k, not on ω or T.
- $\alpha_{2i}(x)$ is small and decreases quickly with *i*. In particular $\alpha_2(0) = -\frac{1}{8}$, $\alpha_4(0) = \frac{1}{128}$, and $\alpha_6(0) = -\frac{1}{3072}$.
- $\alpha_2(x)$ and both ratios $\alpha_4(x)/\alpha_2(x)$ and $\alpha_6(x)/\alpha_4(x)$ take values around -5% for reasonable values of $x = k\tau$, e.g., $x \in [0, 2]$.
- Suggests that the expansion should be accurate for $\omega^2 v_T$ up to ≈ 7 : if $\omega^2 v_T = 7$, then the order *i* term in the expansion $\alpha_{2i}(k\tau)(\omega^2 v_T)^i$ is only about a third, in absolute value, of the order i 1 term.
- However, if $\omega^2 v_T \ge 20$, then the order *i* term can be larger than the order i 1 term, suggesting divergence of the series.

$$\mathbb{E}[\text{VIX}_T] = \sqrt{\xi} \left\{ 1 + \alpha_2(k\tau)\omega^2 v_T + \alpha_4(k\tau)(\omega^2 v_T)^2 + \alpha_6(k\tau)(\omega^2 v_T)^3 \right\} + O(\omega^7)$$



Figure: Left: Graph of functions α_2 , α_4 , and α_6 of Formula (1.3). Right: Graph of α_2 and of ratios α_4/α_2 and α_6/α_4

Numerical experiments: k = 0.25



Figure: VIX future in the one-factor Bergomi model as a function of maturity (in years). Comparison of small vol-of-vol expansion at orders 2, 4, and 6 with the exact quadrature for several sets of parameters. Left: $\omega^2 v_1 \approx 3$. Right: $\omega^2 v_1 \approx 7$

Numerical experiments: k = 2



Figure: VIX future in the one-factor Bergomi model as a function of maturity (in years). Comparison of small vol-of-vol expansion at orders 2, 4, and 6 with the exact quadrature for several sets of parameters. Left: $\omega^2 v_1 \approx 3$. Right: $\omega^2 v_1 \approx 7$

Numerical experiments: k = 10



Figure: VIX future in the one-factor Bergomi model as a function of maturity (in years). Comparison of small vol-of-vol expansion at orders 2, 4, and 6 with the exact quadrature for several sets of parameters. Left: $\omega^2 v_1 \approx 3$. Right: $\omega^2 v_1 \approx 7$

Numerical experiments: $\omega^2 v_1 \approx 15$



Figure: VIX future in the one-factor Bergomi model as a function of maturity (in years). Comparison of small vol-of-vol expansion at orders 2, 4, and 6 with the exact quadrature when $\omega = 8$ and k = 2 ($\omega^2 v_1 \approx 15$; $\omega^2 v_{2/12} \approx 7$)

Contango vs backwardation

- Since we used a flat initial term-structure of forward instantaneous variances $u \mapsto \xi_0^u$, the model generates a decreasing term-structure of VIX futures (backwardation).
- To recover an increasing term-structure (contango), as usually observed in the market, we should use an increasing term-structure of forward instantaneous variances.
- The term-structure implied from the market prices of variances swaps on the SPX $\xi_0^u = \frac{d}{du}(uVS(u))$ is typically increasing, except during those periods when the VIX index blows up.

Expansion of the volatility of the squared VIX implied by VIX future prices

- It is natural to quote the price of a VIX future in terms of the implied (lognormal) volatility of the squared VIX.
- The (undiscounted) time 0 price of the payoff VIX²_T is known from the market prices of variance swaps on the SPX:

$$\operatorname{Price}[\operatorname{VIX}_T^2] = \frac{(T+\tau)\operatorname{VS}(T+\tau) - T\operatorname{VS}(T)}{\tau} = \frac{1}{\tau} \int_T^{T+\tau} \xi_0^u \, du = \Xi_0.$$

• \implies The volatility of the squared VIX implied by the VIX future price for maturity T is the value $\sigma_{\text{VIX}_{2}^{2}}$ such that

$$\mathsf{Price}[\mathsf{VIX}_T] = \sqrt{\Xi_0} \exp\left(-\frac{1}{8}\sigma_{\mathsf{VIX}_T}^2 T\right).$$

R.h.s. is the (undiscounted) time 0 price of the payoff VIX_T in the model where VIX_T² is lognormal with mean Ξ_0 and volatility $\sigma_{\text{VIX}_T^2}$.

$$\sigma_{\mathsf{VIX}_T^2} = \sqrt{-\frac{8}{T}\ln\frac{\mathsf{Price}[\mathsf{VIX}_T]}{\sqrt{\Xi_0}}} = \sqrt{-\frac{8}{T}\ln\frac{\mathsf{Price}[\mathsf{VIX}_T]}{\sqrt{\mathsf{Price}[\mathsf{VIX}_T^2]}}}$$

• No arbitrage \implies Price[VIX_T] $\leq \sqrt{\text{Price}[\text{VIX}_T^2]}$ so $\sigma_{\text{VIX}_T^2}$ is well defined.

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Volatility of VIX² implied by VIX future, as of August 1, 2018





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Expansion of the volatility of the squared VIX implied by VIX future prices

Proposition

In the one-factor Bergomi model, the volatility $\sigma_{VIX_T^2}$ of the squared VIX implied by the VIX future price for maturity T satisfies

$$\sigma_{V\!I\!X_T^2} = \omega I_1 \sqrt{I(2kT)} \Big\{ 1 + \beta_2 \omega^2 v_T + \beta_4 (\omega^2 v_T)^2 \Big\} + O(\omega^6)$$

where $v_T = \frac{1-e^{-2kT}}{2k} = TI(2kT)$ and

$$\beta_2 = \frac{1}{2} \left(\frac{\alpha_4}{\alpha_2} - \frac{\alpha_2}{2} \right), \tag{1.3}$$

$$\beta_4 = \frac{1}{2} \left(\frac{\alpha_6}{\alpha_2} - \alpha_4 + \frac{\alpha_2^2}{3} \right) - \frac{1}{8} \left(\frac{\alpha_4}{\alpha_2} - \frac{\alpha_2}{2} \right)^2.$$
(1.4)

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Expansion of the volatility of the squared VIX implied by VIX future prices

Proposition (cont'd)

In particular, this formula provides a closed form expression of the implied volatility $\sigma_{VIX_T^2}$ in the one-factor Bergomi model at order 5 in small vol-of-vol when $u \mapsto \xi_0^u$ is flat:

$$\sigma_{\mathit{VIX}_T^2} = \omega I(k\tau) \sqrt{I(2kT)} \Big\{ 1 + \beta_2(k\tau) \omega^2 v_T + \beta_4(k\tau) (\omega^2 v_T)^2 \Big\} + O(\omega^6)$$

where the functions $\beta_2(\cdot)$ and $\beta_4(\cdot)$ are defined from the functions $\alpha_i(\cdot)$ by (1.3)-(1.4). In particular, at first order in vol-of-vol ω ,

$$\sigma_{\mathrm{VIX}_T^2} = \omega \frac{1-e^{-k\tau}}{k\tau} \sqrt{\frac{1-e^{-2kT}}{2kT}} + O(\omega^3). \label{eq:VIX_T}$$

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Proo

Numerical inspection of the formula

$$\sigma_{\mathsf{VIX}_T^2} = \omega I(k\tau) \sqrt{I(2kT)} \Big\{ 1 + \beta_2(k\tau) \omega^2 v_T + \beta_4(k\tau) (\omega^2 v_T)^2 \Big\} + O(\omega^6)$$

- Formula is essentially expansion in powers of $\omega^2 v_T \Longrightarrow$ Accurate for $\omega^2 v_T$ small enough, in particular when ν or $\omega \sqrt{T}$ are small enough.
- The domain of accuracy of the implied volatility expansion is actually much larger than that of the price expansion.
- Indeed, both $\beta_2(x)$ and the ratio $\beta_4(x)/\beta_2(x)$ take very small values, around -1%, for $x = k\tau \in [0, 2]$, suggesting that the implied vol expansion should be accurate even for $\omega^2 v_T \approx 20\text{--}30$.
- Moreover, contrary to the ratios $\alpha_{2i}(x)/\alpha_{2i-2}(x)$, both $\beta_2(x)$ and the ratio $\beta_4(x)/\beta_2(x)$ tend to zero, together with their first order derivatives, when x tends to zero.
- Even when v_T becomes extremely large $(k \to 0, T \to \infty)$, the first two ratios of consecutive terms in the expansion (with $\beta_0(x) := 1$)

$$\left|\frac{\beta_{2i}(k\tau)}{\beta_{2i-2}(k\tau)}\omega^2 v_T\right| \le \frac{1}{2k} \left|\frac{\beta_{2i}(k\tau)}{\beta_{2i-2}(k\tau)}\right|\omega^2$$

stay bounded (they tend to zero when v_T tends to infinity).

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Proo

Joint SPX/VIX smile calibration

Numerical inspection of the formula



Figure: Left: Graph of functions β_2 and β_4 . Right: Graph of β_2 and of ratio β_4/β_2

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Figure: Top: Graph of $k \mapsto \frac{\beta_2(k\tau)}{2k}$ and $k \mapsto \frac{1}{2k} \frac{\beta_4(k\tau)}{\beta_2(k\tau)}$ for $0 \le k \le 30$. Bottom: Graph of $k \mapsto \frac{\beta_2(k\tau)}{2k}$ (left) and $k \mapsto \frac{\beta_4(k\tau)}{(2k)^2} \times 10^{-7}$ (right) for $0 \le k \le 100$

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$$\begin{split} \sigma_{\mathsf{VIX}_T^2} &= \omega I(k\tau) \sqrt{I(2kT)} \Big\{ 1 + \beta_2(k\tau) \omega^2 v_T + \beta_4(k\tau) (\omega^2 v_T)^2 \Big\} + O(\omega^6) \\ \left| \frac{\beta_{2i}(k\tau)}{\beta_{2i-2}(k\tau)} \omega^2 v_T \right| &\leq \frac{1}{2k} \left| \frac{\beta_{2i}(k\tau)}{\beta_{2i-2}(k\tau)} \right| \omega^2 \end{split}$$

- The r.h.s. are bounded above by $7 \times 10^{-4} \omega^2$ for all $k \leq 30$. This suggests that, for all T and a very wide range of values of k, the above expansion should be very accurate even for extremely large ω , say, $\omega = 10$.
- Even for this unreasonably large value of ω , the first two correcting terms in the expansion are small whatever the value of k and T:

$$\beta_2(k\tau)\omega^2 v_T \le 3.1 \times 10^{-2}, \qquad \beta_4(k\tau)(\omega^2 v_T)^2 \le 2 \times 10^{-3}.$$

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Numerical experiment



Figure: Implied vol of VIX squared (left) and price of VIX future (right) in the one-factor Bergomi model as a function of maturity (in years). Comparison of small vol-of-vol expansion with the exact quadrature when $\omega = 8$ and k = 2 ($\omega^2 v_1 \approx 15$; $\omega^2 v_{2/12} \approx 7$)



One-factor Bergomi model		

Inspection of the first order formula

$$\sigma_{\mathrm{VIX}_T^2} = \omega \frac{1 - e^{-k\tau}}{k\tau} \sqrt{\frac{1 - e^{-2kT}}{2kT}} + O(\omega^3).$$

- In fact, for practical purposes, the first order formula can be considered exact.
- The implied volatility of a very short VIX_T^2 is the volatility ω of the instantaneous variance ξ_t^t , dampened by the factor $I(k\tau) = \frac{1-e^{-k\tau}}{k\tau}$ which accounts for the mean-reversion of volatility over 30 days.
- For non-zero maturities T, this is multiplied by $\sqrt{I(2kT)} = \sqrt{\frac{1-e^{-2kT}}{2kT}}$.
- For large T, the term-structure of the implied volatility of the squared VIX decays as the power law $T^{-1/2}$.
- Interpretation: Mean-reversion causes the price of the VIX future to converge when T increases, as the Ornstein-Uhlenbeck process X reaches its stationary distribution. Price[VIX_T] = $\sqrt{\Xi_0} \exp\left(-\frac{1}{8}\sigma_{\text{VIX}_T}^2 T\right)$
 - $\implies \sigma_{\text{VIX}_{T}}^{2}T$ must converge, so $\sigma_{\text{VIX}_{T}}^{2}$ behaves like $T^{-1/2}$.
- **For large** k, $\sigma_{\text{VIX}_T^2} \sim \frac{\omega}{k^{3/2}}$.

Two-factor Bergomi model	

Two-factor Bergomi model



Two-factor Bergomi model

- In the one-factor Bergomi model, all forward variances are driven by a single Brownian motion Z.
- A positive move of the short end of the variance curve (*dZ_t* > 0) implies a positive move of the long end of the curve.
- To allow for more flexibility for the dynamics of forward variances, at least 2 factors are needed.
- 2 factors actually enough to mimic power-law-like decay of term-structure of vols of variance swap rates (Bergomi) as well as power-law-like decay of term-structure of ATM implied vols of equity indices.
- In the two-factor Bergomi model (Bergomi 2005), the curve ξ_t^{\cdot} is driven by two Brownian motions Z^1 and Z^2 whose constant correlation is denoted by ρ :

$$\frac{d\xi_t^u}{\xi_t^u} = \omega \alpha_\theta \left\{ \theta_1 e^{-k_1(u-t)} dZ_t^1 + \theta_2 e^{-k_2(u-t)} dZ_t^2 \right\},\$$
$$\alpha_\theta = \left(\theta_1^2 + 2\rho \theta_1 \theta_2 + \theta_2^2 \right)^{-\frac{1}{2}}, \qquad k_1, k_2 > 0, \quad \theta_1, \theta_2 \in [0, 1], \quad \theta_1 + \theta_2 = 1$$

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Pro

Two-factor Bergomi model

$$\begin{aligned} \frac{d\xi_t^u}{\xi_t^u} &= \omega \alpha_\theta \left\{ \theta_1 e^{-k_1(u-t)} dZ_t^1 + \theta_2 e^{-k_2(u-t)} dZ_t^2 \right\}, \\ \alpha_\theta &= \left(\theta_1^2 + 2\rho \theta_1 \theta_2 + \theta_2^2 \right)^{-\frac{1}{2}}, \qquad k_1, k_2 > 0, \quad \theta_1, \theta_2 \in [0,1], \quad \theta_1 + \theta_2 = 1 \end{aligned}$$

- Normalizing factor α_{θ} s.t. ω is the inst vol of the inst variance ξ_t^t .
- For identification purposes, we assume that $k_1 > k_2$: Z^1 drives short end of variance curve only (up to $u - t \approx 1/k_1$) Z^2 drives both its short and long end (up to $u - t \approx 1/k_2 > 1/k_1$).
- In the two-factor model, ξ_t^u admits a two-dimensional Markov representation in terms of two Ornstein-Uhlenbeck processes X^1 and X^2

Pro

Two-factor Bergomi model

$$\begin{split} \xi^{u}_{t} &= \xi^{u}_{0} f^{u}(t, x^{u}_{t}) = \xi^{u}_{0} g^{u}(t, X^{1}_{t}, X^{2}_{t}) \\ dX^{i}_{t} &= -k_{i} X^{i}_{t} dt + dZ^{i}_{t}, \qquad X^{i}_{0} = 0, \qquad i \in \{1, 2\} \\ x^{u}_{t} &:= \alpha_{\theta} \left\{ \theta_{1} e^{-k_{1}(u-t)} X^{1}_{t} + \theta_{2} e^{-k_{2}(u-t)} X^{2}_{t} \right\} \\ f^{u}(t, x) &:= \exp\left(\omega x - \frac{\omega^{2}}{2} v_{t}(u)\right) \\ v_{t}(u) &:= \operatorname{Var}(x^{u}_{t}) = \alpha^{2}_{\theta} \left\{ \theta^{2}_{1} e^{-2k_{1}(u-t)} v^{1}_{t} + \theta^{2}_{2} e^{-2k_{2}(u-t)} v^{1}_{t} \\ &+ 2\theta_{1} \theta_{2} e^{-(k_{1}+k_{2})(u-t)} v^{1,2}_{t} \right\} \\ v^{i}_{t} &:= \frac{1 - e^{-2k_{i}t}}{2k_{i}}, \qquad v^{1,2}_{t} := \rho \frac{1 - e^{-(k_{1}+k_{2})t}}{k_{1}+k_{2}} \\ (X^{1}_{t}, X^{2}_{t}) \sim \mathcal{N}\left(0, \left(\frac{v^{1}_{t}}{v^{1,2}_{t}} - \frac{v^{2}_{t}}{v^{2}_{t}}\right)\right) \end{split}$$

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For $(m,n) \in \mathbb{N}^2$, we define

$$\Xi_{m,n} := \frac{1}{\tau} \int_{T}^{T+\tau} \xi_0^u e^{-(mk_1 + nk_2)(u-T)} du > 0, \qquad I_{m,n} := \frac{\Xi_{m,n}}{\Xi_{0,0}}$$

- When $u \mapsto \xi_0^u$ is flat at level ξ , $\Xi_{m,n} = \xi I((mk_1 + nk_2)\tau)$ and $I_{m,n} = I((mk_1 + nk_2)\tau)$ are known in closed form.
- For clarity, T being fixed, we use the notations $v_1 := v_T^1$, $v_2 := v_T^2$, and $v_{1,2} := v_T^{1,2}$.

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Proposition

In the two-factor Bergomi model, the price of a VIX future satisfies

$$\mathbb{E}[\text{VIX}_T] = \sqrt{\Xi_{0,0}} \left\{ 1 + \gamma_2 (\omega \alpha_\theta)^2 + \gamma_4 (\omega \alpha_\theta)^4 + \gamma_6 (\omega \alpha_\theta)^6 \right\} + O(\omega^7) \quad (2.1)$$

where

$$\begin{split} \gamma_2 &= -\frac{1}{8} \left(\theta_1^2 I_{10}^2 v_1 + 2\theta_1 \theta_2 I_{10} I_{01} v_{1,2} + \theta_2^2 I_{01}^2 v_2 \right), \\ \gamma_4 &= \left(-\frac{1}{16} I_{20}^2 + \frac{3}{16} I_{10}^2 I_{20} - \frac{15}{128} I_{10}^4 \right) \theta_1^4 v_1^2 \\ &+ \left(-\frac{1}{4} I_{20} I_{11} + \frac{3}{8} \left(I_{10}^2 I_{11} + I_{10} I_{20} I_{01} \right) - \frac{15}{32} I_{10}^3 I_{01} \right) \theta_1^3 \theta_2 v_1 v_{1,2} \\ &+ \left(-\frac{1}{8} I_{11}^2 + \frac{3}{8} I_{10} I_{11} I_{01} - \frac{15}{16} I_{10}^2 I_{01}^2 \right) \theta_1^2 \theta_2^2 v_1 v_2 \\ &+ \left(-\frac{1}{8} \left(I_{11}^2 + I_{20} I_{02} \right) + \frac{3}{16} \left(I_{10}^2 I_{02} + I_{20} I_{01}^2 \right) + \frac{3}{8} I_{10} I_{11} I_{01} - \frac{15}{32} I_{10}^2 I_{01}^2 \right) \theta_1^2 \theta_2^2 v_{1,2}^2 \\ &+ \left(-\frac{1}{4} I_{11} I_{02} + \frac{3}{8} \left(I_{11} I_{01}^2 + I_{10} I_{01} I_{02} \right) - \frac{15}{32} I_{10} I_{01}^3 \right) \theta_1 \theta_2^3 v_{1,2} v_2 \\ &+ \left(-\frac{1}{16} I_{02}^2 + \frac{3}{16} I_{01}^2 I_{02} - \frac{15}{128} I_{01}^4 \right) \theta_2^4 v_2^2, \end{split}$$

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Proposition (cont'd)

and
$$\gamma_{6} = \sum_{p=0}^{6} \gamma_{6-p,p}$$
 where
 $\gamma_{6,0} = \left(-\frac{1}{48}I_{30}^{2} + \frac{1}{16}I_{30}^{2} + \frac{3}{16}I_{10}I_{20}I_{30} - \frac{75}{128}I_{10}^{2}I_{20}^{2} - \frac{5}{32}I_{10}^{3}I_{30} + \frac{105}{128}I_{10}^{4}I_{20} - \frac{315}{1024}I_{10}^{6}\right)\theta_{1}^{6}v_{1}^{3}$
 $\gamma_{5,1} = \left(-\frac{1}{8}I_{30}I_{21} + \frac{3}{8}I_{20}^{2}I_{11} + \frac{9}{16}I_{20}I_{10}I_{21} + \frac{3}{8}I_{30}I_{10}I_{11} - \frac{75}{32}I_{10}^{2}I_{20}I_{11} - \frac{15}{32}I_{10}^{3}I_{21} + \frac{105}{164}I_{10}^{4}I_{10}I_{11} + \frac{3}{16}I_{20}I_{30}I_{01} - \frac{75}{64}I_{10}I_{20}I_{01} - \frac{15}{32}I_{10}^{2}I_{20}I_{01} - \frac{945}{512}I_{10}^{5}I_{01}\right)\theta_{1}^{5}\theta_{2}v_{1}^{2}v_{1,2}$
 $\gamma_{4,2} = \left(-\frac{945}{1024}I_{10}I_{01}^{2} + \frac{105}{128}I_{20}I_{10}^{2}I_{01}^{2} - \frac{15}{128}I_{20}^{2}I_{01}^{2} + \frac{105}{64}I_{10}^{3}I_{11}I_{10} - \frac{15}{12}I_{10}^{2}I_{20}I_{11} - \frac{15}{16}I_{10}I_{20}I_{11}I_{0} + \frac{3}{16}I_{10}I_{20}I_{11}I_{11} + \frac{3}{16}I_{20}I_{11}^{2} - \frac{15}{128}I_{20}^{2}I_{01}^{2} + \frac{105}{64}I_{10}^{3}I_{11}I_{10}I_{10} - \frac{15}{12}I_{10}^{2}I_{20}I_{10}I_{11}I_{0} + \frac{3}{16}I_{10}I_{20}I_{11}I_{0} + \frac{3}{16}I_{10}I_{11}I_{11}I_{11} + \frac{3}{16}I_{20}I_{11}^{2} - \frac{15}{128}I_{20}I_{01}^{2} + \frac{3}{16}I_{10}I_{20}I_{11}I_{10} - \frac{15}{16}I_{10}I_{20}I_{11}I_{0} + \frac{3}{16}I_{10}I_{20}I_{11}I_{11} + \frac{3}{16}I_{20}I_{11}^{2} - \frac{15}{16}I_{10}I_{20}I_{11}I_{0} - \frac{15}{16}I_{10}I_{20}I_{11}I_{0} - \frac{15}{16}I_{10}I_{20}I_{11}I_{0} - \frac{15}{16}I_{10}I_{20}I_{11}I_{0} + \frac{3}{16}I_{10}I_{20}I_{11}I_{11} + \frac{3}{16}I_{20}I_{11}I_{10} - \frac{15}{128}I_{20}I_{01}^{2} + \frac{3}{16}I_{10}I_{20}I_{11} - \frac{15}{16}I_{10}I_{20}I_{21}I_{0} + \frac{15}{16}I_{10}I_{20}I_{21}I_{0} + \frac{15}{16}I_{10}I_{20}I_{21}I_{0} + \frac{15}{128}I_{20}I_{21}I_{10} + \frac{15}{128}I_{20}I_{21}I_{01} + \frac{15}{128}I_{10}I_{20}I_{21} + \frac{3}{16}I_{10}I_{20}I_{21} + \frac{3}{16}I_{10}I_{20}I_{11} + \frac{3}{16}I_{10}I_{20}I_{11} + \frac{3}{16}I_{10}I_{20}I_{11} + \frac{3}{16}I_{10}I_{20}I_{21} + \frac{3}{16}I_{10}I_{20}I_{21} + \frac{3}{16}I_{10}I_{20}I_{21} + \frac{3}{16}I_{10}I_{20}I_{21} + \frac{3}{16}I_{10}I_{20}I_{21} + \frac{3}{16}I_{10}I_{20}I_{21} +$

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Proposition (cont'd)

$$\begin{split} \gamma_{3,3} &= + \left(-\frac{945}{256} I_{10}^3 I_{01}^3 + \frac{105}{64} I_{10} I_{01}^3 I_{20} + \frac{105}{16} I_{10}^2 I_{11} I_{01}^2 - \frac{15}{16} I_{10} I_{21} I_{01}^2 - \frac{45}{32} I_{20} I_{11} I_{01}^2 + \frac{105}{64} I_{10}^3 I_{10} I_{11} I_{11} I_{11} I_{11}^2 - \frac{15}{16} I_{10} I_{21} I_{21}^2 - \frac{15}{32} I_{20} I_{11} I_{01} I_{12} - \frac{15}{32} I_{10} I_{11}^2 I_{11} I_{101} + \frac{3}{4} I_{21} I_{11} I_{101} + \frac{3}{8} I_{20} I_{01} I_{12} - \frac{45}{32} I_{10}^2 I_{11} I_{21} - \frac{45}{32} I_{10}^2 I_{11} I_{12} - \frac{45}{32} I_{10}^2 I_{11} I_{11} I_{12} - \frac{45}{32} I_{10}^2 I_{11} I_{10} + \frac{3}{8} I_{10} I_{11} I_{21} - \frac{45}{32} I_{10}^2 I_{11} I_{12} - \frac{45}{32} I_{10}^2 I_{11} I_{11} I_{12} + \frac{3}{8} I_{11}^3 - \frac{1}{4} I_{12} I_{21} \right) \theta_{1}^3 \theta_{2}^3 v_{1} v_{12} v_{2} \\ &+ \frac{3}{8} I_{10} I_{21} I_{02} + \frac{3}{8} I_{20} I_{11} I_{02} + \frac{3}{4} I_{10} I_{11} I_{12} + \frac{3}{8} I_{11}^3 - \frac{1}{4} I_{12} I_{21} \right) \theta_{1}^3 \theta_{2}^3 v_{1} v_{12} v_{2} \\ &+ \left(-\frac{315}{128} I_{10}^3 I_{01}^3 + \frac{105}{64} I_{10} I_{20} I_{01}^3 - \frac{5}{32} I_{30} I_{01}^3 + \frac{105}{32} I_{10}^2 I_{11} I_{01}^2 - \frac{15}{32} I_{10} I_{21} I_{01}^2 - \frac{15}{16} I_{20} I_{11} I_{01}^2 \right) \\ &+ \frac{105}{64} I_{10}^3 I_{10} I_{10} I_{02} - \frac{45}{32} I_{10} I_{20} I_{01} I_{02} + \frac{3}{16} I_{30} I_{01} I_{02} - \frac{15}{32} I_{10}^2 I_{12} I_{01} - \frac{45}{32} I_{10} I_{11}^2 I_{01} + \frac{3}{8} I_{11} I_{21} I_{01} \right) \\ &+ \frac{3}{36} I_{20} I_{12} I_{01} - \frac{15}{16} I_{10}^2 I_{11} I_{02} + \frac{3}{3} I_{10} I_{21} I_{02} + \frac{3}{8} I_{20} I_{11} I_{02} - \frac{5}{32} I_{10}^3 I_{03} + \frac{3}{16} I_{10} I_{20} I_{03} - \frac{1}{24} I_{10} I_{11} I_{12} + \frac{1}{8} I_{10}^3 I_{11} I_{12} + \frac{1}{8} I_{11}^3 - \frac{1}{8} I_{21} I_{12} \right) \theta_{1}^3 \theta_{2}^3 v_{12}^3 \end{split}$$

and $\gamma_{p,6-p}$ is built from $\gamma_{6-p,p}$ by swapping θ_1 and θ_2 , v_1 and v_2 , and $I_{m,n}$ and $I_{n,m}$. In particular, the expansion provides a closed form expression of the prices of VIX futures in the two-factor Bergomi model at order 6 in small vol-of-vol when $u \mapsto \xi_0^u$ is flat.

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Expansion of the volatility of the squared VIX implied by VIX future prices

Proposition

In the two-factor Bergomi model, the volatility $\sigma_{VIX_T^2}$ of the squared VIX implied by the VIX future price for maturity T satisfies

$$\sigma_{VIX_T^2} = \omega \alpha_\theta \sqrt{\theta_1^2 I_{10}^2 I(2k_1 T) + 2\rho \theta_1 \theta_2 I_{10} I_{01} I((k_1 + k_2) T) + \theta_2^2 I_{01}^2 I(2k_2 T)} \\ \times \left\{ 1 + \delta_2 (\omega \alpha_\theta)^2 + \delta_4 (\omega \alpha_\theta)^4 \right\} + O(\omega^6) \\ \delta_2 = \frac{1}{2} \left(\frac{\gamma_4}{\gamma_2} - \frac{\gamma_2}{2} \right), \quad \delta_4 = \frac{1}{2} \left(\frac{\gamma_6}{\gamma_2} - \gamma_4 + \frac{\gamma_2^2}{3} \right) - \frac{1}{8} \left(\frac{\gamma_4}{\gamma_2} - \frac{\gamma_2}{2} \right)^2.$$

In particular, this provides a closed form expression of the implied volatility $\sigma_{VIX_T^2}$ in the two-factor Bergomi model at order 5 in small vol-of-vol when the initial curve $u \mapsto \xi_0^u$ is flat. At first order, this closed form expression reads

$$\sigma_{\mathrm{VIX}_T^2} = \omega \sqrt{\frac{\theta_1^2 I(k_1 \tau)^2 I(2k_1 T) + 2\rho \theta_1 \theta_2 I(k_1 \tau) I(k_2 \tau) I((k_1 + k_2) T) + \theta_2^2 I(k_2 \tau)^2 I(2k_2 T)}{\theta_1^2 + 2\rho \theta_1 \theta_2 + \theta_2^2}} + O(\omega^3).$$

Numerical experiments: $\rho = 0$



Figure: VIX future in the two-factor Bergomi model as a function of maturity (in years). Comparison of small vol-of-vol expansion at orders 2, 4, and 6 with the exact quadrature for parameter set II of Bergomi (*Stochastic Volatility Modeling*, 2016)

Numerical experiments: $\rho = 0$



Figure: Left: Implied volatility of the squared VIX. Right: VIX future computed using the implied volatility expansion at order one. Parameter set II of Bergomi (*Stochastic Volatility Modeling*, 2016)

Numerical experiments: $\rho \neq 0$



Figure: Left: VIX future in the two-factor Bergomi model as a function of maturity (in years). Comparison of small vol-of-vol expansion at orders 2, 4, and 6 with the exact quadrature for parameter set III of Bergomi (*Stochastic Volatility Modeling*, 2016); $\rho = 0.7$. Right: zoom on small T

Numerical experiments: $\rho \neq 0$



Figure: Left: VIX future in the two-factor Bergomi model as a function of maturity (in years). Comparison of small vol-of-vol expansion at orders 2, 4, and 6 with the exact quadrature for parameter set III of Bergomi (*Stochastic Volatility Modeling*, 2016); $\rho = 0.7$. Right: zoom on small T

	Proofs	

Proofs

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• VIX_T² =
$$\frac{1}{\tau} \int_{T}^{T+\tau} \xi_{T}^{u} du = f(T, X_{T})$$
 with
 $f(T, x) = \frac{1}{\tau} \int_{T}^{T+\tau} \xi_{0}^{u} \exp\left(\omega e^{-k(u-T)}x - \frac{\omega^{2}}{2}e^{-2k(u-T)}v_{T}\right) du.$

The Hermite polynomials (of unit variance) H_n satisfy for all $(\lambda, z) \in \mathbb{R}^2$

$$e^{\lambda z - \frac{\lambda^2}{2}} = \sum_{n=0}^{\infty} H_n(z) \frac{\lambda^n}{n!}.$$

As a consequence, for all $(\lambda, z, v) \in \mathbb{R}^3$

$$e^{\lambda z - \frac{\lambda^2}{2}v} = \exp\left(\lambda\sqrt{v}\frac{z}{\sqrt{v}} - \frac{(\lambda\sqrt{v})^2}{2}\right) = \sum_{n=0}^{\infty} H_n\left(\frac{z}{\sqrt{v}}\right)\frac{v^{n/2}\lambda^n}{n!} = \sum_{n=0}^{\infty} H_n(z,v)\frac{\lambda^n}{n!}$$

where

$$H_n(z,v) := v^{n/2} H_n\left(\frac{z}{\sqrt{v}}\right) = \sum_{p=0}^{\lfloor n/2 \rfloor} \frac{(-1)^p n!}{2^p p! (n-2p)!} v^p z^{n-2p}$$
(3.1)

are the Hermite polynomials of variance v.

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The first seven polynomials $H_n(x, v)$ are

$$\begin{aligned} H_0(x,v) &= 1 \\ H_1(x,v) &= x \\ H_2(x,v) &= x^2 - v \\ H_3(x,v) &= x^3 - 3vx \end{aligned} \qquad \begin{aligned} H_4(x,v) &= x^4 - 6vx^2 + 3v^2 \\ H_5(x,v) &= x^5 - 10vx^3 + 15v^2x \\ H_6(x,v) &= x^6 - 15vx^4 + 45v^2x^2 - 15v^3. \end{aligned}$$

In particular,

$$\exp\left(\omega e^{-k(u-T)}x - \frac{\omega^2}{2}e^{-2k(u-T)}v_T\right) = \sum_{n=0}^{\infty} H_n(x,v_T)e^{-nk(u-T)}\frac{\omega^n}{n!}.$$

We get

$$f(T,x) = \sum_{n=0}^{\infty} \Xi_n H_n(x,v_T) \frac{\omega^n}{n!}.$$

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Denote
$$I_n := \frac{\Xi_n}{\Xi_0}$$
, $P_n(x, v) := I_n H_n(x, v)$, and
 $\varepsilon := \frac{1}{\Xi_0} \sum_{n=1}^{\infty} \Xi_n H_n(x, v_T) \frac{\omega^n}{n!} = \sum_{n=1}^{\infty} P_n(x, v_T) \frac{\omega^n}{n!}$. Then
 $\sqrt{f(T, x)} = \sqrt{\Xi_0} \sqrt{1 + \varepsilon} = \sqrt{\Xi_0} \sum_{n=0}^{6} Q_n(x, v_T) \omega^n + O(\omega^7)$

where the polynomials $Q_n(x, v)$ are expressed in terms of the rescaled Hermite polynomials $P_n(x, v)$:

Lemma

$$\begin{array}{ll} \text{Let } \varepsilon = \sum_{n=1}^{6} P_n \frac{\omega^n}{n!} + O(\omega^7). \ \ \, \text{Then } \sqrt{1+\varepsilon} = \sum_{n=0}^{6} Q_n \omega^n + O(\omega^7) \ \, \text{where} \\ \\ Q_0 = 1 & Q_4 = \frac{1}{48} P_4 - \frac{1}{24} P_1 P_3 - \frac{1}{32} P_2^2 + \frac{3}{32} P_1^2 P_2 - \frac{5}{128} P_1^4 \\ \\ Q_1 = \frac{1}{2} P_1 & Q_5 = \frac{P_5}{240} - \frac{P_1 P_4}{96} - \frac{P_2 P_3}{48} + \frac{P_1^2 P_3}{32} + \frac{3}{64} P_1 P_2^2 - \frac{5}{64} P_1^3 P_2 + \frac{7}{256} P_1^5 \\ \\ Q_2 = \frac{1}{4} P_2 - \frac{1}{8} P_1^2 & Q_6 = \frac{1}{1440} P_6 - \frac{1}{480} P_1 P_5 - \frac{1}{192} P_2 P_4 - \frac{1}{288} P_3^2 + \frac{1}{128} P_1^2 P_4 \\ \\ Q_3 = \frac{1}{12} P_3 - \frac{1}{8} P_1 P_2 + \frac{1}{16} P_1^3 & + \frac{1}{32} P_1 P_2 P_3 + \frac{1}{128} P_2^3 - \frac{5}{192} P_1^3 P_3 - \frac{15}{256} P_1^2 P_2^2 + \frac{35}{512} P_1^4 P_2 - \frac{63}{3072} P_1^6 \\ \end{array}$$

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To complete the proof, since

$$\mathbb{E}[\mathrm{VIX}_T] = \mathbb{E}[\sqrt{f(T, X_T)}] = \sqrt{\Xi_0} \sum_{n=0}^6 \mathbb{E}[Q_n(X_T, v_T)]\omega^n + O(\omega^7),$$

it is enough to compute $\mathbb{E}[Q_n(X_T, v_T)]$ for $n \in \{0, 1, \dots, 6\}$.

- P_{2n} (resp. P_{2n+1}) being an even (resp. odd) polynomial in x, Q_1 , Q_3 and Q_5 are odd polynomials in x. As X_T is a symmetric random variable, this implies that $\mathbb{E}[Q_n(X_T, v_T)] = 0$ for $n \in \{1, 3, 5\}$.
- For the computation of $\mathbb{E}[Q_n(X_T, v_T)]$, $n \in \{2, 4, 6\}$, remember that, from the orthogonality property of Hermite polynomials, $\mathbb{E}[P_m P_n(X_T, v_T)] = 0$ whenever $m \neq n$ (in particular, $\mathbb{E}[P_n(X_T, v_T)] = 0$ for $n \neq 0$).
- The other terms can be computed using that $\mathbb{E}[X_T^{2n}] = \frac{(2n)!}{2^n n!} v_T^n$.

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$$\begin{split} \xi^{u}_{t} &= \xi^{u}_{0} f^{u}(t, x^{u}_{t}) = \xi^{u}_{0} g^{u}(t, X^{1}_{t}, X^{2}_{t}) \\ dX^{i}_{t} &= -k_{i} X^{i}_{t} dt + dZ^{i}_{t}, \qquad X^{i}_{0} = 0, \qquad i \in \{1, 2\} \\ x^{u}_{t} &:= \alpha_{\theta} \left\{ \theta_{1} e^{-k_{1}(u-t)} X^{1}_{t} + \theta_{2} e^{-k_{2}(u-t)} X^{2}_{t} \right\} \\ f^{u}(t, x) &:= \exp\left(\omega x - \frac{\omega^{2}}{2} v_{t}(u)\right) \\ v_{t}(u) &:= \operatorname{Var}(x^{u}_{t}) = \alpha^{2}_{\theta} \left\{ \theta^{2}_{1} e^{-2k_{1}(u-t)} v^{1}_{t} + \theta^{2}_{2} e^{-2k_{2}(u-t)} v^{2}_{t} \\ &+ 2\theta_{1} \theta_{2} e^{-(k_{1}+k_{2})(u-t)} v^{1,2}_{t} \right\} \\ v^{i}_{t} &:= \frac{1 - e^{-2k_{i}t}}{2k_{i}}, \qquad v^{1,2}_{t} := \rho \frac{1 - e^{-(k_{1}+k_{2})t}}{k_{1} + k_{2}} \\ [X^{1}_{t}, X^{2}_{t}) \sim \mathcal{N}\left(0, \begin{pmatrix} v^{1}_{t} & v^{1,2}_{t} \\ v^{1,2}^{1} & v^{2}_{t} \end{pmatrix}\right) \end{split}$$

• Denote $\omega_{\theta} := \omega \alpha_{\theta}$,

$$X_t := \begin{pmatrix} X_t^1 \\ X_t^2 \end{pmatrix}, \quad V_t := \mathsf{Cov}(X_t) = \begin{pmatrix} v_t^1 & v_t^{1,2} \\ v_t^{1,2} & v_t^2 \end{pmatrix}, \quad \lambda(\delta) := \omega_\theta \begin{pmatrix} \theta_1 e^{-k_1 \delta} \\ \theta_2 e^{-k_2 \delta} \end{pmatrix}.$$

With these notations (prime = transpose)

$$\xi_t^u = \xi_0^u \exp\left(\lambda(u-t)'X_t - \frac{1}{2}\lambda(u-t)'V_t\lambda(u-t)\right).$$

• Then $\operatorname{VIX}_T^2 = \frac{1}{\tau} \int_T^{T+\tau} \xi_T^u \, du = f(T, X_T)$ with

$$f(T,x) := \frac{1}{\tau} \int_T^{T+\tau} \xi_0^u \exp\left(\lambda(u-T)'x - \frac{1}{2}\lambda(u-T)'V_T\lambda(u-T)\right) du, \ x \in \mathbb{R}^2.$$

$$f(T,x) := \frac{1}{\tau} \int_T^{T+\tau} \xi_0^u \exp\left(\lambda(u-T)'x - \frac{1}{2}\lambda(u-T)'V_T\lambda(u-T)\right) du, \ x \in \mathbb{R}^2.$$

■ For clarity, *T* being fixed, denote

$$X = \begin{pmatrix} X_1 \\ X_2 \end{pmatrix} := X_T, \qquad V = \begin{pmatrix} v_1 & v_{1,2} \\ v_{1,2} & v_2 \end{pmatrix} := V_T, \qquad \lambda_u := \lambda(u - T).$$

Expand the above exponential term in powers of λ_u :

$$\exp\left(\lambda'_{u}x - \frac{1}{2}\lambda'_{u}V\lambda_{u}\right) = \sum_{\nu \in \mathbb{N}^{2}} H_{\nu}(x, V)\frac{\lambda'_{u}}{\nu!}$$

where $\lambda^{\nu} := \lambda_1^{\nu_1} \lambda_2^{\nu_2}$, $\nu! := \nu_1! \nu_2!$, and the $H_{\nu}(x, V)$ are the **dual bivariate Hermite polynomials** (see Takemura and Takeuchi 1988).

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Proof: two-factor Bergomi model

• The first $H_{\nu}(x,V)$ are given by

$$\begin{split} H_{0,0}(x,V) &= 1 & H_{2,1}(x,V) = x_1^2 x_2 - 2v_{1,2} x_1 - v_1 x_2 \\ H_{1,0}(x,V) &= x_1 & H_{4,0}(x,V) = x_1^4 - 6v_1 x_1^2 + 3v_1^2 \\ H_{2,0}(x,V) &= x_1^2 - v_1 & H_{3,1}(x,V) = x_1^3 x_2 - 3v_{1,2} x_1^2 - 3v_1 x_1 x_2 + 3v_1 v_{1,2} \\ H_{1,1}(x,V) &= x_1 x_2 - v_{1,2} & H_{2,2}(x,V) = x_1^2 x_2^2 - v_2 x_1^2 - 4v_{1,2} x_1 x_2 - v_1 x_2^2 + v_1 v_2 + 2v_1 x_2 \\ H_{3,0}(x,V) &= x_1^3 - 3v_1 x_1 & H_{5,0}(x,V) = x_1^5 - 10v_1 x_1^3 + 15v_1^2 x_1 \end{split}$$

$$\begin{split} H_{4,1}(x,V) &= x_1^4 x_2 - 4 v_{1,2} x_1^3 - 6 v_{1,2} x_1^2 x_2 + 12 v_1 v_{1,2} x_1 + 3 v_1^2 x_2 \\ H_{3,2}(x,V) &= x_1^3 x_2^2 - v_2 x_1^3 - 6 v_{1,2} x_1^2 x_2 - 3 v_1 x_1 x_2^2 + 3 \left(v_1 v_2 + 2 v_{1,2}^2 \right) x_1 + 6 v_1 v_{1,2} x_2 \\ H_{6,0}(x,V) &= x_1^6 - 15 v_1 x_1^4 + 45 v_1^2 x_1^2 - 15 v_1^3 \\ H_{5,1}(x,V) &= x_1^5 x_2 - 5 v_{1,2} x_1^4 - 10 v_1 x_1^3 x_2 + 30 v_1 v_{1,2} x_1^2 + 15 v_1^2 x_1 x_2 - 15 v_1^2 v_{1,2} \\ H_{4,2}(x,V) &= x_1^4 x_2^2 - v_2 x_1^4 - 6 v_1 x_1^2 x_2^2 + 3 v_1^2 x_2^2 - 8 v_{1,2} x_1^3 x_2 + 6 \left(v_1 v_2 + 2 v_{1,2}^2 \right) x_1^2 \\ &\quad + 24 v_1 v_{1,2} x_1 x_2 - 3 v_1^2 v_2 - 12 v_1 v_{1,2}^2 \\ H_{3,3}(x,V) &= x_1^3 x_2^3 - 9 v_{1,2} x_1^2 x_2^2 - 3 v_2 x_1^3 x_2 - 3 v_1 x_1 x_2^3 + 9 \left(v_1 v_2 + 2 v_{1,2}^2 \right) x_1 x_2 + 9 v_{1,2} v_2 x_1^2 \\ &\quad + 9 v_1 v_{1,2} x_2^2 - 9 v_1 v_{1,2} v_2 - 6 v_{1,2}^3. \end{split}$$

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$$f(T,x) := \frac{1}{\tau} \int_{T}^{T+\tau} \xi_{0}^{u} \exp\left(\lambda_{u}' x - \frac{1}{2}\lambda_{u}' V \lambda_{u}\right) du, \quad x \in \mathbb{R}^{2}$$
$$\exp\left(\lambda_{u}' x - \frac{1}{2}\lambda_{u}' V \lambda_{u}\right) = \sum_{\nu \in \mathbb{N}^{2}} H_{\nu}(x, V) \frac{\lambda_{u}'}{\nu!}$$

$$\begin{split} f(T,x) &= \sum_{\nu \in \mathbb{N}^2} H_{\nu}(x,V) \frac{1}{\nu!} \frac{1}{\tau} \int_{T}^{T+\tau} \xi_{0}^{u} \lambda_{u}^{\nu} du \\ &= \sum_{\nu \in \mathbb{N}^2} H_{\nu}(x,V) \omega_{\theta}^{\nu_{1}+\nu_{2}} \frac{\theta_{1}^{\nu_{1}} \theta_{2}^{\nu_{2}}}{\nu_{1}! \nu_{2}!} \frac{1}{\tau} \int_{T}^{T+\tau} \xi_{0}^{u} e^{-(\nu_{1}k_{1}+\nu_{2}k_{2})(u-T)} du \\ &= \sum_{\nu \in \mathbb{N}^2} H_{\nu}(x,V) \omega_{\theta}^{\nu_{1}+\nu_{2}} \frac{\theta_{1}^{\nu_{1}} \theta_{2}^{\nu_{2}}}{\nu_{1}! \nu_{2}!} \Xi_{\nu_{1},\nu_{2}} \\ &= \sum_{n=0}^{\infty} \frac{\omega_{\theta}^{n}}{n!} \sum_{p=0}^{n} \frac{n!}{p!(n-p)!} \theta_{1}^{p} \theta_{2}^{n-p} \Xi_{p,n-p} H_{p,n-p}(x,V). \end{split}$$

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The VIX Future in Bergomi Models

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$$f(T,x) = \sum_{n=0}^{\infty} \frac{\omega_{\theta}^{n}}{n!} \sum_{p=0}^{n} \frac{n!}{p!(n-p)!} \theta_{1}^{p} \theta_{2}^{n-p} \Xi_{p,n-p} H_{p,n-p}(x,V), \quad x \in \mathbb{R}^{2}$$

Let us denote $f(T,x) = \Xi_{0,0}(1+\varepsilon)$ with (recall $I_{m,n} := \frac{\Xi_{m,n}}{\Xi_{0,0}}$)

$$\varepsilon := \sum_{n=1}^{\infty} \frac{\omega_{\theta}^n}{n!} P_n(x, V)$$
$$P_n(x, V) := \sum_{p=0}^n \frac{n!}{p!(n-p)!} \theta_1^p \theta_2^{n-p} I_{p,n-p} H_{p,n-p}(x, V)$$

Then

$$\sqrt{f(T,x)} = \sqrt{\Xi_{0,0}}\sqrt{1+\varepsilon} = \sqrt{\Xi_{0,0}}\sum_{n=0}^{6}Q_n(x,V)\omega_{\theta}^n + O(\omega^7)$$

where $Q_n(x,V)$ are built from $P_n(x,V)$ as seen in the one-factor case.

$$\mathbb{E}[\mathsf{VIX}_T] = \mathbb{E}[\sqrt{f(T,X)}] = \sqrt{\Xi_{0,0}} \sum_{n=0}^{6} \mathbb{E}[Q_n(X,V)]\omega_{\theta}^n + O(\omega^7)$$

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The VIX Future in Bergomi Models

$$\mathbb{E}[\mathsf{VIX}_T] = \mathbb{E}[\sqrt{f(T,X)}] = \sqrt{\Xi_{0,0}} \sum_{n=0}^{6} \mathbb{E}[Q_n(X,V)]\omega_{\theta}^n + O(\omega^7)$$

- $H_{\nu}(x, V)$, as a polynomial in x, has same parity as $|\nu| := \nu_1 + \nu_2$ $\implies P_n(x, V)$ has same parity as $n \implies Q_1(x, V)$, $Q_3(x, V)$ and $Q_5(x, V)$ are odd polynomials in x. Since X is a centered random variable, $\mathbb{E}[Q_n(X, V)] = 0$ for $n \in \{1, 3, 5\}$.
- To compute $\mathbb{E}[Q_n(X,V)]$, $n \in \{2,4,6\}$, use the weak orthogonality property of Hermite polynomials: $\mathbb{E}[H_{\mu}H_{\nu}(X,V)] = 0$ whenever $|\mu| \neq |\nu|$. In particular, $\mathbb{E}[P_mP_n(X,V)] = 0$ whenever $m \neq n$, and $\mathbb{E}[P_n(X,V)] = 0$ for $n \neq 0$. For the other terms use

$$\begin{split} \mathbb{E}[X_1^2] &= v_1, \quad \mathbb{E}[X_1X_2] = v_{1,2}, \quad \mathbb{E}[X_1^4] = 3v_1^2, \quad \mathbb{E}[X_1^3X_2] = 3v_1v_{1,2}, \quad \mathbb{E}[X_1^2X_2^2] = v_1v_2 + 2v_{1,2}^2, \\ \mathbb{E}[X_1^6] &= 15v_1^3, \quad \mathbb{E}[X_1^5X_2] = 15v_1^2v_{1,2}, \quad \mathbb{E}[X_1^4X_2^2] = 3v_1v_2 + 12v_1v_{1,2}^2, \quad \mathbb{E}[X_1^3X_2^3] = 9v_1v_{1,2}v_2 + 6v_{1,2}^3. \end{split}$$

$$\begin{split} \mathbb{E}[X_1^{2m}X_2^{2n}] &= \frac{(2n)!}{2^{m+n}}\sum_{i=0}^n\sum_{j=0}^{n-i}\frac{(-1)^{n-i-j}(2m+2i)!}{(2i)!(m+i)!j!(n-i-j)!}v_1^{m-n+j}v_2^jv_{1,2}^{2(n-j)}, \quad m \ge n \\ \mathbb{E}[X_1^{2m+1}X_2^{2n+1}] &= \frac{(2n+1)!}{2^{m+n+1}}\sum_{i=0}^n\sum_{j=0}^{n-i}\frac{(-1)^{n-i-j}(2m+2i+2)!}{(2i+1)!(m+i+1)!j!(n-i-j)!}v_1^{m-n+j}v_2^jv_{1,2}^{2(n-j)+1}, \quad m \ge n \\ \mathbb{E}[X_1^{2m+1}X_2^{2n+1}] &= \frac{(2n+1)!}{2^{m+n+1}}\sum_{i=0}^{n-i}\sum_{j=0}^{n-i}\frac{(-1)^{n-i-j}(2m+2i+2)!}{(2i+1)!(m+i+1)!j!(n-i-j)!}v_1^{m-n+j}v_2^jv_{1,2}^{2(n-j)+1}, \quad m \ge n \\ \mathbb{E}[X_1^{2m+1}X_2^{2m+1}] &= \frac{(2n+1)!}{2^{m+n+1}}\sum_{i=0}^{n-i}\sum_{j=0}^{n-i}\frac{(-1)^{n-i-j}(2m+2i+2)!}{(2i+1)!(m+i+1)!j!(n-i-j)!}v_1^{m-n+j}v_2^jv_{1,2}^{2(n-j)+1}, \quad m \ge n \\ \mathbb{E}[X_1^{2m+1}X_2^{2m+1}] &= \frac{(2n+1)!}{2^{m+n+1}}\sum_{i=0}^{n-i}\sum_{j=0}^{n-i}\frac{(-1)^{n-i-j}(2m+2i+2)!}{(2i+1)!(m+i+1)!j!(n-i-j)!}v_1^{m-n+j}v_2^jv_{1,2}^{2(n-j)+1}, \quad m \ge n \\ \mathbb{E}[X_1^{2m+1}X_2^{2m+1}] &= \frac{(2n+1)!}{2^{m+1}}\sum_{j=0}^{n-i}\sum_{j=0}^{n-i}\frac{(-1)^{n-i-j}(2m+2i+2)!}{(2i+1)!(m+i+1)!j!(n-i-j)!}v_1^{m-n+j}v_2^jv_{1,2}^{2(n-j)+1}, \quad m \ge n \\ \mathbb{E}[X_1^{2m+1}X_2^{2m+1}] &= \frac{(2n+1)!}{2^{m+1}}\sum_{j=0}^{n-i}\sum_{j=0}^{n-i}\frac{(-1)^{n-i-j}(2m+2i+2)!}{(2i+1)!(m+i+1)!j!(n-i-j)!}v_1^{m-n+j}v_2^jv_{1,2}^{2(n-j)+1}, \quad m \ge n \\ \mathbb{E}[X_1^{2m+1}X_2^{2m+1}] &= \frac{(2n+1)!}{2^{m+1}}\sum_{j=0}^{n-i}\sum_{j=0}^{n-i}\frac{(-1)^{n-i-j}(2m+2i+2)!}{(2m+1)!}v_1^{m-i-j}v_1^{m-i-j}v_2^jv_{1,2}^{2(n-i-j)+1}, \quad m \ge n \\ \mathbb{E}[X_1^{2m+1}X_2^{2m+1}X_2^{2m+1}] &= \frac{(2n+1)!}{2^{m+1}}\sum_{j=0}^{n-i}\sum_{j=0}^{n-i}\frac{(-1)^{n-i-j}(2m+2i+2)!}{(2m+1)!}v_1^{m-i-j}v_1^{m-i-j}v_1^{m-i-j}v_1^{m-i-j}v$$

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The VIX Future in Bergomi Models

	Joint SPX/VIX smile calibration

Joint SPX/VIX smile calibration

The joint SPX/VIX smile calibration puzzle

- It looks impossible to jointly calibrate the SPX and VIX smiles using continuous-time stochastic vol models with continuous SPX paths.
- In those models, large ATM SPX skew ⇒ large vol-of-vol, inconsistent with the relatively low VIX implied vols, especially for short maturities.
- However, mean-reversion also comes into play. Increasing mean-reversion means that ATM SPX skew flattens and VIX implied vol decreases. At different speeds?
- Objective: precisely pinpoint the roles of vol-of-vol and mean-reversion.
- Bergomi-G. (2012): Expansion of SPX smile in small vol-of-vol in generic stochastic vol models.
- This talk: Expansion of VIX futures in small vol-of-vol in Bergomi models.
- Putting together both expansions sheds light on the structural joint constraints on SPX and VIX imposed by stochastic vol models in general, using the example of Bergomi models.

	Joint SPX/VIX smile calibration

The joint SPX/VIX smile calibration puzzle

In particular G. (2017) has shown that SPX/VIX market data shows inversion of convex ordering for short maturities T:

$$\mathrm{VIX}^2_{\mathsf{mkt},T} \leq_c \mathrm{VIX}^2_{\mathsf{loc},T}.$$

- G. (2018) has shown that in the Bergomi models inversion of convex ordering requires large mean-reversion and large vol-of-vol.
- Here we directly use approximate formulas of SPX skew and VIX futures in the one-factor Bergomi model to prove that in the Bergomi models joint calibration requires large k and ω .
- Make this statement more precise: How big should $\frac{\omega}{k}$ be? $\frac{\omega^2}{k}$?

Reminder on the ergodic regime:

- The limiting regime where k and ω tend to +∞ while ^{ω²}/_k is kept constant corresponds to an ergodic limit where (ωX_t) quickly reaches its stationary distribution N(0, ^{ω²}/_{2k}). Cf Fouque, Papanicolaou and Sircar (2000).
- Only regime where k, ω are large and the variance of σ_t^2 has a finite limit, which is the natural regime in finance.

The SPX smile in the one-factor Bergomi model

 Bergomi-G. expansion (2012) gives the smile of generic stochastic volatility models at order 2 in vol-of-vol:

$$\widehat{\sigma}(T,K) = \widehat{\sigma}_T^{\mathsf{ATM}} + \mathcal{S}_T \ln\left(\frac{K}{S_0}\right) + \mathcal{C}_T \ln^2\left(\frac{K}{S_0}\right) + O(\omega^3)$$

In the case of the one-factor Bergomi model with a flat initial term structure of variance swaps (ξ^u₀ ≡ ξ), coefficients are explicit functions of ω, k, ρ, ξ, T. In particular, the ATM skew

$$S_T = \frac{\rho\omega}{2}\mathcal{J}(kT) + \frac{\rho^2\omega^2\sqrt{\xi}T}{8}\left(2\mathcal{H}(kT) + 4\frac{\mathcal{J}(kT) - \mathcal{J}(2kT)}{kT} - 3\mathcal{J}(kT)^2\right)$$

where

$$\mathcal{I}(\alpha) = \frac{1 - e^{-\alpha}}{\alpha}, \qquad \mathcal{J}(\alpha) = \frac{\alpha - 1 + e^{-\alpha}}{\alpha^2}$$
$$\mathcal{K}(\alpha) = \frac{1 - e^{-\alpha} - \alpha e^{-\alpha}}{\alpha^2}, \qquad \mathcal{H}(\alpha) = \frac{\mathcal{J}(\alpha) - \mathcal{K}(\alpha)}{\alpha}$$

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SPX skew and implied vol of VIX² at first order in ω (Bergomi1F)

$$\begin{split} \mathcal{S}_T &= \quad \frac{\rho\omega}{2} \frac{kT - 1 + e^{-kT}}{(kT)^2} + O(\omega^2) \\ \sigma_{\mathsf{VIX}_T^2} &= \quad \omega \frac{1 - e^{-k\tau}}{k\tau} \sqrt{\frac{1 - e^{-2kT}}{2kT}} + O(\omega^3) \end{split}$$

Small mean-reversion: cannot jointly calibrate

1

- $S_T \approx \frac{\rho\omega}{4}$. Calibration to very short-term SPX smile: $S_T \approx -1.5$ $\implies \rho\omega \approx -6 \implies \omega \ge 6$.
- $\sigma_{\text{VIX}^2_{\pi}} \approx \omega \geq 6$: too large compared to market data (≈ 3)!
- Vol-of-vol implied by SPX skew $\approx 2 \times$ vol-of-vol implied by VIX futures!

SPX skew and implied vol of VIX² at first order in ω (Bergomi1F)

$$S_{T} = \frac{\rho \omega}{2} \frac{kT - 1 + e^{-kT}}{(kT)^{2}} + O(\omega^{2})$$

$$\sigma_{\text{VIX}_{T}^{2}} = \omega \frac{1 - e^{-k\tau}}{k\tau} \sqrt{\frac{1 - e^{-2kT}}{2kT}} + O(\omega^{3})$$

Large mean-reversion:

• $S_T \approx \frac{\rho \omega}{2kT}, kT \gg 1$. Calibration to SPX smile, $T = \frac{1}{4}$: $\frac{\rho \omega}{2kT} \approx -0.6 \Longrightarrow 2\frac{\rho \omega}{k} \approx -0.6 \Longrightarrow \frac{\omega}{k} \ge 0.3$: ω and k are large. Numerical example: $k = 20, \rho = -1 \Longrightarrow \omega \ge 6$ • $\sigma_{\text{VIX}_T^2} \approx \frac{\omega}{k^{3/2} \tau \sqrt{2T}} \approx \frac{\sqrt{2T}}{\rho \tau \sqrt{k}} S_T$ behaves like $\frac{\omega}{k^{3/2}} \ll \frac{\omega}{k}$! Because of mean-reversion, implied vol of VIX_T^2 is much smaller. Numerical example with $\omega = 6$: $\sigma_{\text{VIX}_T^2} \approx 1$.

 \implies Both ω and k must be large, with $\omega \approx k$ so $\frac{\omega^2}{k}$ large! Large stationary standard deviation of instantaneous vol.

		Joint SPX/VIX smile calibration
Problems		

- $\frac{\omega^2}{k}$ large \implies the small vol-of-vol expansions may be inaccurate, and the volatility is difficult to simulate (very large variance).
- Calibration only to VIX future, not to the full VIX smile. Use skewed Bergomi model (Bergomi 2008).
- Term-structure of SPX ATM skew requires at least two mean-reversion scales. The slow mean-reversion component ruins the $\frac{1}{L^{3/2}}$ behavior.

Proof

Joint SPX/VIX smile calibration

Two-factor Bergomi model: varying all parameters



 $\omega \in [3,8], k_1 \in [20,100], k_2 \in [8,20], \theta_2 \in [0,0.3], \rho_{S1}, \rho_{S2} \in [-0.99,-0.5], \ T=0.1$

Term-structure of SPX ATM skew

One-factor Bergomi model with large mean-reversion and vol-of-vol: $S_T \sim \frac{1}{T}$. To mimic a power-law decay $S_T \sim \frac{1}{T^{\alpha}}$: 2-factor Bergomi model and rough volatility model.



	Joint SPX/VIX smile calibration

SPX ATM skew, May 7, 2018



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	Joint SPX/VIX smile calibration

SPX ATM skew, May 7, 2018



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	Joint SPX/VIX smile calibration

SPX ATM skew, May 7, 2018



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However... SPX ATM skew, Jan 18, 2018


Rough Bergomi model: Power-law kernel $K(heta) = u heta^{H-rac{1}{2}}$

- **No Markov representation** for ξ_t^u .
- Instantaneous variance $\sigma_t^2 := \xi_t^t$ is not a semimartingale. One cannot write Itô dynamics $d\xi_t^t = \cdots dt + \cdots dZ_t$ for the instantaneous variance. No notion of a dynamic volatility of instantaneous spot variance.

• However we can compare the values of $Var\left(ln\frac{\xi_t^u}{\xi_0^u}\right)$ in the power-law and exponential kernel models:

$$\nu^{2} \frac{u^{2H} - (u-t)^{2H}}{2H} \quad \longleftrightarrow \quad \omega^{2} e^{-2k(u-t)} \frac{1 - e^{-2kt}}{2k}$$
(4.1)

$$u = t \to 0:$$
 $\nu^2 \frac{t^{2H}}{2H} \longleftrightarrow \omega^2 \frac{1 - e^{-2kt}}{2k} \approx \omega^2 t$ (4.2)

$$\nu \frac{t^{H-\frac{1}{2}}}{\sqrt{2H}} \longleftrightarrow \omega \tag{4.3}$$

■ $\nu \frac{t^{H-\frac{1}{2}}}{\sqrt{2H}}$ can be interpreted as a short term volatility of instantaneous spot variance.

•
$$\left[\nu\right] = \operatorname{time}^{-H}; \left[\nu\theta^{H-\frac{1}{2}}\right] = \left[\nu\frac{t^{H-\frac{1}{2}}}{\sqrt{2H}}\right] = \operatorname{vol}.$$

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Rough Bergomi model: Power-law kernel $K(heta) = u heta^{H-rac{1}{2}}$

• Short-term ATM skew in SV models $\sim \rho\omega$. Explains why the ATM skew in such rough volatility models behaves like $T^{H-\frac{1}{2}}$ for short maturities T (Alós, Fukasawa...), which is one of the reasons why this model has been introduced (Gatheral, Jaisson, Rosenbaum, Friz, Bayer).

In the limit
$$H \to 0$$
, for fixed ν , $\nu^2 \frac{t^{2H}}{2H} \to +\infty$ for any $t > 0$.

- In order for $Var(\sigma_t^2)$ to tend to a finite limit, we must impose that $\frac{\nu^2}{2H}$ tend to a finite limit \implies A natural limiting regime, analogous to the ergodic regime described above for the exponential kernel, is $H, \nu \rightarrow 0$, with $\frac{\nu^2}{2H}$ kept constant.
- However in this ergodic limit the SPX skew is $\sim \sqrt{H}T^{H-\frac{1}{2}}...$

		Joint SPX/VIX smile calibration

Joint calibration with continuous SPX models? Numerical tests



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Joint calibration: Calibrating first to VIX market

Skewing the models on ξ_t^u :

Following Bergomi (2008), we use a linear combination of two lognormal random variables to model the instantaneous variance σ_t^2 so as to generate positive VIX skew:

$$\sigma_t^2 = \xi_0^t \left((1 - \lambda) \mathcal{E} \left(\omega_0 \int_0^t e^{-k(t-s)} dZ_s \right) + \lambda \mathcal{E} \left(\omega_1 \int_0^t e^{-k(t-s)} dZ_s \right) \right)$$

or

$$\sigma_t^2 = \xi_0^t \left((1-\lambda) \mathcal{E}\left(\nu_0 \int_0^t (t-s)^{H-\frac{1}{2}} dZ_s \right) + \lambda \mathcal{E}\left(\nu_1 \int_0^t (t-s)^{H-1/2} dZ_s \right) \right)$$

with $\lambda \in [0,1]$.

- $\mathcal{E}(X)$ is simply a shorthand notation for $\exp\left(X \frac{1}{2}\operatorname{Var}(X)\right)$.
- Also (independently) introduced by De Marco.

Skewed rough Bergomi: Calibration to VIX future and VIX options (March 21, 2018



The VIX Future in Bergomi Models

Skewed rough Bergomi: Calibration to VIX future and VIX options (March 21, 2018



Skewed rough Bergomi: Calibration to VIX future and VIX options



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Skewed rough Bergomi: Calibration to VIX future and VIX options



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Image: Image: A marked block in the second s

The VIX Future in Bergomi Models

- Not enough ATM skew for SPX, despite pushing negative spot-vol correlation as much as possible.
- I get similar results when I use the skewed 2-factor Bergomi model instead of the skewed rough Bergomi model.



Joint calibration: Calibrating first to SPX market

Consider only continuous models on SPX that are calibrated to SPX smile:

$$\frac{dS_t}{S_t} = \frac{a_t}{\sqrt{\mathbb{E}[a_t^2|S_t]}} \sigma_{\mathrm{lv}}(t, S_t) \, dW_t$$

and optimize on (a_t) so as to match VIX options — or compute the infimum of VIX implied vols within those models.

Natural candidates for (a_t) : skewed rough or 2-factor Bergomi model. More generally: $a_t = \sigma_i(X_t)$, $t \in [T_i, T_i + \tau]$

■ The leverage function

$$l(t, S_t) = \frac{\sigma_{\text{loc}}(t, S_t)}{\sqrt{\mathbb{E}[a_t^2 | S_t]}}$$

does not mean revert; it fights against inversion of convex ordering.Numerically estimate

$$\mathsf{VIX}_{T_i}^2 \quad = \quad \frac{1}{\tau} \int_{T_i}^{T_i + \tau} \mathbb{E} \left[\frac{\sigma_i(X_t)^2}{\mathbb{E}[\sigma_i(X_t)^2 | S_t]} \sigma_{\mathrm{loc}}(t, S_t)^2 \Big| \mathcal{F}_{T_i} \right] \, dt$$

(use least squares Monte Carlo or neural networks)

Joint calibration: Calibrating first to SPX market (Aug 1, 2018)



Why jumps can help

- For a continuous model to calibrate jointly to SPX and VIX options, the distribution of $\mathbb{E}\left[\frac{1}{\tau}\int_{T}^{T+\tau}\sigma_{t}^{2}dt\Big|\mathcal{F}_{T}\right]$ should be as narrow as possible, but without killing the SPX skew. The problem of ergodic/stationary (σ_{t}) is that they produce flat SPX skew.
- Jump-Lévy processes are precisely examples of processes that can generate deterministic realized variance together with a smile on the underlying.
- This explains why jumps have proved useful in this problem.

		Joint SPX/VIX smile calibration
Conjecture		

Consider continuous models on SPX that are calibrated to SPX smile:

$$\frac{dS_t}{S_t} = \frac{a_t}{\sqrt{\mathbb{E}[a_t^2|S_t]}} \sigma_{\rm loc}(t, S_t) \, dW_t.$$

Define

$$\mathsf{VIX}_T^2 = \frac{1}{\tau} \int_T^{T+\tau} \mathbb{E} \left[\frac{a_t^2}{\mathbb{E}[a_t^2|S_t]} \sigma_{\mathrm{loc}}^2(t, S_t) \middle| \mathcal{F}_T \right] dt.$$

Conjecture: Continuous-time continuous-paths models for the SPX cannot fit VIX smile for small T:

$$\inf_{(a_t)} \mathbb{E}\left[(\mathsf{VIX}_T - K)_+ \right] > C_{\mathsf{VIX}}^{\mathsf{mkt}}(T, K).$$

Controlled singular Mc-Kean equation, mean-field HJB PDE.



The joint SPX/VIX smile calibration puzzle solved

- **Exact joint calibration of SPX and VIX smiles.**
- Completely different approach: instead of parametric continuous-time models we use nonparametric discrete-time models.
- Discrete-time allows to decouple SPX skew and VIX implied vol.
- Nonparametric gives flexibility to fit the whole smiles.
- The model is solution to a dispersion-constrained martingale transport problem.
- Numerically built using the Sinkhorn algorithm.

Talk tomorrow at 3:15pm.



Julien Guyon The VIX Future in Bergomi Models

One-factor Bergomi model	I wo-factor Bergomi model		Joint SPX/VIX smile calibration
A few selected refer	ences		
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