# Modeling $\theta_T$ as a Double Mean-Reverting Process in SVI Parameterization

In the context of the **Stochastic Volatility Inspired (SVI)** parameterization,  $\theta_T$  represents the total variance up to maturity T. When modeling  $\theta_T$  as a **double mean-reverting process**, we're considering a stochastic volatility model where the variance itself mean-reverts to a stochastic long-term mean, which also mean-reverts to a constant level. This adds an extra layer of dynamics to capture more complex market behaviors.

## **Double Mean-Reverting Process**

#### First Mean Reversion (Variance to Stochastic Mean Level):

The instantaneous variance  $v_t$  mean-reverts to a stochastic mean level  $m_t$ :

$$dv_t = \kappa_v (m_t - v_t) dt + \sigma_v \sqrt{v_t} dW_t^v$$

- $v_t$ : Instantaneous variance at time t.
- $\kappa_v$ : Speed of mean reversion of  $v_t$  toward  $m_t$ .
- $\sigma_v$ : Volatility of the variance process.
- $dW_t^v$ : Brownian motion driving  $v_t$ .

#### Second Mean Reversion (Mean Level to Constant Level):

The mean level  $m_t$  mean-reverts to a constant long-term mean  $\theta$ :

$$dm_t = \kappa_m(\theta - m_t)dt + \sigma_m dW_t^m$$

- $m_t$ : Stochastic mean level at time t.
- $\kappa_m$ : Speed of mean reversion of  $m_t$  toward  $\theta$ .
- $\sigma_m$ : Volatility of the mean level process.
- $dW_t^m$ : Brownian motion driving  $m_t$ .
- $\theta$ : Constant long-term mean level.

## Computing $\theta_T$ Under Double Mean Reversion

The total variance  $\theta_T$  up to time T is given by the expected integrated variance:

$$\theta_T = \mathbb{E}\left[\int_0^T v_t \, dt\right]$$

To derive  $\theta_T$  under the double mean-reverting process, follow these steps:

## 1. Compute the Expected Mean Level $\mathbb{E}[m_t]$

Solve the stochastic differential equation (SDE) for  $m_t$ :

$$\mathbb{E}[m_t] = m_0 e^{-\kappa_m t} + \theta (1 - e^{-\kappa_m t})$$

•  $m_0$ : Initial mean level at t = 0.

#### 2. Compute the Expected Variance $\mathbb{E}[v_t]$

Given the dependency of  $v_t$  on  $m_t$ , the expected variance is:

$$\mathbb{E}[v_t] = v_0 e^{-\kappa_v t} + \kappa_v \int_0^t e^{-\kappa_v (t-s)} \mathbb{E}[m_s] \, ds$$

•  $v_0$ : Initial variance at t = 0.

Substitute  $\mathbb{E}[m_s]$  into the integral:

$$\mathbb{E}[v_t] = v_0 e^{-\kappa_v t} + \kappa_v \int_0^t e^{-\kappa_v (t-s)} \left[ m_0 e^{-\kappa_m s} + \theta (1 - e^{-\kappa_m s}) \right] ds$$

### 3. Integrate $\mathbb{E}[v_t]$ Over Time to Find $\theta_T$

Compute  $\theta_T$  by integrating  $\mathbb{E}[v_t]$  from 0 to T:

$$\theta_T = \int_0^T \mathbb{E}[v_t] \, dt$$

This results in:

$$\theta_T = \int_0^T \left[ v_0 e^{-\kappa_v t} + \kappa_v \int_0^t e^{-\kappa_v (t-s)} \left( m_0 e^{-\kappa_m s} + \theta [1 - e^{-\kappa_m s}] \right) ds \right] dt$$

## 4. Simplify the Expression

While the integral may seem complex, it can be simplified using standard integration techniques and properties of exponential functions. The key steps involve:

- Evaluating the double integral.
- Applying the convolution of exponential functions.
- Simplifying the resulting expressions.

**Note:** Due to the complexity, the final expression may not be closed-form but can be computed numerically.

# Final Formula for $\theta_T$

An approximate expression for  $\theta_T$  is:

$$\theta_T = \left(\frac{v_0}{\kappa_v}\right) \left(1 - e^{-\kappa_v T}\right) + \left(\frac{\kappa_v m_0}{\kappa_v - \kappa_m}\right) \left(\frac{1 - e^{-\kappa_m T}}{\kappa_m} - \frac{1 - e^{-\kappa_v T}}{\kappa_v}\right) + \theta \left(T - \frac{1 - e^{-\kappa_m T}}{\kappa_m}\right)$$

This formula assumes  $\kappa_v \neq \kappa_m$ . If  $\kappa_v = \kappa_m$ , the expression needs adjustment to avoid division by zero.

#### Considerations

- Correlation Between Brownian Motions: If  $dW_t^v$  and  $dW_t^m$  are correlated, this affects the variance of  $v_t$  but not the expectation  $\mathbb{E}[v_t]$ .
- Parameter Estimation: Estimating the parameters  $\kappa_v$ ,  $\kappa_m$ ,  $\sigma_v$ ,  $\sigma_m$ ,  $v_0$ , and  $m_0$  requires calibration to market data.
- Numerical Methods: In practice, numerical integration or simulation may be necessary to compute  $\theta_T$  accurately.

#### Conclusion

By modeling  $\theta_T$  as a double mean-reverting process, you capture richer dynamics in the implied volatility surface. The formula involves integrating the expected variance over time, accounting for both layers of mean reversion.

#### **Key Formula:**

$$\theta_T = \int_0^T \mathbb{E}[v_t] dt$$

with  $\mathbb{E}[v_t]$  computed based on the mean-reverting processes of  $v_t$  and  $m_t$ .

## References

- Gatheral, J. (2006). The Volatility Surface: A Practitioner's Guide. Wiley.
- Christoffersen, P., Heston, S., & Jacobs, K. (2009). The Shape and Term Structure of the Index Option Smirk: Why Multifactor Stochastic Volatility Models Work So Well. Management Science.

These references provide deeper insights into stochastic volatility models and the implementation of double mean-reverting processes in financial modeling.