In statistical analysis, we often run into the problem of matrix inference such as covariance matrices, integrated volatility matrices, precision matrices, quantum density matrices, PCA, and matrix completion. As the number of variables increases, classical estimation methods designed for finite-dimensional matrices are neither effective nor efficient. So, it is important to develop effective and efficient estimation methods for high-dimensional matrices. During the last decade, researchers have dedicated to the study of high-dimensional matrix inferences. Most of these studies are based on i.i.d. observations. However, we often encounter dependent observations (e.g. high-frequency financial data), and the asymptotic theories developed for i.i.d. observations are not applicable to dependent observations. We investigated inferences of high-dimensional integrated volatility matrices based on non-synchronized and noisy observations coming from Ito processes in a setting where both the number of observations and dimensionality of the matrix go to infinity.