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Matrix-variate Gaussian graphical models (GGM) have been widely used for modeling matrix-variate data. Since the support of sparse precision matrix represents the conditional independence graph among matrix entries, conducting support recovery yields valuable information. A commonly used approach is the penalized log-likelihood method. However, due to the complicated structure of precision matrices in the form of Kronecker product, the log-likelihood is non-convex, which presents challenges for both computation and theoretical analysis. In this paper, we propose an alternative approach by formulating the support recovery problem into a multiple testing problem. A new test statistic is developed and based on that, we use the popular Benjamini and Hochberg's procedure to control false discovery rate (FDR) asymptotically. Our method involves only convex optimization, making it computationally attractive. Theoretically, our method allows very weak conditions, i.e., even when the sample size is finite and the dimensions go to infinity, the asymptotic normality of the test statistics and FDR control can still be guaranteed. We further provide the power analysis result. The finite sample performance of the proposed method is illustrated by both simulated and real data analysis.