Learning the conditional dependence structures in high dimensional graphical models is of fundamental importance in many contemporary applications. Despite the fast growing literature, a practical issue of reproducibility remains largely unexplored as most of existing methods for graph recovery do not guarantee the false discovery rate (FDR) control. In this talk, we propose a new procedure called uniform knockoff filter that controls the overall FDR in graph recovery via control variables, regardless of the magnitudes of signal strength and regularization parameters. Compared with controlling the FDR in a nodewise way, the proposed procedure enjoys not only theoretical guarantee and robustness of FDR control but also significantly higher power by utilizing a uniform threshold for the statistics generated from a large-scale mixture of penalized regressions. The strict FDR guarantee is established by a novel sequentially conditional independence argument to deal with the correlations between test statistics generated from different nodes. Our new methodology and results are evidenced by simulation and real data examples.