In this paper, we use fixed point theory and semidefinite programming to compute the performance bounds on convex block-sparsity recovery algorithms. As a prerequisite for optimal sensing matrix design, computable performance bounds would open doors for wide applications in sensor arrays, radar, DNA microarrays, and many other areas where block-sparsity arises naturally. We define a family of quality measures for arbitrary sensing matrices as the optimal values of certain optimization problems. The reconstruction errors of convex recovery algorithms are bounded in terms of these quality measures. We demonstrate that as long as the number of measurements is relatively large, these quality measures are bounded away from zero for a large class of random sensing matrices, a result parallel to the probabilistic analysis of the block restricted isometry property. As the primary contribution of this work, we associate the quality measures with the fixed points of functions defined by a series of semidefinite programs. This relation with fixed point theory yields polynomial-time algorithms with global convergence guarantees to compute the quality measures.