Outcome-dependent sampling designs are common in many different scientific fields including epidemiology, ecology, and economics. As with all observational studies, such designs often suffer from unmeasured confounding, which generally precludes the nonparametric identification of causal effects. Nonparametric bounds can provide a way to narrow the range of possible values for a nonidentifiable causal effect without making additional untestable assumptions. The nonparametric bounds literature has almost exclusively focused on settings with random sampling, and the bounds have often been derived with a particular linear programming method. We derive novel bounds for the causal risk difference, often referred to as the average treatment effect, in six settings with outcome-dependent sampling and unmeasured confounding for a binary outcome and exposure. Our derivations of the bounds illustrate two approaches that may be applicable in other settings where the bounding problem cannot be directly stated as a system of linear constraints. We illustrate our derived bounds in a real data example involving the effect of vitamin D concentration on mortality.