Model forms and estimation for linear, log and logit risk GLM models.

Model Type	Linear	Log Risk	Logit risk
Model Form	$Risk = \beta_0 + \beta_1 X_1 + \beta_k X_k$	$In(Risk) = \beta_0 + \beta_1 X_1 + \beta_k X_k$	logit(Risk)= $\beta_0 + \beta_1 X_1 + \beta_k X_k$
Outcome distribution	binomial	binomial	binomial
Link function	identity	In()	logit()
Simple model	Risk(outcome X_1) = $\beta_0 + \beta_1 X_1$	In[Risk(outcome X_1)] = $\beta_0 + \beta_1 X_1$	logit[Risk(outcome X_1)] = $\beta_0 + \beta_1 X_1$
Risk(outcome X ₁ = ₀)	$R_0 = \beta_0 + 0^* \beta_1 = \beta_0$	In(R ₀) = $\beta_0 + 0*\beta_1 = \beta_0$ so R ₀ = exp[β_0]	In(Odds ₀) = $\beta_0 + 0*\beta_1 = \beta_0$ so Odds ₀ = exp[β_0]
Risk(outcome $X_1 = 1$)	$R_1 = \beta_0 + 1^*\beta_1 = \beta_0 + \beta_1$	In(R ₁) = $\beta_0 + 1*\beta_1 = \beta_0 + \beta_1$ so R ₁ = exp[$\beta_0 + \beta_1$]	In(Odds ₁) = $\beta_0 + 1*\beta_1 = \beta_0 + \beta_1$ so Odds ₁ = exp[$\beta_0 + \beta_1$]
Risk comparison	Risk Difference	Risk Ratio	Odds Ratio
	RD = R ₁ - R ₀ = $[\beta_0 + {}_1*\beta_1] - [\beta_0 + {}_0*\beta_1]$ = $[\beta_0 + \beta_1] - [\beta_0]$ = β_1	$In(RR) = In(R_1 / R_0) = In(R_1) - In(R_0)$ $= [\beta_0 + 1*\beta_1] - [\beta_0 + 0*\beta_1]$ $= [\beta_0 + \beta_1] - [\beta_0]$ $= \beta_1$	$In(OR) = In(O_1 / O_0) = In(O_1) - In(O_0)$ $= [\beta_0 + 1*\beta_1] - [\beta_0 + 0*\beta_1]$ $= [\beta_0 + \beta_1] - [\beta_0]$ $= \beta_1$
	95% CI = β_1 +/- ($_1$.96*SE(β_1))	so RR = $\exp(\beta_1)$ and 95% CI = $\exp(\beta_1 + /- (1.96*SE(\beta_1)))$	so OR = $\exp(\beta_1)$ and 95% CI = $\exp(\beta_1 + / - (1.96 * SE(\beta_1)))$
R Commands	glm(death ~ bord5, family = "binomial"(link = "identity"), data = dat)	glm(death ~ bord5, family = "binomial"(link = "log"), data = dat)	glm(death ~ bord5, family = "binomial"(link = "logit"), data = dat)