

Suppose we hypothesize that the variable x causes the variable y, and we want to estimate the marginal effect of x on y. So, we estimate the population equation:

$$y_i = \beta_0 + \beta_1 x_i + \lambda y_i \in \mathcal{C}_i$$

and find:

Coefficients:

Estimate Std. Error t value Pr(>|t|)
(Intercept) 1.98142 0.17845 11.10 <2e-16 ***
x -0.02331 0.29188 -0.08 0.936

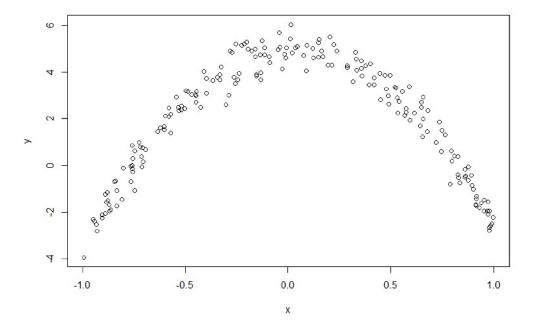
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 2.521 on 198 degrees of freedom Multiple R-squared: 3.22e-05, Adjusted R-squared: -0.005018 F-statistic: 0.006376 on 1 and 198 DF, p-value: 0.9364

What do you conclude? x is insignificant

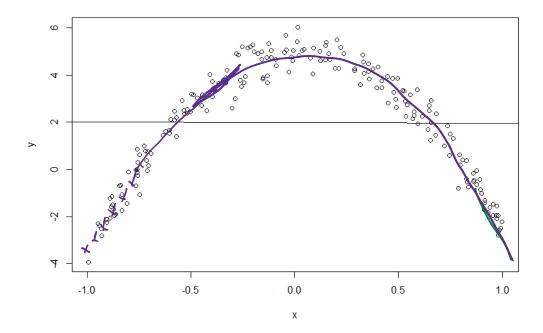
× cannot cause y

We are missing the possibility of a nonlinear relationship between y and x. plot(x, y)



Plot the fitted line form the linear regression:

abline($lm(y \sim x)$)



The linear model is *misspecified* (a form of omitted variable bias). We can approximate the nonlinear relationship using a polynomial, and instead specify the population model:

$$y_i = \beta_0 + \beta_1 x_i + \beta_2 x_i^2 + \beta_3 x_i^3 + u_i^*$$
.

Usually a quadratic form is enough, but we have included x_i^3 as well.

We create the new variables:

We find that x_i^3 is insignificant, so we remove it from the estimated model:

$$summary(1m(y \sim x + x2))$$

How to interpret the estimated model? Have to consider specific values for x_i .

predict
$$|x=-1|$$
 - predict $|x=-1|$ = m.e. at $|x=-1|$ predict $|x=1|$ = " $|x=1|$