# Simple derivation of omitted variables bias 

## EDS 222

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Omitted variables bias is a common violation of the exogeneity assumption of Ordinary Least Squares (OLS), and causes estimated regression coefficients to be biased relative to true population parameters. Omitted variables bias arises when there exists a variable that you are not including in your regression but that satisfies the following two conditions:

1. The omitted variable is correlated with your dependent variable of interest
2. The omitted variable is correlated with at least one of your independent variables

Note that if only one of these conditions is met, you do not have a problem. To see how this bias arises mathematically, suppose the following relationship represents the true population relationship between $y$ and $x_{1}$ and $x_{2}$ :

$$
y=\beta_{0}+\beta_{1} x_{1}+\beta_{2} x_{2}+\varepsilon
$$

But suppose you only are really interested in $x_{1}$, and therefore you only include $x_{1}$ in your regression, ignoring $x_{2}$. What goes wrong?

First, note that condition $\# 1$ above holds as long as $\beta_{2}>0$, since the true population model tells us that a one unit change in $x_{2}$ causes a $\beta_{2}$ unit change in $y$. If the second condition also holds, we can write $x_{2}$ as a function of $x_{1}$ :

$$
x_{2}=\delta_{0}+\delta_{1} x_{1}+e
$$

If you do not include $x_{2}$ in your regression, its effect on $y$ is subsumed in your error term, i.e. variation in $y$ that is not explained by your model:

$$
y=\beta_{0}+\beta_{1} x_{1}+\nu
$$

where $\nu=\beta_{2} x_{2}+\varepsilon$.
We can substitute our expression for $x_{2}$ into this expression and rearrange terms to see that:

$$
\begin{aligned}
y & =\beta_{0}+\beta_{1} x_{1}+\nu \\
& =\beta_{0}+\beta_{1} x_{1}+\beta_{2}\left(\delta_{0}+\delta_{1} x_{1}+e\right)+\varepsilon \\
& =\beta_{0}+\beta_{2} \delta_{0}+\left(\beta_{1}+\beta_{2} \delta_{1}\right) x_{1}+\beta_{2} e+\varepsilon
\end{aligned}
$$

When we regress $y$ only on $x_{1}$, ignoring $x_{2}$, we therefore obtain:

$$
y=\underbrace{\beta_{0}+\beta_{2} \delta_{0}}_{\text {intercept }}+\underbrace{\left(\beta_{1}+\beta_{2} \delta_{1}\right)}_{\text {slope }} x_{1}+\eta
$$

where $\eta$ is mean zero because we assume that both $e$ and $\varepsilon$ are mean zero.
What's the problem? Our estimated intercept is now $\beta_{0}+\beta_{2} \delta_{0}$ and our estimated slope is now $\beta_{1}+\beta_{2} \delta_{1}$, both of which are biased estimators of the true $\beta_{0}$ and $\beta_{1}$ that we are after.

Note that these expressions help you think through which direction your bias is likely to go in practice. If $\beta_{2}$ and $\delta_{1}$ are both positive, meaning that $y$ and $x_{2}$ are positively related as well as $x_{2}$ and $x_{1}$, your slope coefficient will be biased upward when you omit $x_{2}$ (and therefore your estimated slope coefficient should fall when you add $x_{2}$ into the regression). In contrast, if either $\beta_{2}$ or $\delta_{1}$ is negative, your slope coefficient will be biased downward when you omit $x_{2}$, and adding $x_{2}$ into your regression should increase your estimated slope coefficient.

