# Causal Diagrams and the Identification of Causal Effects

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The structural equations derived from the causal graph must be regarded as **stable autonomous mechanisms**. That is, the function should not change when the values of any variable change. I wonder if this stability condition would be violated if the edge between two variables were represented by a vector function that takes on two several functional forms depending on the value of some input. For example, is $Y = f_Y(X, Z_2, Z_3, \varepsilon_Y)$ allowed to be $Y = X + Z_2 + Z_3$ if $Z_3$ is zero and $Y = X \times Z_2 \times Z_3$ if $Z_3$ is non-zero? I do not understand why such an equation would be invalid. In fact, any sort of binary choice may change the functional form of the effect of $X$ on $Y$. If I am correct about this, then I am not sure what Pearl is ruling out by stating that structural equations must be stable autonomous mechanisms.

A new concept introduced in this chapter is the **front-door criterion**. I had never seen an argument such as the one presented in the toy example of Figure 3.5 that is the equivalent in economics. It basically states that if $X$ and $Y$ have a common unobserved confounder, but the effect of $X$ on $Y$ goes through a single observed mediator $Z$, then the causal effect of $X$ on $Y$ can be obtained from the effect of $X$ on $Z$ and $Z$ on $Y$. Perhaps the existence of such observed mediators is quite uncommon. The relevance, however, is that when there is a single immediate cause $Z$, then the general cause $X$ can be identified.

An incredible advantage of causal graphs is the ability to **query graphs for identification**. That is, the graph embeds assumptions which are hopefully sufficient for identifying causal effects without having to explicate the model in more detail. Some cool general conditions can be derived from graphs. For example, a necessary condition for identifying the effect of $X$ on $Y$ is the absence of a confounding arc between $X$ and any child of $X$ that is an ancestor of $Y$. Indeed, the constraints posed by the graph are complete in the sense that they are sufficient for deriving every valid statement about causal processes, interventions, and counterfactuals (something that is not possible in the potential outcomes framework).

The **Rules of *do* Calculus** were extremely confusing. What are we trying to do with them? If we have a graph, can't we simply use Bayes-ball to determine identification? If anyone has an intuitive answer, please share.