Chapter 3: Making Assumptions

Policy effects

It is helpful to classify the assumptions used in policy analysis into one of three categories:

1. Policy or behavioral effect assumptions,
2. biological or engineering assumptions,
3. and counting assumptions.

Policy effect assumptions describe how behavior changes in response to a change in policy (for example, how does menu labeling change the share of consumers who order low calorie meals). Biological or engineering assumptions describe natural processes (for example, the relationship between calories consumed and weight). The other category encompasses everything else. I've named it "counting assumptions" for lack of a better term.

Before discussing policy effect assumptions, we'll briefly address the second and third categories.

Biological or engineering assumptions describe natural or mechanical processes. For example, what is the relationship between calories consumed and weight? How does smoking affect the likelihood of developing lung cancer? Or, what is the impact of wearing a helmet on the likelihood of suffering a severe head injury during a bicycle accident?

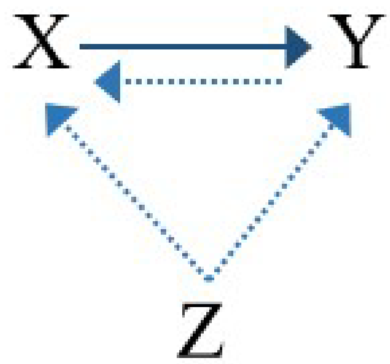
Counting assumptions are generally assumptions about rates, percentages, averages, and totals. How often do people eat out at restaurants? How many calories do they consume? What share of the population is obese? What is the average cost of treating diabetes? What share of bike riders use helmets? The research that underlies these assumptions relies on measurement, counting, and tabulation. Sometimes it is hard to find evidence on which to base counting assumptions, but that is just because someone hasn't performed the relevant count yet.

Policy effect assumptions are much more difficult to get right because they involve predicting changes in behavior. For example, if you require people to wear bike helmets, will they bike less?

In most applications individuals are the actors, but in some cases we are interested in the behavior of firms or even states. The Republican's American Health Care Act gives states the option of waiving various insurance regulations established by the Affordable Care Act. The Congressional Budget Office needed to consider how states would behave under the Act to model its effects.

Internal validity and external generalizability

An estimate of the impact of variable X on variable Y is confounded if there is an unobserved variable Z that is related to both X and Y. Estimates from randomized trials are inherently unconfounded. Randomization equalizes the distribution of the unobserved variable Z between the treatment and control groups.



Suppose we want to estimate the impact of graduating from college on health. A study that compares health between college graduates and non-graduates will be subject to several sources of bias.

- College graduates have other characteristics – such as growing up in more stable, well-off homes – that are related to health.
- Just as education influences health, health also influences educational attainment. People who expect to live longer get more education. They have a longer time over which to reap the benefits. In the case, the direction of causation is not clear.
- People with serious chronic diseases or mental illnesses may have trouble getting into and staying enrolled in college.

When estimating causal effects, statisticians speak of the "assignment process". What is the mechanism by which some humans end up with a college degree and others do not? If the assignment process depends on factors related to health, then estimates from cross sectional studies will be biased. Controlling for individual and family characteristics in a multivariable regression can reduce the degree of bias, but it does not eliminate it. There are always unobserved factors that cannot be measured.

Estimates of the impact of changes in policy on behavior are often based on observational, non-randomized studies. Studies have to be evaluated based on how they address confounding and reverse causation.

Studies that assess biological relationships can also be biased by confounding and reverse causation. Claims about the impact of drinking red wine on cardiovascular health are based on surveys where respondents are asked about prior wine consumption and health. People who drink wine tend to be better-educated and have higher incomes. We can control for some, but not all of these differences, leading studies to overstate the impact of drinking wine on health.

Hidden assumptions

When reading and conducting policy analyses, be aware of "hidden assumptions": assumptions that are implicit rather than explicit. Sometimes these implicit assumptions turn out to be more important than the assumptions that are stated explicitly.

For example, several analyses have projected the impact of Medicare-for-All on health care spending. A major source of savings to overall health spending (as opposed to spending by the federal government) is that Medicare reimbursement rates are much lower than private insurers' reimbursement rates. Shifting everyone who is currently privately insured into Medicare results in billions of dollars of savings as a result of the fee diffential.

Policy analysts calculate savings using assumptions about the difference in reimbursement rates and total spending by category. For example, if hospital spending among individuals with private insurance is $200 billion, and Medicare payment rates are 90% of private insurers' payments, then Medicare-for-All will reduce hospital spending by $40 billion = ([1.0-0.9] × $400).

There is a hidden, implicit assumption behind this calculation: that the volume and intensity of treatment is unaffected by fee changes. Put another way, hospitals continue to treat patients the same way after the fee cut. But that isn't exactly true. There are a number of studies that show that reductions in reimbursement levels change treatment decisions. In most cases, reductions in fees cause treatment intensity to decline, but the opposite is possible. Is the hidden assumption a bad assumption? It depends on the magnitude of the responsiveness of treatment intensity to fee changes. If the response is sufficiently small, then analysts were correct in ignoring it. If not, they may have mis-estimated (probably underestimated) savings.

The point is this: train yourself to be on the lookup for hidden assumptions. Just because an assumption is hidden does not mean the authors of the analysis were trying to mislead you. They may have correctly believed that it was inconsequential. But maybe it wasn't.

A case in point: In 1978 California enacted building codes to reduce electricity and gas consumption. Engineers projected that the revised codes, which affected everything from insulation to air conditioners, would reduce energy use by 77% (see the Table).[1] The projections were inaccurate. A later study[1] found that newer homes, which were subject to the new energy-saving building requirements, actually used more electricity than older homes

[1] Levinson A. How much do building energy codes save? Evidence from California houses. *American Economic Review* 2016;106(10):2867-2894.

The engineers' projections were based on the mechanical relationships between the various energy-saving features and energy use. The real-world experience reflects these relationships as well as human behavior.

The study did not measure how behavior changed in response to the building codes, but we can speculate. Energy-efficient systems are cheaper to run, and so homeowners may have set their thermostats at cooler temperatures in the summer and warmer temperatures in the winter. They may have been more careless about leaving doors and windows open. Whatever the reason, the original analysis that failed to consider how policy changes would change behavior missed the mark by a wide margin. The implicit assumption in the engineers' analysis was homeowners would behave the same way regardless of whether they were in an old or new home. It turned out to be incorrect.

Table 1—Projected Costs and Savings from 1980 California Energy Codes: Single-Family Homes, Sacramento

	Business as usual (1)	Regulation (2)	Difference (3)
Insulation	—	$2,831	$2,831
Window glazing	$879	2,108	1,229
Overhang	—	468	468
Shading	—	360	360
Caulking, sealing, etc.	—	551	551
Thermostat	82	138	56
Heating system	1,360	1,360	—
Cooling system	1,129	965	−164
Duct insulation	—	61	61
Total building envelope	$3,450	$8,842	$5,392
Water heater	284	2,736	2,452
Lighting	97	333	236
Total initial cost	$3,831	$11,911	$8,080
Total energy (1,000 BTU)	187,209	43,025	−144,184
Energy savings			−77%

Note: The median California home price in 1980 was $80,000.
Source: Horn et al. (1980)

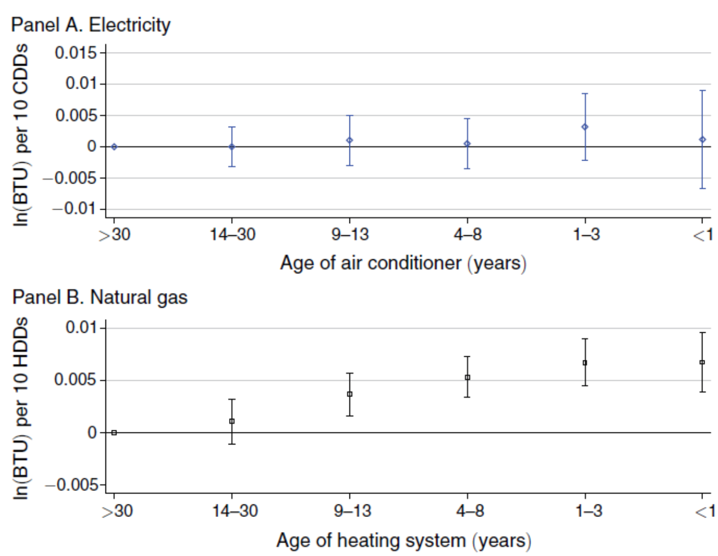


Figure 7. Energy Use and Age of Air Conditioner and Heater

Generalizability

Generalizability or external validity refers to the degree to which an estimate from a study is applicable to the larger world.

In the case of policy analysis, generalizability refers to the similarity between the population affected by the policy change and the population included in the study on which an assumption is based. If you were to redo the study on the population affected by the policy change, would you get the same result? "Population" here should be read broadly to incorporate characteristics of individuals as wells aspects of the time and place.

Suppose you wanted to project the impact of a policy that would provide college scholarships to low-income students on future earnings. When looking for estimates of the impact of entry to college on future earnings, you would have to consider whether estimates are applicable to the students who will be eligible for the program and for whom the scholarship program will affect their decision to attend college.

Sources for estimates of policy effects

Medline, which indexes articles in medical and public health journals, and Econlit, which indexes articles in economics journals, are your best bets for finding good estimates of policy effects. (In Emory's library system you access Medline via the Ovid platform. Outside of Emory, you can use Pubmed.) There is some overlap between them.

Be careful about using Google. The first hits are not necessarily the best. The *Journal of the American Association* published a study showing that hospitals with high nurse staffing levels have lower patient mortality rates.[2] The study received a lot of attention. As often happens when a study makes a splash, other researchers reexamined the question using different datasets and study designs. Some of these reached a different conclusion. If you Google "nurse staffing patient mortality" the *Journal of the American Association* paper is the first hit. There are good studies that do not appear in the first 50 hits. You will find these using Medline and Econlit, but not Google.

Another reason to be wary of Google: Some poor quality studies receive a lot of media attention, which boosts the study in Google's rankings. Studies that show that coffee/dark chocolate/wine/green tea are associated with better health outcomes get covered in the press. Studies that show that coffee/dark chocolate /wine/green tea are unrelated to health outcomes do not.

Don't try this at home

It is almost always preferable to base assumptions about the impact of policies on previously-conducted studies rather than trying to conduct an original study. Performing a good original study takes time and an in-depth understanding of the policy and data sources.

Casual analyses – analyses done quickly with limited knowledge of policy, data, and study design – are likely to lead you astray, though you see them all the time in the press. The Law Center to Prevent Gun Violence assigns a grade to each state based on its gun control measures. In 2016, Illinois earned a B+, indicating that the state has laws that restrict access to firearms, and Florida earned an F for its less restrictive laws.[3] The 2015 murder rate was 6.9 per 100,000 in Illinois and 6.3 per 100,000 in Florida. So, obviously allowing easy access to firearms reduces the murder rate, right? Perhaps, but you don't really learn much from this casual analysis.

A number of studies have examined the impact of gun laws on deaths. How do they differ from a simple comparison of two states?

- They do not ignore data. They include all 50 states.
- They adjust for other factors (for example, percent of residents in poverty) that may affect murder rates.

[2] Aiken LH, Clarke SP, Sloane DM, Sochalski J, Silber JH. Hospital nurse staffing and patient mortality, nurse burnout, and job dissatisfaction. *Journal of the American Medical Association* 2002 Oct 23-30;288(16):1987-93.

[3] Law Center to Prevent Gun Violence 2016 Gun Law State Scorecard. http://gunlawscorecard.org/

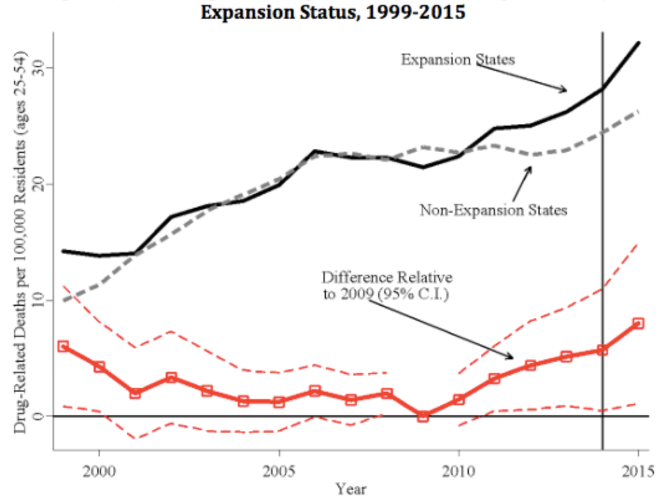
- They carefully consider measurement issues. Should the outcome be murder rates or gun deaths (which include suicides)? What about people who were shot and survived?
- They compare changes in deaths in states that changed gun laws to changes in states that did not, thereby controlling for unobserved factors that differ between states.

Here are two cases of casual analysis gone wrong.

Case 1. Some prescription opioids are expensive. Senator Ron Johnson (R-WI) argued that Medicaid expansion under the Affordable Care Act helped fuel the opioid epidemic by making it easier for patients to obtain low-cost drugs. Here is a quote from an August 15, 2017 editorial in the *Wall Street Journal*.[4]

> Wisconsin Sen. Ron Johnson presents intriguing evidence that the Medicaid expansion under ObamaCare may be contributing to the rise in opioid abuse. According to a federal Health and Human Services analysis requested by the Senator, overdose deaths per million residents rose twice as fast in the 29 Medicaid expansion states—those that increased eligibility to 138% from 100% of the poverty line—than in the 21 non-expansion states between 2013 and 2015.
>
> There were also marked disparities between neighboring states based on whether they opted into ObamaCare's Medicaid expansion. Deaths increased twice as much in New Hampshire (108%) and Maryland (44%)—expansion states—than in Maine (55%) and Virginia (22%). Drug fatalities shot up by 41% in Ohio while climbing 3% in non-expansion Wisconsin.

Figure 1. Age-Adjusted Drug-Poisoning Mortality Rate for Ages 25-54 by Medicaid Expansion Status, 1999-2015



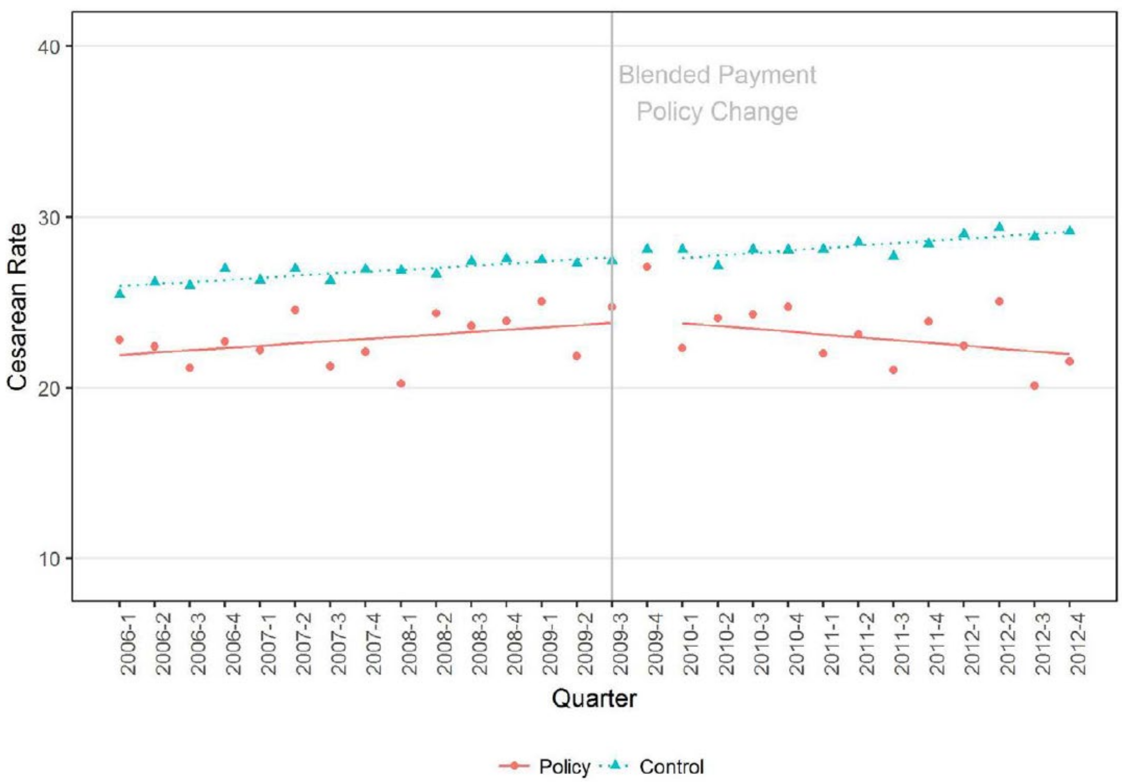
Different versions of this claim have been made in many venues. Two researchers[5] took a closer look. They found that drug-related deaths increased more rapidly in states that expanded Medicaid under the Affordable Care Act. However, drug-related death rates were growing more rapidly in expansions states *before* the Medicaid expansion occurred in 2014. In fact increases in drug deaths may have served as the impetus for some states to expand Medicaid. These data are uninformative about the impact of Medicaid expansion on opioid abuse.

[4] Medicaid's Opioid Fix. *Wall St. Journal* August 15, 2017.
[5] Goodman-Bacon A, Sandoe E. Did Medicaid Expansion Cause The Opioid Epidemic? There's Little Evidence That It Did. *Health Affairs Blog* August 23, 2017.

Case 2. Before October 2009, Medicaid in Minnesota paid hospitals $5,266 for a Cesarean birth and $3,144 for a vaginal birth. Medicaid paid physicians $1,147 for a Cesarean birth and $776 for a vaginal birth. Concerned that the higher payment rates for C-sections were leading to its overuse, the state adopted a blended payment rate in October 2009. Medicaid would pay the same amount regardless of delivery mode.

In 2015 Medicaid reversed the policy and went back to the old approach. One of the factors that influenced the decision was internal data showing that Cesarean section rates did not decline.

The figure below shows results from an independent study of the impact of the policy.[6] An analysis focusing only on the Cesarean section rate in Minnesota (the red line) would show that the Cesarean section rate was around 22% before the policy and 22% after the policy. It did not change. But….rates in a group of control states (the blue line) were going up before the policy change and continued to increase after it. Viewed against this backdrop, it appears the policy reduced the use of Cesarean section, as intended.



[6] Kozhimannil KB, Graves AJ, Ecklund Am, Shah N, Aggarwal R, Snowden. Cesarean delivery rates and costs of childbirth in a state Medicaid program after implementation of a blended payment policy. *Medical Care* In press.