L4: Studies on the demand for health care and health inequality

Marcelo Coca Perraillon

University of Colorado
Anschutz Medical Campus

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Outline

- A detour on causal inference
- Another detour on elasticities
- Do demand curves slope downward?
- Does health insurance affect health outcomes?
- The RAND health insurance experiment
- The Oregon health insurance experiment
- Health disparities and economics

Causal inference

- Before we talk about study results, we need to take a brief detour and talk about causality, and later, elasticities
- If you made it this far in your education, by know you know that **correlation does not imply causation**
- If something happens after another thing happens, it doesn't mean that one of them caused the other
- If a person who has a health plan with higher copays uses less medical care than a person with lower copays, it doesn't mean that it is because of the higher copays
- If we look at the data and find that people who take antidepressants have worse outcomes, it doesn't mean that antidepressants are bad for health
- If the health outcomes of a person who is covered by Medicaid compared to a similar person without Medicaid are worse, it doesn't mean that Medicaid is bad for health
- The more interesting question is: **under which circumstance correlation does imply causation?**

Populations, samples, inference, causal inference

- We have this model in statistics, econometrics, biostatistics (same stuff, different jargon) that is very powerful
- We assume that there is a population out there that is very large (infinity for technical reasons) – people with Medicaid, people who have depression
- We take a sample from that population, we analyze it, and then we make **inferences about the population**
- **Inference**: "a conclusion reached on the basis of evidence and reasoning"
- To be able make good inferences, a lot of conditions must hold, and that's when life gets fairly complicated
- Even the decennial "census" is not truly a census and is also based on sampling and adjusting for non-response
- To make inferences are about cause and effect, we need even more conditions to hold – that's **causal inference**

Randomization

- A powerful method that in the history of humanity scale was developed today, about 4 hours ago, is **randomization**
- The idea is very simple: you have a large number of “units” (people, hospitals, classrooms, ect)
- You randomly divide the units into two or more groups. You them apply a treatment to one group and not the other (or different versions of a treatment)
- You compare **average** outcomes among the groups to determine if a treatment (aka exposure in epi) causes the outcome
- The reason randomization works is that the groups are, on average, identical. If you truly used a random system to assign them to the different groups and sample sizes are large enough, the fact that one received the treatment has nothing to do with anything else – it was random
- If the group (as a group!) are the same and the only thing that changes is the treatment, then one group provides a **conterfactual** for the other
- **Conterfactual**: relating to or expressing what has not happened or is not the case.

Definition of causal effects

- The definition of causal requires an alternative universe to make sense
- What we need to understand is, what would have happened to the control had the control group received the treatment? And the other part too: what would have happened to the treated group had the treated group not been treated? The conterfactuals
- Since we can't observe both universes, we rely on randomization to obtain **average** treatment effects (that's often called the "fundamental problem of causal inference")
- In a sense, causal inference is a **prediction problem**. We want to predict what would have happened. We use one group to make predictions about the other
- **We can't obtain individual-level treatment effects** (unless we start making strong assumptions)
- Note that the **key ingredient in this mind-bending story was random treatment assignment**

What if treatment is not random?

- Outside controlled experiments, treatment assignment is not random
- In an **observational study** (that is, without manipulation), individuals not taking an antidepressant are not comparable to those who do not take antidepressants
- Individuals who obtain Medicaid are different than "similar" individuals who do not have Medicaid. The reason is that we can only compare things we can observe. They may look "similar" in things we can see but not in things we cannot see
- One of them is disease. Low-income individuals tend to obtain Medicaid **because** they are sicker
- People who enroll in high copay plans are different than those who don't
- **Without experiments, it's very difficult to use observational data to make causal statements**
- Think about using observed prices and quantities to estimate supply and demand curves. How could we estimate any if what we observe are equilibrium prices and quantities?

The key question to ask

- The key question when you try to come up with a method to study observation data is this: **Why some people ended up receiving "treatment"**?
- Treatment can be actual treatment as we often use the word or it can be a policy change or a different set of conditions: having insurance, having higher copays, etc
- Once you start thinking about the reasons why some people received treatment, you notice the **selection problem**
- Antidepressants? Severity of depression, family history, suicidal thoughts. Medicaid? Disease. Higher copay? Expectation of lower health care needs (often higher copays mean lower premiums)

Not all is lost

- Coming up with research designs using observational data is not easy but it's not impossible either
- There a lot of clever things that we could do to get answers, although it's hard to know if the clever things work
- In general, these methods are called "quasi-experimental" or "natural experiments;" they come in different names
- If you are interested in more details on causal inference, see these class notes: `https://clas.ucdenver.edu/marcelo-perraillon/sites/default/files/attached-files/w2_causal_inference_perraillon_0.pdf`
- Or take my other class: `https://clas.ucdenver.edu/marcelo-perraillon/teaching/health-services-research-methods-i-hsmp-7607`

Elasticity

- Elasticity is one of those econ concepts that confuses students even though it's fairly simple
- When we talk about how a change in the the price of something affects the quantity demanded, units matter
- A \$20 increase in the price of of a hamburger is not the same as \$20 increase in the price of a new Tesla
- Intuitively, percentages matter. \$20 increase in the price of a hamburger could be a 50% increase, while for a new Tesla is a minuscule increase
- Economists use elasticities to measure the effect of price changes in the same scale: **percentages**. That's it. Really, that's all you need to remember
- If prices increased by 1 percent, what is the percent decrease in quantity demanded?

Elasticity, calculation

- Percent change: a change from \$12 to \$20 is a 66.67% increase: $\frac{(20-12)}{12} = 0.666667$
- Let's call the original price P_1 and the new price P_2. We can then write the formula as $\frac{(P_2 - P_1)}{P_1}$ or $\frac{\Delta P}{P_1}$
- The elasticity tells how a 1 percent change in the price of a product changes the quantity demanded:

  $\epsilon = \frac{\frac{\Delta Q}{Q_1}}{\frac{\Delta P}{P_1}} = \frac{\Delta Q}{\Delta P}\frac{P_1}{Q_1}$
- The Law of Demand tells us that the price elasticity of demand is negative since a price increase leads to a reduction in the quantity demanded

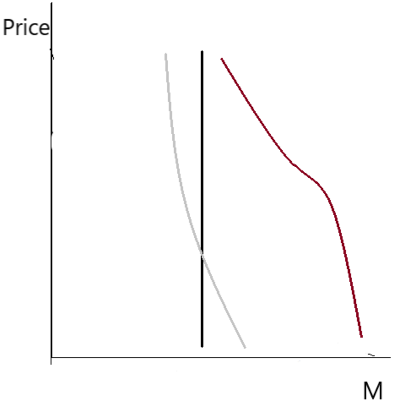
Elasticity, calculation

- When calculating percent changes, the base matters. The change from \$12 to \$20 could be expressed the other way around, as a reduction $\frac{(12-20)}{20} = -0.4$
- (People get confused with this a lot. If the stock market declines by 50% one day, it needs to increase by much more than 50% to get back to the same level. Say, it was 100. 50% decline is 50. To get back to 100, it needs to increase by a 100%)
- To avoid the issue of defining elasticities using a starting point, the **arc elasticity** used. Pick up the mid point instead:

  $E = \frac{\frac{\Delta Q}{(Q_1+Q_2)/2}}{\frac{\Delta P}{(P_1+P_2)/2}}$
- Dividing by two is the same as multiplying by $\frac{1}{2}$ so that will cancel out (your textbook has the formula without dividing by 2)
- Elasticity less than 1 in absolute value are usually considered "inelastic"

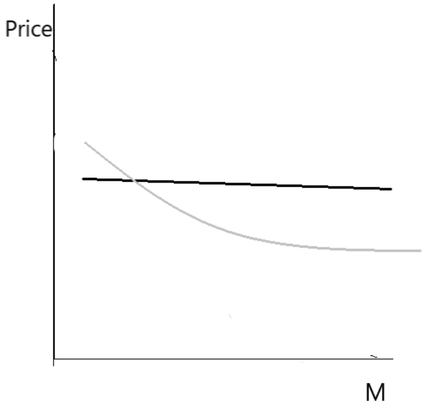
Elasticity tells us about the slope of the demand curve

- Is the demand curve sort of vertical or close to horizontal?
- If more vertical, then the demand is inelastic (close to zero). People demand the same quantity regardless of the price. Below are 3 different demand curves



More elastic

- The flatter the curve the more elastic (close to infinity). Small price changes have large effects on the quantity demanded



Elasticity, intuition

- Intuitively, things are that are cheaper or essential or not a big proportion of our income will be inelastic: salt, sugar, flour, water
- Things that are not essential or can be a large part of our budgets are going to be more elastic: cocktails, restaurant meals, ski passes, gym memberships, cars. The ability to find substitutes matter, of course

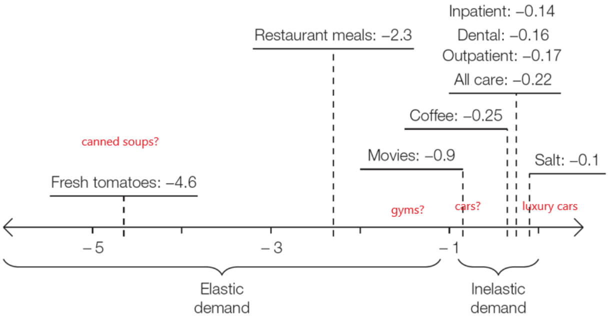


Figure 2.5. *Elasticities of various goods.*

Source: Developed from Newhouse (1993) and Gwartney et al. (2008).

Figure: Adapted form BHT, Chapter 2

What is the elasticity of health care products and services?

- This is a fundamental question in health economics with implications for health reform and policy
- Historically, the first question was whether the demand for health care "slopes downward" or was sort of vertical
- If people care so much about their health, aren't they going to have a rather vertical demand curve? Regardless of price, they will not change their quantity demanded
- This is the question the RAND health insurance experiment tried to answer
- The historical context matters. The RAND HIE was in the 80s, when health care prices and income inequality were not like they are today
- There is not much of a surprise regarding RAND HIE findings: health care elasticity is not zero – the law of demand holds

Big picture

- Read your textbook... But your textbook presents the RAND health insurance experiment and the Oregon “experiment” together
- I think that’s a conceptual mistake. Very different populations with different research questions and different circumstances
- RAND: what is the effect of prices (copays) on quantity demanded in a **representative sample with insurance coverage in the 80s**?
- Oregon: What is the effect of obtaining Medicaid coverage versus no coverage in a **low-income population around 2008**?
- Different research questions and settings even if both can tell us something about the demand for health care
- Both are less able to tell us something about the effect of insurance on health outcomes (we’ll see why)

RAND HIE basics

- Obviously, you do need to read your textbook, but also see Aron-Dine, Einav, and Finkelstein (2013) (PhD students, not a suggestion...)
- Between 1974 and 1981 5,800 individuals from around 2000 households in six different geographical areas were randomly allocated to receive different "treatments," which in this case meant different insurance plans
- People were selected as to be representative of the US population
- The health care received was "held constant," although some had different plans
- The main difference between the plans was the amount of **cost-sharing**: some plans have none (which means **free**, from the point of the view of patient) to almost none up a certain amount ($4000 in 2011 dollars)
- Following your textbook: Free, 25%, 50%, and 95% (there were other plans)
- One reason we will never see an experiment like this is the price tag: about $295 million in 2001 dollars

RAND HIE

Table 1

Plan Summary Statistics and Refusal and Attrition Rates

Plan	*Individuals (families)*	*Average out-of-pocket share*[c]	*Share refusing enrollment*	*Share attriting*	*Share refusing or attriting*
Free Care	1,894 (626)	0%	6%	5%	12%
25% Coinsurance	647 (224)	23%	20%	6%	26%
Mixed Coinsurance[a]	490 (172)	28%	19%	9%	26%
50% Coinsurance	383 (130)	44%	17%	4%	21%
Individual Deductible[b]	1,276 (451)	59%	18%	13%	28%
95% Coinsurance	1,121 (382)	76%	24%	17%	37%
All plans	5,811 (1,985)	34%	16%	10%	24%
p-value, all plans equal			<0.0001	<0.0001	<0.0001
p-value, Free Care vs. 95%			<0.0001	<0.0001	<0.0001
p-value, Free Care vs. 25%			0.0001	0.5590	0.0001
p-value, 25% vs. 95%			0.4100	0.0003	0.0136

Notes: "Coinsurance rate" refers to the share of the cost that is paid by the individual. In the 25 percent, mixed, 50 percent, and 95 percent coinsurance rate plans, families were assigned out-of-pocket maximums of 5 percent, 10 percent, or 15 percent of family income, up to a limit of $750 or $1,000. In the individual deductible plan, the out-of-pocket maximum was $150 per-person up to a maximum of $450 per family. The sample counts for the 95 percent coinsurance rate plans include 371 individuals who faced a 100 percent coinsurance rate in the first year of the experiment. Refusal and attrition rates are regression-adjusted for site and contact month fixed effects and interactions, because plan assignment was random only conditional on site and month of enrollment (see Newhouse et al. 1993, appendix B). "Contact month" refers to the month in which the family was first contacted by the experiment and is used in lieu of month of enrollment because month of enrollment is available only for individuals who agreed to enroll. Refusal and attrition rates exclude the experiment's Dayton site (which accounted for 1,137 enrollees) because data on Dayton refusers were lost. An individual is categorized as having attrited if he leaves the experiment at any time prior to completion.

[a] The "Mixed Coinsurance" plan had a coinsurance rate of 50 percent for dental and outpatient mental health services, and a coinsurance rate of 25 percent for all other services.

Figure: Source: Dine, Einav, and Finkelstein (2013)

RAND HIE, main findings

- Remember that in the RAND HIE, nobody was uninsured. The point of RAND was about the impact of cost-sharing (copays) on quantity demanded
- I'll use your textbook numbers. The most quoted number of the RAND HIE is the **overall elasticity**: -0.2. A 10% increase in copays reduces quantity demanded by 2%
- **Outpatient care**: As copayments increased, the number of outpatients episodes decreased – a large decrease: 36% difference from free to 95%
- The same was true for those with chronic and acute conditions. So a person with diabetes may not not visit the doctor as much; same as a person who has a bad headache
- Or people might skip on cancer screening; that's clearly not good

RAND HIE, main findings

- Similar results were found for other types of utilization like inpatient and outpatient
- The exact numbers are different than outpatient visits but not that different
- There was even a difference for ER use. You would think that ER visits would be more inelastic
- The probability of ER visits went down from 22% for the free group to 15% for the 95% (remember, there was a cap to out of pocket expenses; it's not that they had to pay 95% of price of a surgery, for example). That's a 30 percent decline
- So the law of demand holds in health care
- **See this another way:** If we make health care free for all, that means that utilization, and therefore costs, will increase, not decrease
- For a comprehensive description of RAND HIE, see Joseph Newhouses's (1993) book "Free for all?"

The Oregon Medicaid "experiment"

- The Oregon Medicaid experiment is more recent, around 2008. The reason I put experiment in quotation marks is that it wasn't really an experiment
- Oregon had some extra money for their Medicaid program. Rather than giving more Medicaid coverage to some people, they had a lottery to give people the chance to receive Medicaid
- So they accidentally created a sort of randomized experiment since the lottery was, well, random. So it was (sort of) random who got Medicaid
- One important caveat is that not all the people who won the lottery actually enrolled. Some decided not to. **What was randomized was the opportunity to enroll in Medicaid, not the same as randomizing receiving Medicaid**
- This creates some technical issues. The groups are not comparable since we don't know why some people decided to not enroll in Medicaid. Maybe this are the people that are healthier so they didn't bother to enroll?
- The analysis of the Oregon used **instrumental variables** in the analysis. See towards the end of these slides for an intro to this method: `https://clas.ucdenver.edu/marcelo-perraillon/sites/default/files/attached-files/week_10_rdd_perraillon_0.pdf`

The Oregon Medicaid “experiment”

- Note the key difference with RAND HIE
- Those who got Medicaid would incur Medicaid copays, which in general are low or non-existing – vary by state
- Those who did not win the lottery presumably had no insurance and must pay out-of-pocket or just don't pay if they need emergency care
- We still can get some information about elasticities, but the setting is different and the population very different
- Not to mention the world in 2008 is very different than the world around 1980
- There is also the underlying (rather political) issue behind Medicaid: Medicaid is often seen as a very costly program without much apparent benefits

What are the main findings?

- Similar to RAND's for outpatient but no so much for inpatient and ER
- ER utilization was a surprise. One way low-income people can get medical is care is by going to the ER, since care cannot be denied
- The logic was that having access to Medicaid would significantly reduce ER visits
- But that did not happen. One reasonable explanation is that just having Medicaid does not translate into having access to a regular doctor

What about health and other outcomes?

- If people do not seek medical care because of prices, is health affected?
- Both RAND and Oregon did not find much evidence of an effect on health (with some exceptions here and there)
- There are many reasons for this finding, the most likely being that the follow-up was limited
- There are other observational or quasi-experimental studies that can better answer this question
- The Oregon experiment found effects on financial security and mental health
- A note on the term "**moral hazard**:" Different usage. Original: "medical insurance increases the demand for medical care" or more often used as in "price sensitivity of health care demand." The problem is that moral hazard implies an underlying *mechanism*. Why is price sensitivity a "moral" hazard? The law of demand is not related to morality. Better to save the term for: "tendency for insurance against loss to reduce incentives to prevent or minimize the cost of loss." Not sure if moral either by just a word

Health inequality

- Related but somewhat different, what do economics and the Grossman model can tell us about health disparities?
- Why some people are in better health than others?
- If we understand the "why," can we design policy interventions to reduce health inequality?
- We will review some hypotheses, all interconnected – and difficult to separate cause and effect:
  1. Income
  2. Income inequality and stress
  3. Racism/discrimination
  4. Education
  5. Early life experiences
  6. Access to care (or access to *better* care)
  7. Different time preferences (the marshmallow hypothesis)

Grossman model, summary

- I'll mix the one-period and lifetime versions to keep the notation simpler (we would need to discount budget constraint)
- Lifetime **utility** (dynamic): $\sum_{t=0}^{T} \frac{1}{(1+\rho)^t} U(H_t, Z_t)$
- **Production functions**:
  1. $H_{t+1} = I_t + (1-\gamma_t)H_t$, or: $H_{t+1} = \theta H(M_t, T_t^H) + (1-\gamma_t)H_t$
  2. $Z_t = Z(T_t^Z, J_t)$
- **Constraints** (one-period):
  1. $\Theta_t = T_t^W + T_t^Z + T_t^H + T_t^S$
  2. $J_t * P_J + M_t * P_M = w * T_t^W$
- Remember a feature (quirk?) of this model: **wage is exogenous**. But wages depend on skills, knowledge, education, which are also investment decisions that take time and resources. Education in Grossman affects production efficiency, so it's there – it's just that we don't model where it's coming from
- The other human capital model (Becker's) is about skill formation (formal, like getting a degree) or informal (on-the-job training, knowledge/skills obtained by other means). That determines wage – it's harder to talk about health disparities with just the Grossman side of human capital

Income

- What is it about income that could have an effect on health? **You can buy more things**
- Imagine two identical people with the same preferences. One has a higher wage than the other
- The person with higher wages will "produce" more health because this person can consume more J and more M. That means that the person with higher wages has an expanded production possibility frontier
- Said another way, the optimal level of health for this person will be higher. In a sense, the person with higher wage has more incentives to stay healthy because his time is more valuable than the person with lower wages. This is a bit odd to make sense outside the Grossman model's logic
- This of course begs the question, why is it that one person has higher wages if they are identical? Where is wage coming from? In economics, it's linked to productivity (and formal education or on-the-job training), but in Grossman wage is "exogenous." **Let's not forget about trust-fund kids here – it's also luck**

Income inequality

- Income inequality is related but somewhat different: is it the **level of income** that matters or the fact that some people make less than others?
- In a country where we *perceive* that anybody has a chance to prosperity and be president, does not being prosperous and a leader implies poorer health?
- In other words, **relative income**, not just absolute income matters
- This is related to the idea that stress has pervasive effects on health (**allostatic load theory**) – "allostatic" is the "the process by which the body responds to stressors in order to regain homeostasis"
- There is plenty of evidence of this in animals, from monkeys to chickens (as in "pecking order")
- In the Grossman model, this would be reflected in the rate of depreciation γ_t
- We saw that a higher depreciation rate makes investments in health more costly. If that comes along with less income to buy M or J, the situation is even worse

Racism and discrimination

- If we are talking about the allostatic load theory, we need to talk about racism and discrimination
- Both are **insidious** ("proceeding in a gradual, subtle way, but with harmful effects") and **pervasive** ("spreading widely throughout an area or a group of people")
- One mechanism is stress, but of course not the only one
- Using the Grossman model, discrimination and stress affect every single lever in the model
- They affect educational attainment (therefore the marginal efficiency of health capital), wages, sick time, and the depreciation rate
- The saddest part is that racism and discrimination can have an impact by just knowing/believing it's there, everywhere (impostor syndrome? Feelings of not belonging?). **Don't fall into this trap**

Education

- Another source of health inequality is education or knowledge more generally – "human capital"
- Similar to income: education makes people better at "producing" health, identical people with different levels of education will have different levels of health
- We saw last week the many ways in which education can have an effect on health
- As with wages, this begs the question of **why people would have different levels of educations**, which leads us to find explanations about early life factors
- **One way of thinking about investments in education and health is that they are complementary**. They are synergistic – so much evidence showing that education impacts health outcomes
- **Feel better**: you're getting a degree and increasing your life expectancy, all in one

Time preferences

- We saw this already, one way in which education affects health in the idea of time preferences, or the discount rate
- How we make trade-offs between present and future has an impact on our decisions. In Grossman, it's the discount rate (ρ): $\sum_{t=0}^{T} \frac{1}{(1+\rho)^t} U(H_t, Z_t)$
- Exercise doesn't feel that great. Eating a hamburger with fries tastes better than a salad. Studying takes a lot of effort – hanging out with friends or watching TV feels better. Checking your email or Twitter or shopping while in class gives you immediate gratification
- We do the hard things because we think the effort will pay-off in the **future**, not now
- You probably have heard of the marshmallow experiments
- **But is delaying gratification innate**? Not sure. There is evidence that inheritance is a factor, but not everything: `https://www.ncbi.nlm.nih.gov/pmc/articles/PMC3036802/`

Barker hypothesis

- The barker hypothesis (or "fetal origins") has generated a lot of interest in medicine, epidemiology, and economics
- The idea is that the environment during gestation (especially nutrition)"programs" the fetus to develop disease in the future
- This view has been fairly controversial, too. The Barker studies were observational
- As I told you last class: think about why people get "treatment"? Treatment here is being exposed to bad things during gestation: mother smoking, poor nutrition, stress, environmental toxins. Obviously, it's not random
- But... some kind of are, so we can study them better: hurricanes, earthquakes, policies implemented in one place but not others, natural events
- Although, you then have to ask: is it random that people live in a hurricane-prone area? Is it random that some people were exposed to famine?

Barker hypothesis

- In the Grossman model, the dynamics of health is given by $H_{t+1} = I_t + (1 - \gamma_t)H_t$
- But in this model, early health shocks would not last a lifetime, **they would eventually fade away**

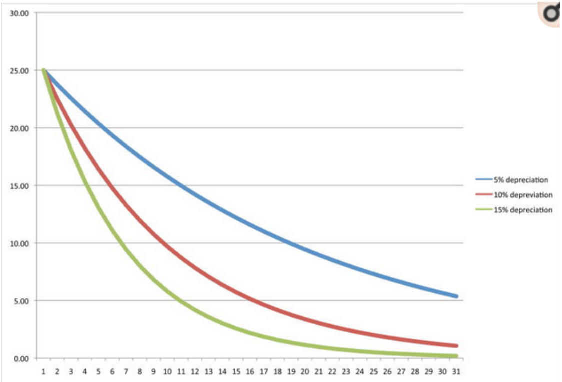


Figure: From Almond and Currie (2011)

Barker hypothesis

- Other models have been proposed based on the idea that investments are **complementary**: investments during pregnancy and after are complements; it's the fact that they complement each other that makes the effect sustainable – in this way, a good start in life has a long-term effect, but so does a bad start
- (The idea of complementary in time has been used to model addiction as well)
- Although there is some evidence on the Barker hypothesis, it probably doesn't explain a large portion of health disparities
- The effects are perhaps not without the possibility of "fixing" with early childhood interventions
- It does highlight the importance of **early interventions**: prenatal care, nutrition, programs to prevent smoking and/or drug use during pregnancy – even stress-reduction interventions like yoga or meditation during pregnancy

Policy

- Taking all these potential explanations together, we can see the importance of policy proposals that target each possible cause
- Some are about health care, but others are actually not about the medical system: they are about **socioeconomic disparities**
- **But we can't address each cause independently**. The human capital models (not just Grossman's) provide a framework to think about these problems
- It also brings back the issue of **choice**. Is the level of health a choice? To a certain extent. It's also about circumstances – and bad luck
- How we frame this problem matters a lot. Look at all the causes again; people with different political views (different "conceptual frameworks") tend to think of the origin of each in a different way
- A lot of this is related to the concept of agency. Is it about personal efforts/behavior or about circumstances? Nature or nurture?