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Econ 280—Bethany College

**Lecture 07: Of Uncertainty, Risk, and Probability**

1. Risk versus Uncertainty
	1. On the surface, there appears no difference between risk and uncertainty. If an investment has risk (and all investments have risk), then the result of the investment is uncertain.
	2. But economist Frank Knight (1921) argues it is worth drawing a distinction between the two.
		1. *Risk* is quantifiable, with all options, but not the outcome, known. A drug can either be approved with such-and-such a chance nor not approved with such-and-such a chance.
		2. *Uncertainty* (or *Knightian Uncertainty*) describes a state where not only the outcome is unknown, but we lack the information necessary to accurately predict the odds. Determining which drugs in thirty years will be popular is impossible to reasonably estimate.
	3. When risk captures most of what faces a business or industry, an exact calculation can be made to determine what course of action to choose.
	4. But when uncertainty dominates consideration, no objective assessment can be made. A lot of uncertainty can discourage a firm or industry from acting at all.
		1. One theory of the economic slowdown is that firms face a lot of uncertainty with regards to public policy. There are many unknowns concerning health care reform, financial reform, Eurozone policy, etc. that many firms are adopting a “wait and see” approach.
2. Probability calculation
	1. It is conventional to express probabilities as fractions or decimals, bounded between zero and one.
	2. If multiple random events *both* have to happen, multiply the probabilities together.
		1. Ex.: finding a deer *and* accurately firing a gun (probability of finding a deer times probability of shooting it equals probably of successfully hunting a deer).
		2. Note this technique only applies if the events are independent. The occurrence of one event doesn’t affect the probability of another event.
	3. If *either* one of several random events have to happen, add the probabilities together.
		1. Ex.: killing exactly one deer or killing exactly two deer (probability of killing one deer plus the probability of killing two deer equals the probability of killing one or two deer).
		2. Note this simple addition only applies if the random events can’t both occur at the same time, or if they are mutually exclusive. If they can occur at the same time, subtract the probability that they will both occur.
	4. Since all probabilities are fractions, more necessary conditions decrease final probability and more sufficient conditions increase it.
3. Ellsberg Paradox
	1. People tend to shy away from decisions involving true uncertainty, or they have *ambiguity aversion*. We prefer risk, which is quantifiable, to uncertainty, which is not. (Exactly how much depends on the person.) We can illustrate this with the Ellsberg Paradox.
	2. Imagine a big bucket of ninety poker chips.
		1. 30 of these chips are red.
		2. 60 of these chips are a mixture of black and/or yellow. There could be 60 yellow and 0 black, 40 yellow and 20 black, etc.
	3. Now you may play either one of two games:
		1. Select a chip at random and get $1 if you select a red one. You thus have a 33⅓% chance of success.
		2. Select a chip at random and get $1 if you select a black one. You thus have between 0% and 66⅔% chance of success.
		3. Most people prefer the first option. This makes sense if people assume there are more red chips than black chips.
	4. Now consider a different set of win circumstances:
		1. The chip is red or yellow. A 33⅓% to 100% chance of success.
		2. The chip is black or yellow. A 66⅔% chance of success.
		3. Most people prefer the second option. This makes sense if people assume there are more black chips than red chips.

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| **Game 1** |  | **Game 2** |
| Red | 33⅓% |  | Red or Yellow | 33⅓% to 100% |
| Black | 0% to 66⅔% |  | Black or Yellow | 66⅔% |

* 1. Thus the paradox: the games are functionally the same. Suppose there are forty yellow chips. What are the probabilities of success?

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| **Game 1** |  | **Game 2** |
| Red |  |  | Red or Yellow |  |
| Black |  |  | Black or Yellow |  |

* 1. What explains this inconsistency is that people prefer the option with the defined probability, the one without the range.
1. Simpson Paradox
	1. Statistics are really useful, but they can also be deceptive since how rare numbers are presented can radically change the result. Consider a suit filed against UC Berkley in 1973, claiming gender bias.
		1. The plaintiffs argued Berkley was biased against women for graduate school admissions. If men are significantly more likely to be admitted than women, that is evidence of gender bias.
		2. The investigation looked at not just admittance rates for all programs, but each program individually. For simplicity, we will use made up numbers but these numbers will emulate the paradox investigators found.

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|   | **Men** |  | **Women** |
|  | *Applied* | *Accepted* | *%* |  | *Applied* | *Accepted* | *%* |
| Program A | 900 | 450 |  |  | 100 | 80 |  |
| Program B | 100 | 10 |  |  | 900 | 180 |  |
| Total |  |  |  |  |  |  |  |

* + 1. Disaggregating these numbers (describing acceptance rates by major) suggests there’s an anti-men bias. Aggregating the numbers suggests there’s an anti-women bias.
	1. Thus the *Simpson Paradox*—when a correlation present when separated into different groups is reversed when groups are combined.
		1. The paradox arises because we subconsciously assume assignment is random: men and women are equally likely to apply to either program.
		2. But look again: that’s not the case. Nine times as many men than women apply for Program A, which is a tougher program to get into. Nine times as many women than men apply for Program B which is an easier program to get into.
	2. By adjusting for population, we can fix this problem. This is called a *weighted average*.
		1. 90% of men applied to Program A, 50% were accepted.

= 0.90\*0.50 = 0.45

* + 1. 10% of men applied to Program B, 10% were accepted.

= 0.10\*0.10 = 0.01

* + 1. Before, you might have been intuitively adding 0.50 + 0.10 = 0.6; you weren’t adjusting for population.

= 0.45 + 0.01 = 0.46

Which is what we got when we did the total, above.

* 1. So the Simpson Paradox isn’t “really” a paradox. The strange conclusion just comes from being mathematically incomplete. But it’s such as easy mistake to make, it’s worth highlight.