Empirical Law & Economics: First Meeting

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Goals of the Course

- Introduce fundamental techniques commonly used in empirical analysis in law & economics
- Emphasize common methods of isolating causal relationships
- Develop skill in critiquing empirical studies

Topics

Methodological:

- Describing Data & Hypothesis Testing
- Regression Analysis
- Problem of Causal Inference:
  - Differences-in-differences
  - Instrumental Variables
  - Randomization across Decision-makers
  - Regression Discontinuity
  - Insights from Economic Theory

Topics

Substantive:

- Tort law
  - Kessler & McClennan
- Criminal Behavior:
  - Levitt, Aiger & Doyle, Chen & Shapiro
- Social Connections:
  - Cohen et al., Fisman & Wang
- Crime (II): Reproductive Policies
  - Donohue & Levitt, Edlund et al.
- Racial Bias:
  - Price & Woflers, Anwar et al.

Scope of this Session

- **Describing Data**
  - Histograms and Distributions
  - Measures Describing Data:
    - Central Tendency
    - Variability
  - Special Distribution: The Normal
- **Hypothesis Testing**
  - Type I and II Errors

Scope of this Session (cont)

- **Documenting correlation: O.L.S. Regression**
  - Structure and interpretation
- **Correlation vs. causation: Common research designs and techniques**
  - Difference-in-differences
    - Kessler & McClennan
  - Natural experiments/instrumental variables
    - Levitt

Motivational Example I

- **What are Rates of Personal Bankruptcy across US States?**
  - Variable of interest: (Bankruptcy Filings / Population) x 100
  - N = number of observations = 50
- **Example:**

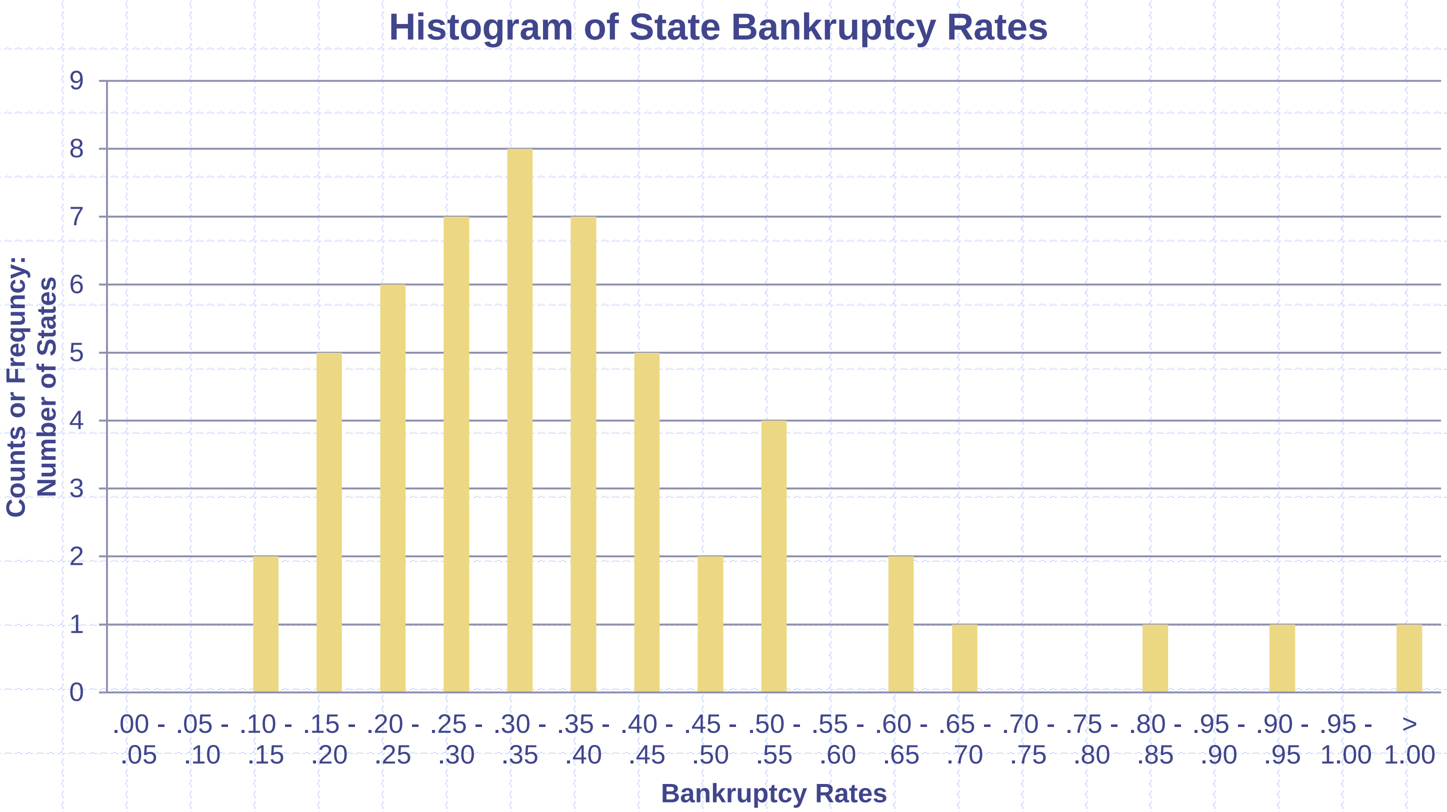
State	Bankruptcy Rate Per Capita
Alabama	0.809
Alaska	0.143
Arizona	0.252
Arkansas	0.643
California	0.181
Colorado	0.318
Connecticut	0.224

How many states have particular bankruptcy rates?

Bankruptcy Rate	Frequency or Counts: Number of States
.00 - .05	0
.05 - .10	0
.10 - .15	2
.15 - .20	5
.20 - .25	6
.25 - .30	7
.30 - .35	8
.35 - .40	7
.40 - .45	5
.45 - .50	2
.50 - .55	4
.55 - .60	0
.60 - .65	2
.65 - .70	1
.70 - .75	0
.75 - .80	0
.80 - .85	1
.95 - .90	0
.90 - .95	1
.95 - 1.00	0
> 1.00	1

How many states have particular bankruptcy rates?

- Graphical Representation I: Histograms

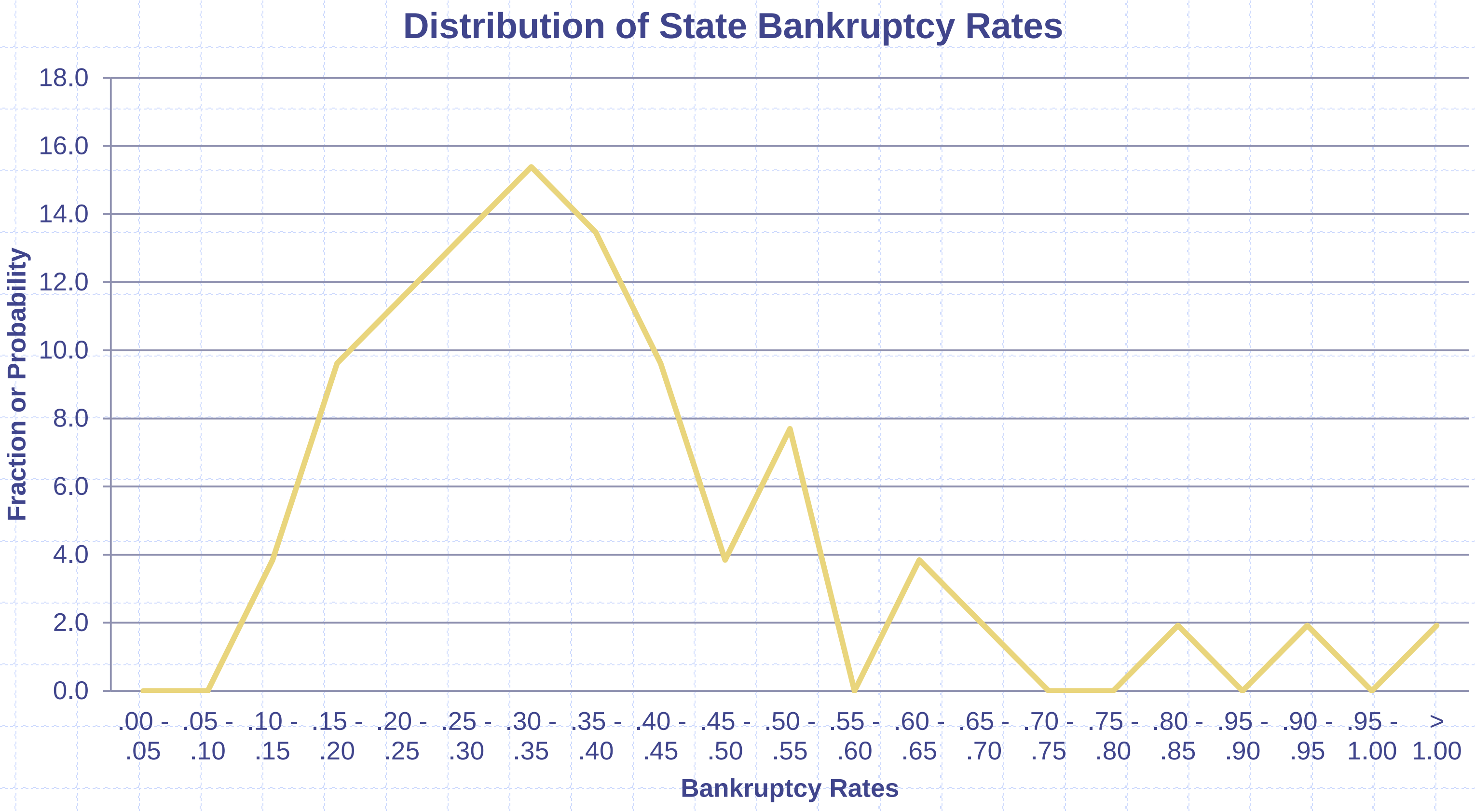


What is the fraction of states have particular bankruptcy rates?

Bankruptcy Rate	Percentage of States
.00 - .05	0.0
.05 - .10	0.0
.10 - .15	3.8
.15 - .20	9.6
.20 - .25	11.5
.25 - .30	13.5
.30 - .35	15.4
.35 - .40	13.5
.40 - .45	9.6
.45 - .50	3.8
.50 - .55	7.7
.55 - .60	0.0
.60 - .65	3.8
.65 - .70	1.9
.70 - .75	0.0
.75 - .80	0.0
.80 - .85	1.9
.95 - .90	0.0
.90 - .95	1.9
.95 - 1.00	0.0
> 1.00	1.9

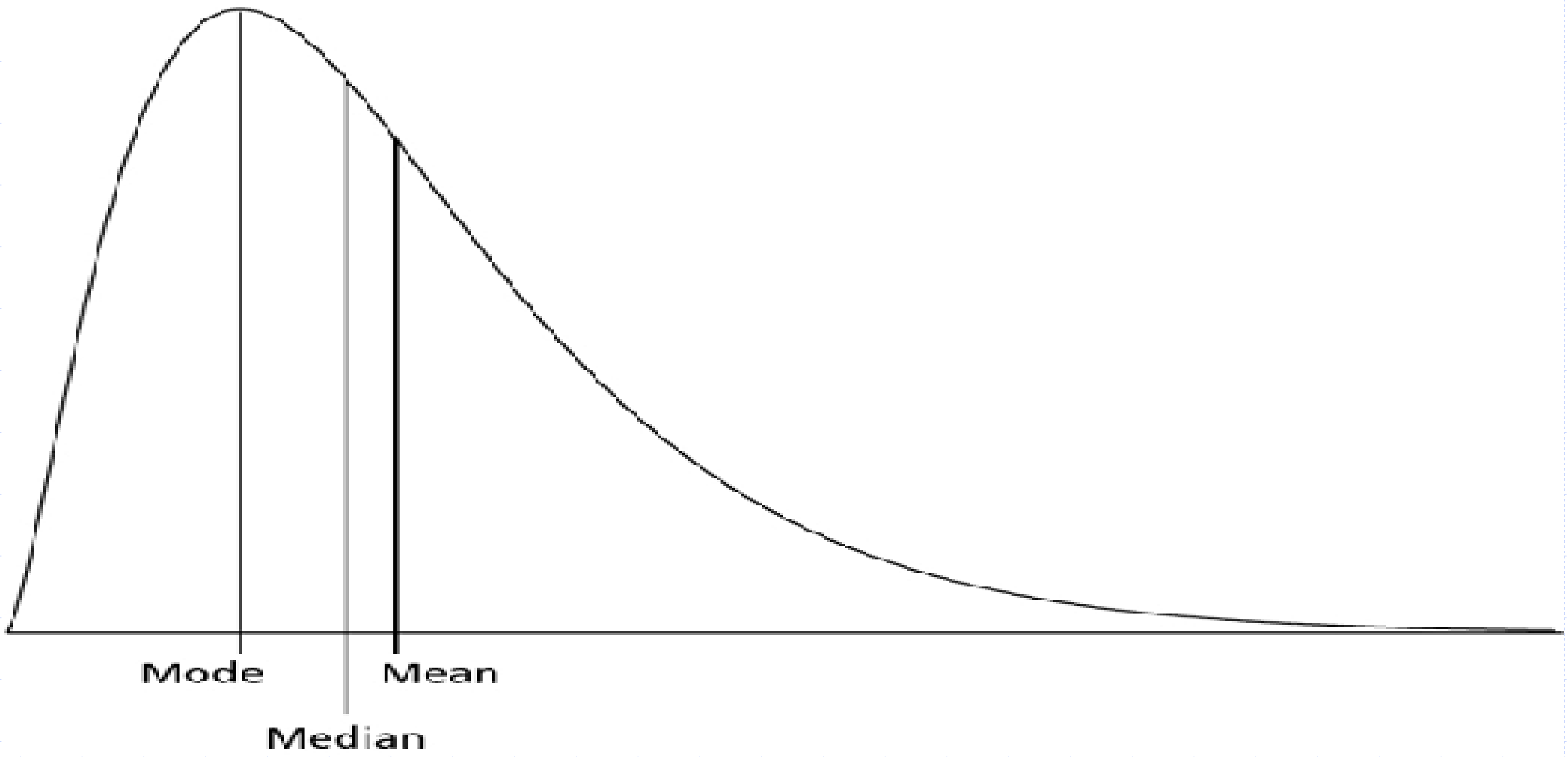
How many states have particular bankruptcy rates?

- Graphical Representation II:



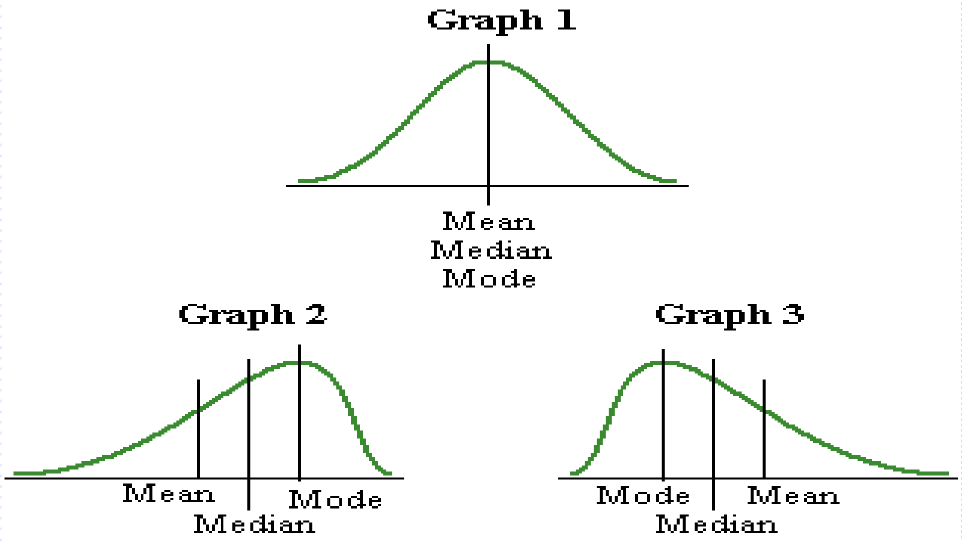
What is the probability a state has a particular bankruptcy rate?

- Probability Distribution



How to describe the distribution of the data?

- **Central Tendency**
  - Mean (“Average”) = .333
  - Median = .315
  - Mode = .304
- **Skewness**
  - Question: When does the mean = median?



How to describe the distribution of the data (con't)?

Variability

- Range = max value – min value =

  = 1.099 - .143 = .956
- Variance

  = sum of squared deviations from the mean

  = .0373
- Standard Deviation

  = square root of variance

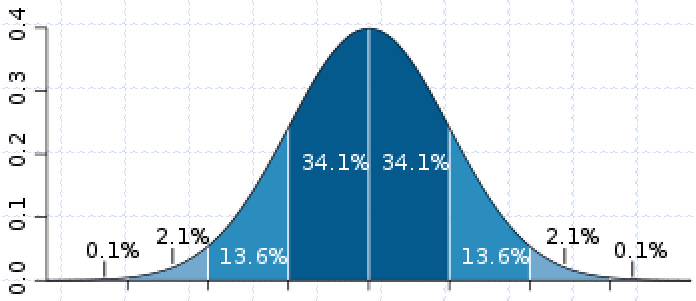
  = .193
- Standard Error

  = standard deviation divided by square root of number of observations

  = .027

A special distribution: The Normal

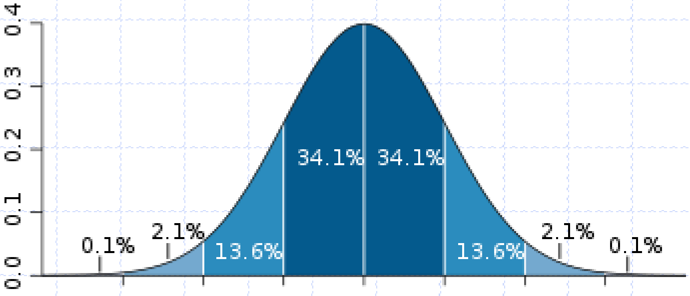
- a.k.a. “Gaussian”
- Some properties of the Normal
  - Unimodal
  - Bell-shaped, symmetric
  - Mean = Median
  - 68% of values fall w/in 1 stand dev of the mean
  - 95% of values fall w/in 2 stand dev of the mean
  - 99.7% of values fall w/in 3 stand dev of the mean



Another property of the Normal

- **(Background)**

- **Central Limit Theorem:**
  - Regardless of the distribution of the population, means from a random sample are distributed normally. . . for large sample sizes
  - How large is large? N= 30?



Hypothesis Testing

- Rather than describe a distribution, we often wish to test a hypothesis.
- Example: Is the average American adult taller than 5.5 feet (1.7 meters)?
  - Let X = heights of all American adults
  - Null H_0 : Mean of X = 5.5 feet
  - Alternative H_A : Mean of X is not 5.5 feet.
- We cannot measure the height of every adult American.
  - We cannot observe the full "population"
  - So we take a "sample," a subset (hopefully representative of the population).
  - Characteristics of the *sample* – e.g., mean, variance, etc. – are "estimates" of the characteristics of the *population*.
- We compute the corresponding sample characteristics (e.g., sample mean height is equal to 5.4 or x=5.4 feet). Called the "test statistic."

Hypothesis Testing

- Do we stop there?

- No. We want to know whether the test statistic we observed could occur even though the true population value is the value assumed in the null hypothesis.

- That is, we want to know: how likely it is that if the null were true, we would observe the test statistic by chance? Or, what is the probability of observing our test statistic, if the null were true?
  - $Pr(x=5.4|X=5.5)$ = probability of observing sample characteristic if null hypothesis were true.
  - Call this the “p-value.”

Hypothesis Testing

- If there's a very low probability of observing the sample characteristic, we can "reject the null hypothesis."
- If there's a very high probability of observing the sample characteristic, then we can "reject the alternative hypothesis."
- Notice that we never "accept" either hypothesis. This is the paradox of empirical analysis. We can never prove the truth. We can only reject claims about the truth.

Hypothesis Testing

- If we find that the probability of observing the sample estimate is very low if the null is true, we say the estimate is "statistically significant."
  - This means that it is highly unlikely to observe a sample estimate of this magnitude by chance.
- How low must the probability be before we can say the estimates is "statistically significant."
  - Conventional thresholds: 5% and 1%.
- Notice that, the lower the threshold, the greater the risk that we will fail to reject the null hypothesis even though it is false.

Hypothesis Testing, cont

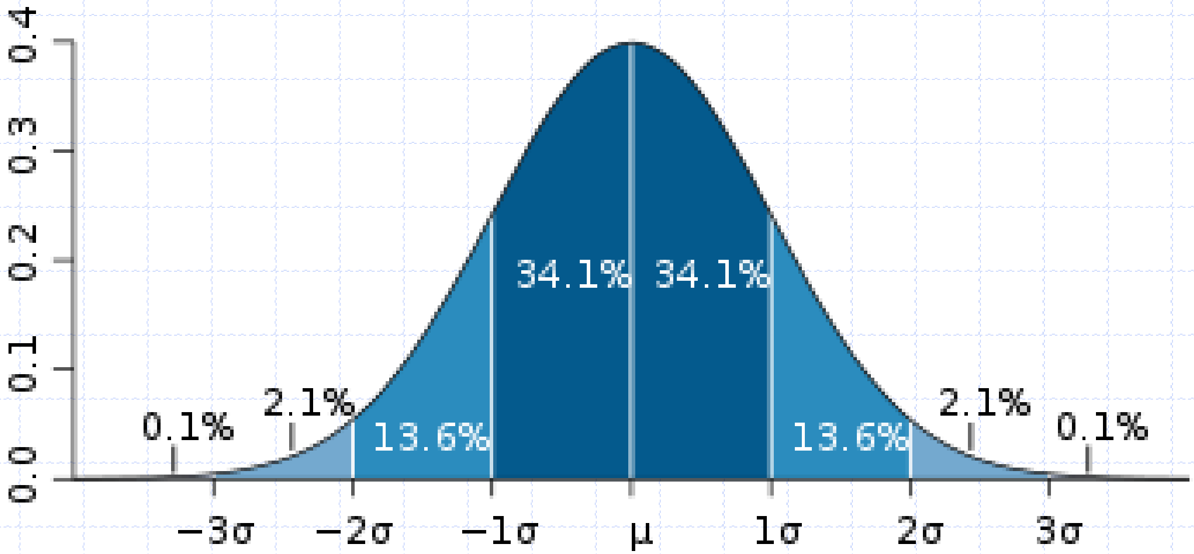
- **Possible outcomes of tests and balancing of errors**

		The Null Hypothesis is . . .	
Test Result says . . .		**True**	**False**
	Do not reject	Accurate	Type II Error (Failed to reject falsity)
	Reject	Type I Error (rejecting truth)	Accurate

How do we compute statistical significance?

- Recall that sample characteristics are "estimates" of population characteristics.
- Every estimate is a random variable: You will obtain a different estimate from different samples, solely due to chance.
- If we want to compute the probability of observing an estimate (a particular outcome of a random variable), we need to know the distribution of the random variable.
- A key theorem from statistics is the "Central Limit Theorem," which says that the sample mean is an estimate with a normal distribution, at least when the sample size is large.

How do we compute statistical significance?



Once we know that the sample mean is normally distributed, we can use standard formulas to compute the probability of observing a sample mean equal to x when the hypothesized population mean is X.

Hypothesis Testing (recap)

Forming the hypothesis:

- Null hypothesis
- Example: is the average bankruptcy rate in US states zero?
  - Null H_0 : Mean of X = 0
  - Alternative H_A : Mean of X ≠ 0

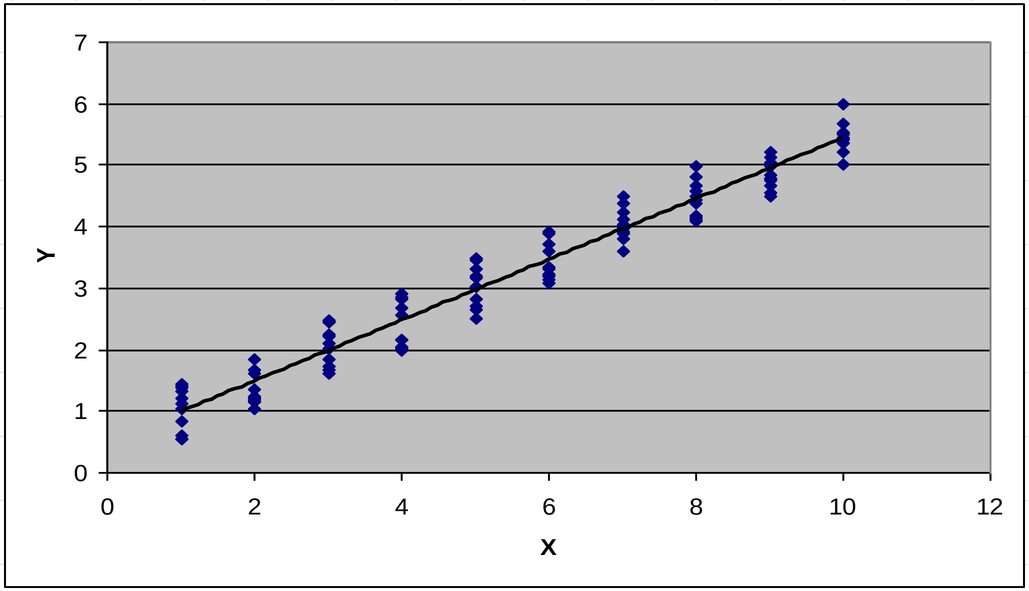
- Let's say we have an estimate of the mean bankruptcy rate that is greater than zero.
  - If we can say that this result would have occurred by chance only 5% of the time or less ➔ this result is statistically significant at the .05 level.
  - Or, we say the null is rejected at the 5% level of significance.
  - Or, we say the result is "statistically significant."
  - Why focus on 5%?

Regression Analysis: Motivational Example

- **Does predatory lending raise the frequency of bankruptcy?**
  - Hypothesis: an increase in predatory lending → an increase in bankruptcy filings.
  - This is a causal claim.
- **What data do we need to test this hypothesis?**
  - **Data on the outcome:** Bankruptcy filings (Y)
  - **Data on the hypothesized cause:**
    - Number of payday lenders (X_1)
  - **Other causes of bankruptcy ("controls"):**
    - Socioeconomic: Poverty rate, Unemployment rate, etc. (X_2)
    - Legal: exemption laws, garnishment laws, etc. (X_3)

Regression: Structure

- **Consider bankruptcy rate as "function" of predatory loans and other controls**
  - **In other words, $Y = f(X_1, X_2\ X_3)$**
  - **Assuming a linear relationship: $Y = X_1\beta_1 + X_2\beta_2 + X_3\beta_3$**
  - "Betas" measure the relationship between the X and Y variables ==> how much Y changes as X increases by one unit

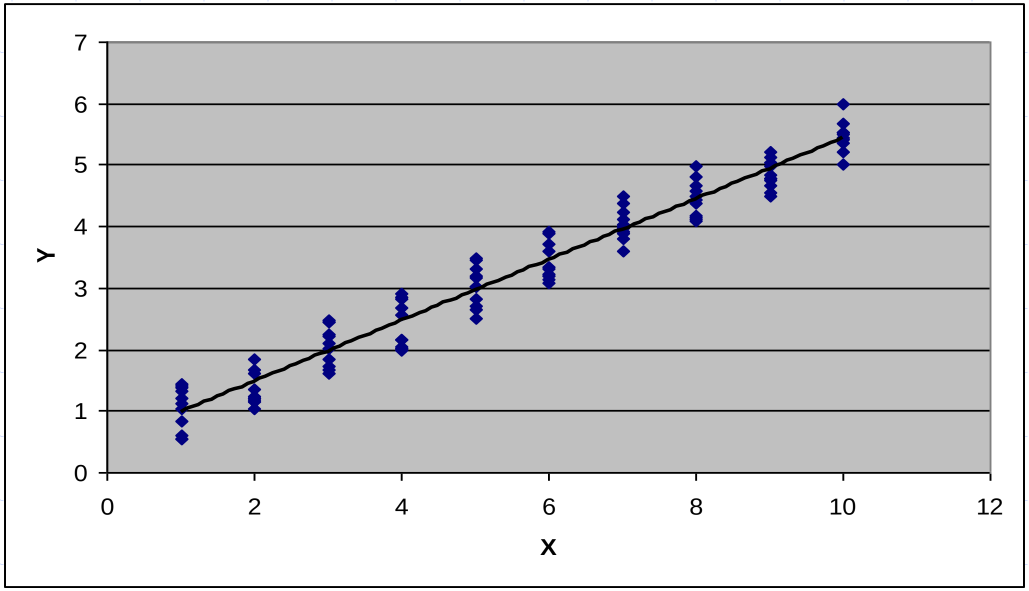


Regression Structure, Cont.

- **But our model isn't perfect: it will describe the world with error (ε)**
  - $Y = X_1\beta_1 + X_2\beta_2 + X_3\beta_3 + \varepsilon$
- **This model is good for one geographic area, but what if we want to study multiple areas?**
  - We need a different Y and X for each area.
  - $Y_i = X_{1i}\beta_1 + X_{2i}\beta_2 + X_{3i}\beta_3 + \varepsilon_i$
- **What if we want to study multiple areas in multiple periods?**
  - We need a different Y and X for each area in each period.
  - $Y_{it} = X_{1it}\beta_1 + X_{2it}\beta_2 + X_{3it}\beta_3 + \varepsilon_{it}$

Regression: Structure, cont

- Criteria for choosing the line
  - Minimize sum of squared deviations or errors
- Properties of this criteria: Estimates are . . .
  - Unbiased
  - Consistent
  - “Best” or “Efficient”



Regression: Interpretation

- **Assessing the betas**
  - **Sign**: does Y increase when X increases?
  - **Size**: how much does Y increase for every unit by which X increases?
    - Is that a large change? What is the <u>social</u> significance?
    - Need to compare to summary statistics.
  - **Significance**: how likely are we to observe this relationship due to random chance?
    - t-statistic: ratio of coefficient to standard error
    - The magic number: 1.96
- **Other diagnostics**
  - R^2, F-tests
  - The other betas

Regression: An Example

Explanatory Variables:	**(1)**	**(2)**
Payday Lenders	.0015*** (.0001)	.0013*** (.0003)
Poverty Rate	.011 (.010)	.009 (.015)
Unemployment Rate	.042*** (.009)	.038*** (.011)
Exemption Laws	--	.152* (.092)
Usury Laws	--	.172** (.072)
N	500	500
R^2	.2971	.3012
F-test (p value)	.00320	.00098

Interpreting the Magnitudes

Summary Statistics		
Variables:	**Mean**	**Std. Dev.**
Bankruptcy Rate (per capita x 100)	.333	.450
Payday Lenders	400.2	150.8
Poverty Rate	15.423	4.1
Unemployment Rate	8.000	2.57
Exemption Laws	.200	.1901
Usury Laws	.400	.3876
N = 500		

Regression Estimates	
Variables	**Estimates**
Payday Lenders	.0013*** (.0003)
Poverty Rate	.009 (.015)
Unemployment Rate	.038*** (.011)
Exemption Laws	.152* (.092)
Usury Laws	.172** (.072)

Interpreting the Magnitudes, cont

- **What would a 10% increase in the sample mean number of payday lenders imply for the bankruptcy rate?**
  - (.1 * 400.2) * (.0013) = .052
  - Is .0052 large or small?
  - Relative to sample mean of bankruptcy of .333, it is .052 / .333 = .15
- **What would a 1 standard deviation increase in the number of payday lenders imply for the bankruptcy rate?**
  - (150.8) * (.0013) = .196
  - Is this large or small? Relative to mean of bankruptcy rate? Or to standard deviation of bankruptcy rate?
- **Economists' favorite: "Elasticity"**
  - % change in Y for a % change in X

What does a regression tell us?

- **Regression estimates prove <u>correlation</u>**
  - By themselves, regression estimates do not isolate causation
- Why is it important to isolate causation?
  - Example from above: usury laws and personal bankruptcy
  - What is the policy implication of this estimate?

Fundamental Ambition of Empirical Law & Economics

To test economic theories that imply causal relationships between law and behavior:

- **Crime**: changes in probability/magnitude of punishment cause behavioral changes in potential criminals/tortfeasors
- **Corporate finance**: changes in capital structure cause changes in firm value/manager performance
- **Employment law**: changes in workplace regulations cause changes in workplace safety, employment levels, wages, etc.
- **Discrimination**: changes in education cause changes in wages, but the effect may vary by race.
- **Lending**: laws that raise creditor collection costs will cause lenders to raise interest rates or lower loan volume

How can correlation alone prevent fulfilling this ambition?

- **Reverse causation (simultaneity)**
  - Policing deters crime, but also responds to crime.
  - Earnings respond to education investments, but education investments responds to anticipated earnings
- **Another problem: Omitted Variables**
  - **Correlation between two variables (e.g., education and wages) may be due to a third, unobserved factor (e.g., ability) that affects both**
    - That is, individuals who invest in education are more likely to benefit from education, due to ability.
  - **Example:** States that adopt laws anticipate benefiting from these laws.
    - States that don't adopt laws may anticipate no benefit. The difference between these two states will overstate the effects of the law.

How can correlation alone prevent fulfilling this ambition?

- **Another problem: Omitted Variables (con't)**
  - **Correlation between two variables (e.g., education and wages) may be due to a third, unobserved factor (e.g., ability) that affects both**
    - That is, individuals who invest in education are more likely to benefit from education, due to ability.
  - **Second Example:** Interest rates rise in response to costly regulations, but people move in response to costly regulation and high interest rates.
    - Due to mobility, the correlation between regulation and interest rates could <u>understate</u> the effect of regulation.

➔ These are often called "selection effects" or "endogeneity problems"

Ideally, how to isolate causal effects?

- A <u>**Counterfactual**</u>
  - Observe an individual after applying some treatment. Record the effects (T).
  - Reverse time. Observe the individual again, but with no treatment. Record the effects (C).
  - Compare T to C to get the true "effect" of the treatment.

- **This is generally impossible: "Fundamental Problem of Causal Inference"**

How do natural scientists establish causation?

- Conduct a clinical trial:
  - Randomize
  - Affected group=Treatment group (adopted law)
  - Unaffected group=Control group (no law)

	Group:		
Period:	Treatment (1)	Control (2)	Difference of (1) – (2):
(A) After Adoption	T	C	T-C
(B) Before Adoption	t	c	t-c
Difference of (A)- (B):	$\Delta t = T - t$	$\Delta c = C - c$	$D = \Delta t - \Delta c$

This is what we care about