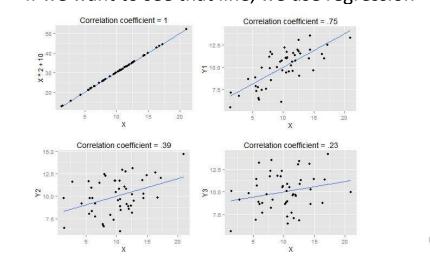


Regression

- Correlation implies an invisible line
- If we want to see that line, we use regression



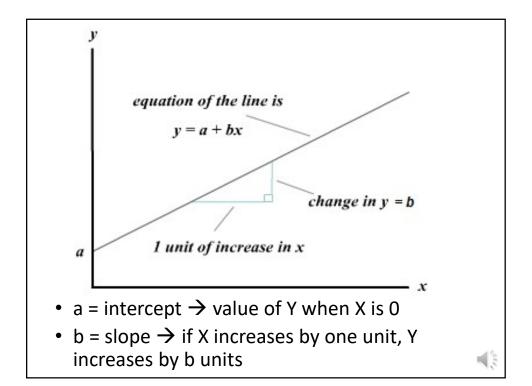
Dependent and Independent Variable

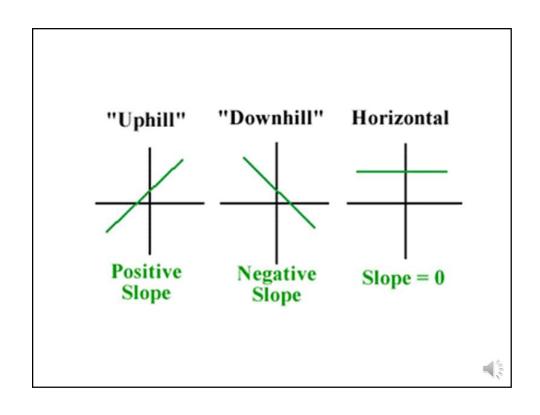
- Two variables → bivariate regression
- For correlation, X and Y are equal partners
- For regression, X is used to predict Y
- X = independent variable, Y = dependent variable
- We say: "We regressed Y on X"
- Both X and Y are interval/ratio



Finding the Best Fit

- Bivariate regression line is like a twodimensional mean - it runs though the middle (equal spread on each side)
- Line of best fit -- minimizing the distances between all data points and the line
- "Least squares" regression square all the distances from the line, add them up, and minimize that value





Formulas for Regression Slope and Intercept

$$b = \frac{n(\sum XY) - (\sum X)(\sum Y)}{n(\sum X^2) - (\sum X)^2}$$
$$a = \frac{(\sum Y) - b(\sum X)}{n}$$



Example of Calculation

	X	Y	XY	X ²
	5	2	10	25
	3	4	12	9
	7	1	7	49
	2	6	12	4
	4	5	20	16
	6	2	12	36
	4	3	12	16
	2	7	14	4
	8	1	8	64
	1	6	6	1
Σ	42	37	113	224



Example of Calculation

	X	Y	XY	X ²
Σ	42	37	113	224

$$b = \frac{10*113 \quad *37}{10*224 - \quad *42} = -0.89$$

$$b = \frac{10*113}{10*224 - *42} = -0.89$$

$$b = \frac{n(\sum XY) - (\sum X)(\sum Y)}{n(\sum X^2) - (\sum X)^2}$$

$$a = \frac{37 - (-0.89) \times 42}{10} = 7.4$$

$$a = \frac{37 - (-0.89) * 42}{10} = 7.4$$

$$a = \frac{(\sum Y) - b(\sum X)}{n}$$



Writing an Equation

- Y' = a + b*X
- Y' = (Y prime) = predicted rather than actual value of Y
- Example: intercept = 7.4, slope = -0.89
- We write: Y' = 7.4 0.89*X
- What about the actual Y?
- To get it, we need to include an error term, e:
- Y = a + b*X + e



Prediction using Regression

- We can use a regression line to predict one variable based on another
- E.g., predict college GPA from one's SAT
- But regression is often used without prediction
- To predict, for a given value of X, we use the regression equation to calculate the predicted value of Y
 yes, you're incredibly predictable, but that's what statisticians like about you

Error of Estimate (Error of Prediction)

- Error of estimate = distance between an actual value and regression line (i.e., difference between prediction and reality)
- Standard error of estimate all differences are squared, then we calculate their average and take its square root (like a two-dimensional standard deviation)

Example:	Predicted	and Actual	Values
-----------------	------------------	------------	---------------

	X	Y	Y' = 7.4 - 0.89*X	error = Y - Y'	$error^2 = (Y - Y')^2$
	5	2	2.95	-0.95	0.9025
	3	4	4.73	-0.73	0.5329
	7	1	1.17	-0.17	0.0289
	2	6	5.62	0.38	0.1444
	4	5	3.84	1.16	1.3456
	6	2	2.06	-0.06	0.0036
	4	3	3.84	-0.84	0.7056
	2	7	5.62	1.38	1.9044
	8	1	0.28	0.72	0.5184
	1	6	6.51	-0.51	0.2601
Σ				0	6.3464

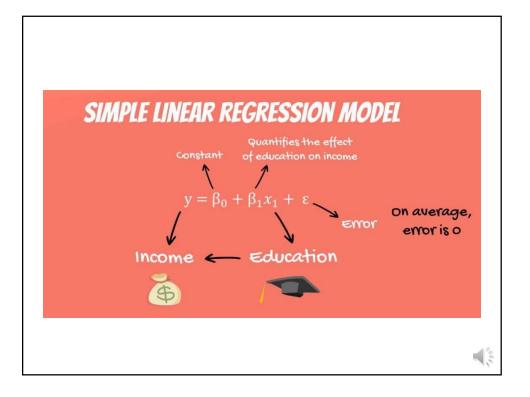


 Standard error of estimate – all differences are squared, then we calculate their average and take its square root (like a two-dimensional standard deviation)

 Divide by df=n-k where k is number of coefficients in regression

• Here it's 2 – a & b: df=10-2=8

• Sqrt(6.3464/8)=0.89



Testing Hypotheses About Regression Coefficients

- Hypothesis test determines if independent variable X has an effect on the dependent variable Y in the population
- In bivariate regression, two coefficients: constant (intercept) a and slope b
- For effect of X on Y → focus on the slope b
- If slope is significantly different from zero → there is a linear relationship in the population



Hypotheses Testing for Regression: Step by Step

- 1. State hypotheses:
- H0: β = 0
- H1: β > 0 ____ directional
- H1: β < 0 _
- H1: β ≠ 0 non-directional
- 2. Select alpha: 0.05, 0.01, .001, .10
- 3. Test statistic: Student's t
- $4. t = b/SE_b$
- 5. Use the table to find critical value:

Table B2 (df=n-2, alpha, one-tailed vs. two-tailed)

- 6. Compare computed value and critical value
- 7. State your decision about HO
- 8. Make a substantive conclusion



 $SE_{b} = \frac{\sqrt{\sum_{i=1}^{H} (y_{i} - y_{i}^{i})^{2}/n - 2}}{\sqrt{\sum_{i=1}^{n} (x_{i} - \overline{x})^{2}}}$

Example: Commuting and Stress

Do employed Americans who spend more time commuting by car have higher levels of stress? In a nationally representative sample of 75 employed individuals, we regress stress on time spent commuting by car and get: slope b =

0.247, standard error = .133.

Can we conclude that commuting time increases stress?



Example: Step by Step

- 1. State hypotheses:
- H0: $\beta = 0$
- H1: $\beta > 0$
- 2. Select alpha: 0.05
- 3. Test statistic: Student's t
- 4. $t = b/s_h = .247/.133 = 1.86$
- 5. Use the table to find critical value: Table B2 (df=n-2 = 75-2=73, alpha = .05, one-tailed) \rightarrow 1.666
- 6. Compare computed & critical value: 1.86 > 1.666
- 7. State your decision: We reject H0 in favor of H1.
- 8. Conclusion: Based on the sample of 75 employed individuals, we are 95% sure that the time spent commuting by car is associated with increased levels of stress among employed Americans (this relationship is statistically significant at .05 level)



Regression in Stata: Problem

- Problem: We would like to determine whether, for the U.S. population, one's level of education affects the age when that person has their first child.
- H0: One's level of education has no effect on the age when that person has her or his first child.
- H1: One's level of education affects the age when that person has her or his first child. [nondirectional → two-tailed]
- H0: $\beta = 0$
- H1: β ≠ 0



Regression in Stata								
reg agekdbr	n educ	Shows to	ent of determina he percent of va t first birth that ed by education.	ariance is				
Source	SS	df	MS		Number of obs			
	5816.50574 39171.7504				R-squared	0.0000 = 0.1293		
Total	44988.2561	1428	31.504381	ANOVA	Adj R-squared = Root MSE = table			
agekdbrn	Coef.	Std. E	Err. t	P> t	[95% Conf.	Interval]		
educ _cons	.6272258 15.80311	.04308	•	0.000	.5427011 14.65472	.7117506 16.95149		
Regression ii predicted ag someone wi	education birth income	on increas creases by	(b). Shows that as es by one year, age .63 of a year (or if .71 of a year).	e at first				

Conclusion

- b = .627, t = 14.56, p < .001 (two-tailed) → reject null
- The positive effect of education on one's age at first childbirth is statistically significant at 0.001 level → we are 99.9% confident that in the population, higher levels of education are linked to higher age at first childbirth
- In addition, we can say that we are 95% sure that one year increase in education is associated with between .54 and .71 of a year increase in one's age at first childbirth



Confidence Intervals in Regression in Stata

- The output shows a 95% confidence interval by default
- Use level option to change:
- . reg agekdbrn educ, level(99.9)

Source	SS	df	MS	Numb	er of ob	s =	1,429
 +				· F(1,	1427)	=	211.89
Model	5816.50574	1	5816.50574	Prob	> F	=	0.0000
Residual	39171.7504	1,427	27.4504207	R-so	quared	=	0.1293
 +				Adj	R-square	d =	0.1287
Total	44988.2561	1,428	31.504381	. Root	MSE	=	5.2393
agekdbrn	Coef.	Std. Err.	t	P> t	[99.9%	Conf.	<pre>Interval]</pre>
 +							
educ	.6272258	.0430891	14.56	0.000	.4851	457	.769306

 We are 99.9% sure that one year increase in education is associated with a between one half and three quarters of a year increase in the age at first childbirth.

Probability(.48<beta<.77)=.999

Two-tailed vs One-tailed Test for Regression in Stata

- The output shows a two-tailed test for regression coefficients
- But what if our research hypothesis is directional?
- If you want one-tailed test, just divide p-value (the value in P>|t|) by 2!



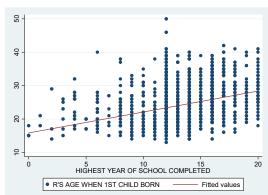
How to Decide Which Variable Is Your Dependent One?

- Make a statement both ways, e.g.:
 - The length of one's commute affects the level of stress they have. Commute → Stress
 - The level of stress one has affects the length of one's commute. Stress → Commute
- Select the one that makes more sense
- Independent variable → Dependent variable
- In Stata:
 - reg dep indep
 - scatter dep indep
 - lowess dep indep



Scatterplot with a Regression Line

graph twoway (scatter agekdbrn educ) (lfit agekdbrn educ)

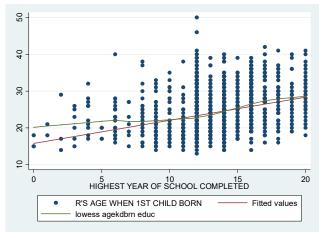


- Independent variable horizontal axis (X)
- Dependent variable vertical axis (Y)



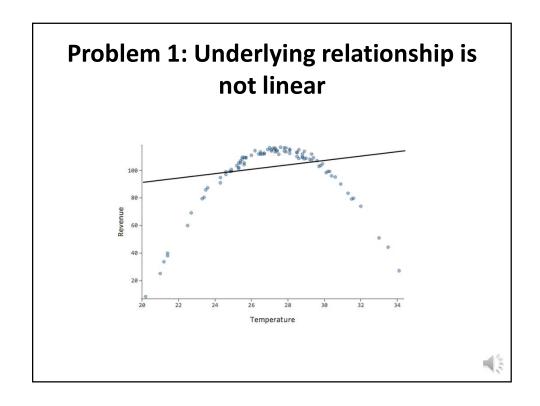
Regression and Lowess Combo

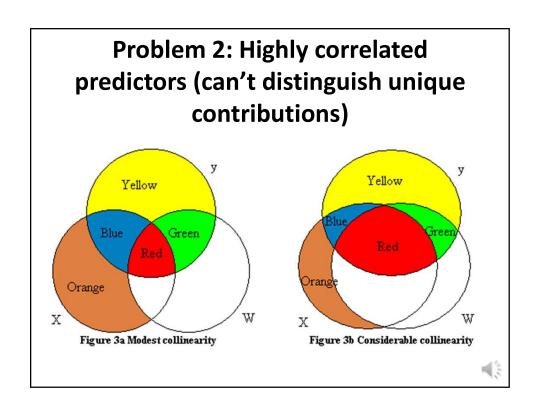
graph twoway (scatter agekdbrn educ) (lfit agekdbrn
educ) (lowess agekdbrn educ)







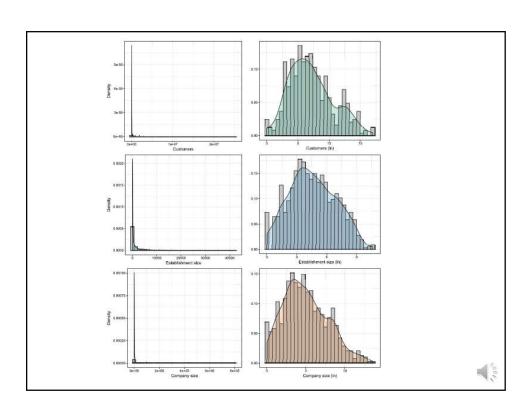


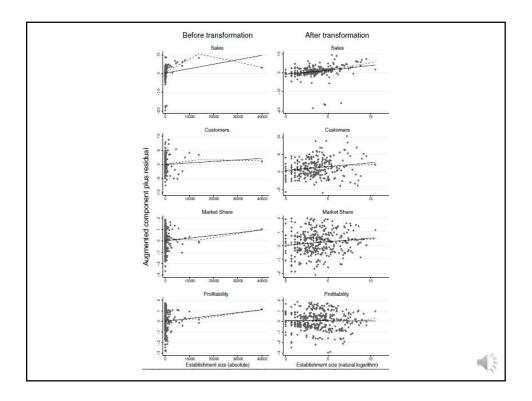


Problem 3: Variables Are Skewed or Have Extreme Outliers

- American Sociological Review: Does Diversity Pay?: Race, Gender, and the Business Case for Diversity
- https://www.asanet.org/wpcontent/uploads/savvy/images/journals/docs/ pdf/asr/Apr09ASRFeature.pdf
- Response/reanalysis:
- http://journals.sagepub.com/doi/pdf/10.1177 /0003122417714422







Original Article Abstract

The value-in-diversity perspective argues that a diverse workforce, relative to a homogeneous one, is generally beneficial for business, including but not limited to corporate profits and earnings. This is in contrast to other accounts that view diversity as either nonconsequential to business success or actually detrimental by creating conflict, undermining cohesion, and thus decreasing productivity. Using data from the 1996 to 1997 National Organizations Survey, a national sample of for-profit business organizations, this article tests eight hypotheses derived from the value-in-diversity thesis. The results support seven of these hypotheses: racial diversity is associated with increased sales revenue, more customers, greater market share, and greater relative profits. Gender diversity is associated with increased sales revenue, more customers, and greater relative profits. I discuss the implications of these findings relative to alternative views of diversity in the workplace.



Does Diversity Pay? A Replication of Herring (2009)

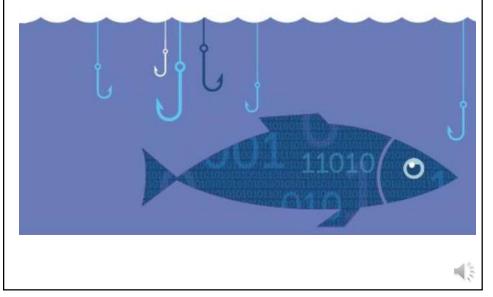
In an influential article published in the *American* Sociological Review in 2009, Herring finds that diverse workforces are beneficial for business. His analysis supports seven out of eight hypotheses on the positive effects of gender and racial diversity on sales revenue, number of customers, perceived relative market share, and perceived relative profitability. This comment points out that Herring's analysis contains two errors. First, missing codes on the outcome variables are treated as substantive codes. Second, two control variables—company size and establishment size—are highly skewed, and this skew obscures their positive associations with the predictor and outcome variables. We replicate Herring's analysis correcting for both errors. The findings support only one of the original eight hypotheses, suggesting that diversity is nonconsequential, rather than beneficial, to business success.

Problem 4: Causation Issues

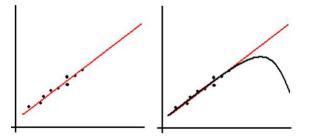
- Regression cannot prove causation (especially with cross-sectional data)
- We risk overlooking reverse causality (Y→X)
- Omitted variable bias ("third variable" explanations, etc.)



Problem 5: "Fishing" for effects (p-hacking and inflated alpha)



Problem 6: Extrapolation



- Red line = prediction based on regression
- Black line = the actual trend



