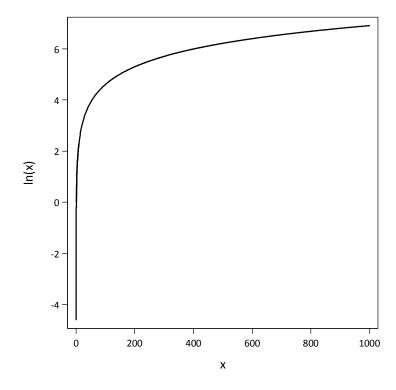
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QUANT I: Transforming X to Specify Diminishing Returns to X

```
set obs 1000
egen x = fill(.01,.02)
gen ln_x = ln(x)
egen y = fill (0,1)
gen ln_y = ln(y)
twoway (line ln_y y) (line ln_x x), legend(off) xtitle("x") ytitle (ln(x))
```



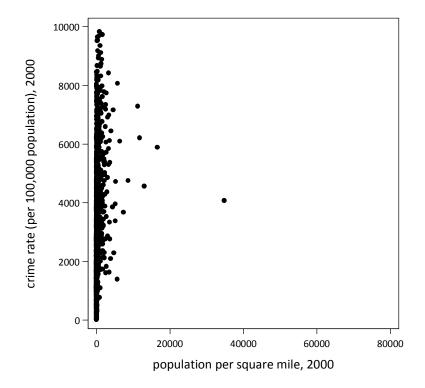
\*A log transformation stretches out low values and compresses high values

<sup>\*</sup>thus when x's marginal effect on y diminishes as x grows large (which is true of many social phenomena), the relationship between y and ln(x) is more likely to be linear than the relationship between y and x.

<sup>\*</sup>another interpretation: change in y is predicted less well by the  $\frac{absolute}{change}$  change in x than the  $\frac{bercentage}{change}$  change in x.

<sup>\*</sup>Why does this matter? OLS Assumption 1: we assume we have correctly specified a population model that is linear in its parameters. Violation of this assumption can lead to bias and imprecision.

<sup>\*</sup> An example where we look at the relationships among crime, poverty and population density:



\*looks like there are some outliers. Let's see what they are:

## . list county state density if density>=10000

_	<b></b>		
	county	state	density
2245. 2295. 2296. 2315. 2806.	Yukon-Koyukuk   Yellowstone National Park   South Boston   Suffolk   Queens	AK MT VA MA NY	.   .   .   11692   20453
2808. 2810. 2811. 2812. 2867.	Hudson   Hudson   New York   Bronx   Kings   Philadelphia	NJ NY NY NY PA	12957   66835   31730   34723   11241
2990.	San Francisco	CA	16526   

<sup>\*</sup>note this includes all with value "." which Stata treats as a very large number.

<sup>\*</sup>we don't want these observations to play too strong a role in our analysis; leave them out for now.

twoway (scatter crimerate density, msize(tiny)) (lowess crimerate density, lw(thick)) if density<10000, legend(off)</pre>

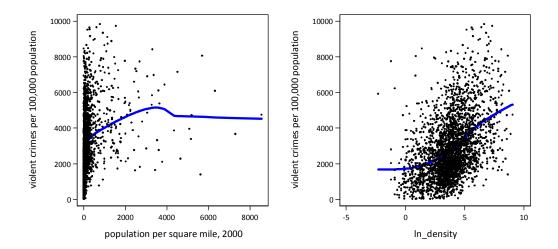
graph save Graph "density.gph", replace

\*we have reason to think that while density is associated with crime, this association might be diminishing in density. To see if this is the case, let's create a log transformation of density:

gen ln\_density = ln(density)
twoway (scatter crimerate ln\_density, msize(tiny)) (lowess crimerate ln\_density,
lw(thick)) if density<10000, legend(off)</pre>

graph save Graph "ln\_density.gph", replace

graph combine "density.gph" "ln\_density.gph", ycommon



- \* ln\_density appears to be a better predictor of crime than density.
- \* Bivariate regressions confirm this:

. reg crimerate density if density<10000</pre>

Source	SS	df	MS		Number of obs = $2662$	
Model   Residual   			618563579 2767930.03  2999345.15		F( 1, 2660) = 223.48 Prob > F = 0.9000 R-squared = 0.0775 Adj R-squared = 0.0772 Root MSE = 1663.7	
crimerate	Coef.	Std. E	rr. t	P> t	[95% Conf. Interval]	
density   _cons	.8876232 2686.712	.05937 34.188			.7711945 1.004052 2619.674 2753.75	

. reg crimerate ln\_density if density<10000</pre>

Source	SS	df	_		Number of obs = F( 1, 2660) =	
Model     Residual	1.5874e+09 6.3939e+09	1 2660	1.5874e+09 2403706.28		Prob > F = R-squared = Adj R-squared =	0.0000 0.1989
	7.9813e+09				Root MSE =	
crimerate	Coef.	Std.	Err. t	P> t	[95% Conf. In	terval]

crimerate	Coef.				-	Interval]
ln_density		17.89808	25.70 14.65	0.000	424.8525 949.4638	495.0436 1242.822

<sup>\*</sup>interpretation: a one-percent increase in population density is associated with an increase in the crime rate of approximately 460 crimes per 100,000 people.

. pwcorr povrate crimerate density ln\_density if density<10000</pre>

	povrate	crimer~e	density	ln_den~y
povrate	1.0000			
crimerate	0.0643	1.0000		
density	-0.1174	0.2784	1.0000	
<pre>ln_density</pre>	-0.2511	0.4460	0.5579	1.0000

<sup>\*</sup>ln\_density is much more highly correlated with poverty and crime than density. This will have implications for our estimates.

<sup>\*</sup>This improved specification has implications for our estimates of other variables. Let's say we want to look at the association between poverty and crime, controlling for density. First look at correlation matrix:

. reg crimerate povrate density if density<10000

Source	SS	df	MS		Number of obs		
Model   Residual	702809198 7.2784e+09		351404599 2737287.8		R-squared	= 0.0000 = 0.0881	
Total	7.9813e+09	2661	2999345.15		Adj R-squared Root MSE		
crimerate	Coef.	Std.	Ērr. t	P> t	[95% Conf.	Interval]	
povrate   density   _cons	28.90484 .9321349 2246.886	5.210 .0595 86.26	895 15.64		.8152884	1.048981	
					1	mated more precisely	
. reg crimera	te povrate l	n_dens	ity if densit	y<10000	because effect properly speci	t of density is now more fied.	
. reg crimera		n_dens df	ity if densit		properly speci	fied. = 2662	
	SS  1.8959e+09	df 2	MS  947949932		properly speci Number of obs F( 2, 2659) Prob > F R-squared	fied. = 2662 = 414.21 = 0.0000 = 0.2375	
	SS 1.8959e+09 6.0854e+09	df  2 2659	MS  947949932		properly speci Number of obs F( 2, 2659) Prob > F	fied. = 2662 = 414.21 = 0.0000 = 0.2375	
Source  +   Model   Residual	SS 1.8959e+09 6.0854e+09 7.9813e+09	df  2 2659	MS  947949932 2288588.79  2999345.15		properly speci Number of obs F( 2, 2659) Prob > F R-squared Adj R-squared	fied.  = 2662 = 414.21 = 0.0000 = 0.2375 = 0.2370 = 1512.8	

0.16 0.873

-212.5944

250.3746

Association between povrate and crimerate now found to be much larger. Looking back at the correlation matrix, can you see why?

18.89011

118.0527

\_cons