Final Paper Presentation

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$$zTemp_{ct} = \frac{\text{Temp}_{ct} - \overline{\text{Temp}_c}}{\sigma_{\text{Temp},c}},$$

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The precipitation z-scores are similarly defined. For example, $zTemp_{ct} = 0$ means the temperature was exactly the average for that county, whereas $zTemp_{ct} = 1$ means the temperature was one standard-deviation above the average (an unusually warm year).

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County Population by year:

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California Counties Land Area:

`https://onlinecalifornia.us/countyarea.shtml`

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$$\ln(\text{HousePrice}_{ct}) = \beta_0 + \beta_1 \text{zTemp}_{ct} + \beta_2 \text{zPrecip}_{ct} + \beta_3 \text{CountyPop}_{ct} + \beta_4 \text{CountyDensity}_{ct}$$

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Potential Omitted Variables: County Crime Levels, County Public Services, County Education Level, Federal Interest Rates, **County Quality of Education**.

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Results: Summary Statistics

. summarize

Variable	Obs	Mean	Std. dev.	Min	Max
year	391	2014.512	2.881283	2010	2019
id	0				
county	0				
temp	391	60.44552	4.506983	50.7	76.5
temp_hist	391	58.33478	4.127856	51.7	72.2
precip	391	24.49714	17.73149	2.06	82.59
precip_hist	391	24.9302	14.13778	3.38	63.39
county_pop	391	973216.7	1672957	65084	1.01e+07
median_house	391	415511.5	228933.4	130800	1233600
sq_mi	391	2721.832	3387.598	46.69	20052.5
sd_temp	390	1.335813	.0912748	1.186779	1.521001
temp_dev	390	1.581177	.9970067	−.7024201	3.511163
sd_precip	390	9.357683	4.940643	1.295387	19.86239
precip_dev	390	−.0875689	.9638408	−2.207122	2.308191
county_den~y	391	1023.308	2912.476	22.05497	18880.89
ln_median_~e	391	12.80006	.5204693	11.78142	14.02545

Results: OLS Estimates

```
. reg ln_median_house temp_dev precip_dev county_pop county_density
```

Source	SS	df	MS		
Model	25.0446496	4	6.26116239	Number of obs	= 390
Residual	80.443615	385	.208944454	F(4, 385)	= 29.97
				Prob > F	= 0.0000
Total	105.488265	389	.271178058	R-squared	= 0.2374
				Adj R-squared	= 0.2295
				Root MSE	= .4571

ln_median_ho~e	Coefficient	Std. err.	t	P>|t|	[95% conf.	interval]
temp_dev	.1065086	.0244269	4.36	0.000	.0584817	.1545355
precip_dev	.0905436	.0251663	3.60	0.000	.0410631	.1400241
county_pop	4.14e-08	1.41e-08	2.93	0.004	1.36e-08	6.92e-08
county_density	.0000683	8.06e-06	8.47	0.000	.0000524	.0000841
_cons	12.5302	.0457692	273.77	0.000	12.44021	12.62019

Results: Fixed Effects

```
. areg ln_median_house temp_dev precip_dev county_pop county_density
    i.year, absorb(county) cluster(county)

Linear regression, absorbing indicators                 Number of obs     =        390
Absorbed variable: county                               No. of categories =         39
                                                        F(13, 38)         =     105.81
                                                        Prob > F          =     0.0000
                                                        R-squared         =     0.9895
                                                        Adj R-squared     =     0.9880
                                                        Root MSE          =     0.0572
                                              (Std. err. adjusted for 39 clusters in county)
```

ln_median_ho~e	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
temp_dev	.0229511	.0138943	1.65	0.107	-.0051764	.0510786
precip_dev	.0162229	.0067624	2.40	0.021	.0025332	.0299126
county_pop	5.15e-07	2.38e-07	2.16	0.037	3.21e-08	9.97e-07
county_density	.0000434	.0000235	1.85	0.072	-4.09e-06	.0000909
year						
2011	-.0447335	.0166063	-2.69	0.010	-.0783512	-.0111159
2012	-.1094107	.0157365	-6.95	0.000	-.1412676	-.0775538
2013	-.0221942	.0184837	-1.20	0.237	-.0596126	.0152242
2014	.0099602	.0343066	0.29	0.773	-.0594898	.0794102
2015	.1229077	.0289061	4.25	0.000	.0643903	.181425
2016	.1763045	.0302735	5.82	0.000	.115019	.2375899
2017	.2400476	.0312436	7.68	0.000	.1767981	.303297
2018	.3256774	.0304895	10.68	0.000	.2639546	.3874002
2019	.365822	.0261581	13.99	0.000	.3128677	.4187764
_cons	12.11328	.2249491	53.85	0.000	11.65789	12.56866

Thank You!