

ARE213 Problem Set #3

Peter Alstone & Frank Proulx

December 1, 2013

Part A: Linear models to motivate RD

(i) LM results comparison

Using a series of linear models (with heteroskedasticity consistent “robust” standard errors), we find that for a range of model formulations there is a significant effect on housing price from the presence of hazardous waste cleanup sites, but not in the direction one would expect. Instead of a reduction in housing value we estimate an increase in the value, which does not seem likely to be true. The coefficient for the hazardous waste indicator variable (npl2000) takes a wide range of values depending on which additional explanatory variables are included in the model, from 0.04 (i.e., approximately a 4% increase) for the simple model only including 1980 housing values and npl2000 to estimate 2000 housing values, to 0.09 for a model including both housing and demographic characteristics.

Requirements for Unbiased Estimates [add to this]: For our estimates to be unbiased we would need to include all of the potential sources of variation in housing price in a linear model. A particular challenge is that there are very few sites with NPL2000 status (only 2% of sites), so while the overall sample size is large there is very little support for estimates related to NPL2000 status compared to other covariates. Critically, the overlap assumption must hold for the regression to be successful.

(ii) Comparing covariates

We compare the covariates between census tracts and sites in a series of contingency tables and find that there are wide disparities between census tracts with and without NPL2000 status. This erodes confidence that there is support in the data to use tract-level linear regression models, since the overlap assumption may be violated from wide differences in the other characteristics on the tract level. On the site level, simply comparing over / under the trigger limit for the national priorities list (HRS score of 28.5) seems to solve some but not all the problems with overlap. While many covariates cannot be said to come from different distributions there are still some that have significant differences. Narrowing into a window from 16.5 - 40.5 (with the 28.5 dividing line) results in comparisons for which the hypothesis that the covariates are from the same distribution is not rejected. Overall, these comparisons motivate the regression discontinuity design. By narrowing in on a region where overlap in distribution for the covariates holds we have a fighting chance to identify a treatment effect, albeit with difficulty in establishing external validity.

Part B: RDD setup

Based on the plot of the density distribution (Figure 1) using default values for bandwidth and bin width ($h \approx 12.6$, $b \approx 1.6$), it does not appear that there is a significant discontinuity in the neighborhood of $HRS=28.5$. The estimated value lines appear to nearly match with each other, and more importantly

Table 1: Linear models for effect of NPL(2000) on housing value (with many additional state fixed effects omitted)

	simple model	+housing char.	+demographics	+state fixed effects
	(1)	(2)	(3)	(4)
npl2000	0.040*** (0.012)	0.055*** (0.012)	0.090*** (0.010)	0.068*** (0.009)
lnmeanhs8	0.856*** (0.011)	0.866*** (0.018)	0.619*** (0.022)	0.514*** (0.022)
firestoveheat80		0.074*** (0.020)	0.182*** (0.023)	0.230*** (0.033)
nofullkitchen80		-1.776*** (0.176)	-0.751*** (0.164)	-0.559*** (0.152)
zerofullbath80		1.243*** (0.139)	1.044*** (0.124)	0.863*** (0.116)
bedrms1_80occ		0.421* (0.249)	0.404* (0.237)	0.240 (0.234)
bedrms2_80occ		-0.436* (0.229)	0.156 (0.216)	-0.004 (0.214)
bedrms3_80occ		-0.524** (0.230)	-0.147 (0.217)	-0.153 (0.214)
bedrms4_80occ		-0.111 (0.226)	0.004 (0.217)	-0.213 (0.214)
bedrms5_80occ		0.721*** (0.231)	0.732*** (0.222)	0.430* (0.220)
blt0_1yrs80occ		-0.216*** (0.045)	-0.010 (0.044)	0.109** (0.045)
blt2_5yrs80occ		-0.295*** (0.029)	0.011 (0.028)	0.039 (0.026)
blt6_10yrs80occ		-0.271*** (0.021)	-0.048** (0.021)	0.002 (0.021)
blt10_20yrs80occ		-0.242*** (0.017)	-0.136*** (0.015)	-0.123*** (0.014)
blt20_30yrs80occ		-0.191*** (0.017)	-0.181*** (0.014)	-0.156*** (0.013)
blt30_40yrs80occ		-0.190*** (0.026)	-0.121*** (0.025)	-0.104*** (0.023)
occupied80		0.730*** (0.050)	0.242*** (0.046)	-0.093** (0.044)
pop_den8			0.00001*** (0.00000)	0.00001*** (0.00000)
shrbk8			-0.161*** (0.014)	-0.058*** (0.013)
shrhsp8			-0.329*** (0.021)	-0.100*** (0.022)
child8			-0.630*** (0.058)	-0.431*** (0.052)
old8			-0.737*** (0.047)	-0.447*** (0.044)
shrfors8			1.377*** (0.048)	0.567*** (0.041)
ffh8			-0.006 (0.034)	-0.084*** (0.032)
smhse8			0.407*** (0.022)	0.323*** (0.022)
hsdrop8			0.010 (0.025)	0.042* (0.024)
no_hs_diploma8			-0.537*** (0.039)	-0.262*** (0.034)
ba_or_better8			0.112*** (0.034)	0.450*** (0.035)
unemp8			-0.654*** (0.071)	-1.420*** (0.076)
povrat8			-0.275*** (0.051)	0.118** (0.048)
welfare8			1.271*** (0.070)	0.284*** (0.067)
avhhin8			0.00001*** (0.00000)	0.00001*** (0.00000)
as.factor(statefips)2				-0.129*** (0.027)
as.factor(statefips)4				0.011 (0.015)
as.factor(statefips)5				-0.150*** (0.025)
as.factor(statefips)6				0.340*** (0.017)
as.factor(statefips)8				0.207*** (0.015)
as.factor(statefips)9				0.157*** (0.015)
as.factor(statefips)10				0.230*** (0.018)
as.factor(statefips)11				0.102*** (0.024)
as.factor(statefips)12				-0.005 (0.013)
as.factor(statefips)13				0.182*** (0.015)
as.factor(statefips)15				0.081** (0.038)
as.factor(statefips)16				0.039* (0.020)

Notes:

***Significant at the 1 percent level.

**Significant at the 5 percent level.

*Significant at the 10 percent level.

Table 2: Contingency table for a range of factors by npl2000 status

	N	0 N = 47260	1 N = 985	Combined N = 48245	Test Statistic
npl1990 : 0	48245	100% (47260)	24% (239)	98% (47499)	$\chi^2_1 = 36355, P < 0.001^1$
1		0% (0)	76% (746)	2% (746)	
pop_den8	48245	580 2677 6178	147 522 1701	548 2605 6080	$F_{1,48243} = 525, P < 0.001^2$
shrbk8	48245	0.00 0.02 0.08	0.00 0.02 0.07	0.00 0.02 0.08	$F_{1,48243} = 0.35, P = 0.55^2$
shrhsp8	48245	0.01 0.02 0.06	0.01 0.01 0.03	0.01 0.02 0.06	$F_{1,48243} = 39, P < 0.001^2$
child8	48245	0.24 0.29 0.33	0.26 0.30 0.33	0.24 0.29 0.33	$F_{1,48243} = 35, P < 0.001^2$
shrfor8	48245	0.02 0.04 0.08	0.02 0.03 0.06	0.02 0.04 0.08	$F_{1,48243} = 44, P < 0.001^2$
ffh8	48245	0.10 0.15 0.24	0.09 0.13 0.20	0.10 0.15 0.24	$F_{1,48243} = 40, P < 0.001^2$
smhse8	48245	0.42 0.53 0.63	0.47 0.56 0.64	0.42 0.53 0.63	$F_{1,48243} = 34, P < 0.001^2$
hsdrop8	48245	0.05 0.11 0.19	0.06 0.12 0.19	0.05 0.11 0.19	$F_{1,48243} = 3.8, P = 0.051^2$
no_hs_diploma8	48245	0.18 0.29 0.43	0.23 0.33 0.43	0.19 0.29 0.43	$F_{1,48243} = 42, P < 0.001^2$
ba_or_better8	48245	0.08 0.14 0.24	0.07 0.11 0.18	0.08 0.14 0.24	$F_{1,48243} = 52, P < 0.001^2$
unemprt8	48245	0.04 0.06 0.08	0.04 0.06 0.08	0.04 0.06 0.08	$F_{1,48243} = 22, P < 0.001^2$
povrat8	48245	0.05 0.08 0.14	0.05 0.08 0.13	0.05 0.08 0.14	$F_{1,48243} = 0.02, P = 0.9^2$
welfare8	48245	0.03 0.05 0.09	0.03 0.05 0.09	0.03 0.05 0.09	$F_{1,48243} = 4.2, P = 0.041^2$
favinc8	48245	18786 22882 27697	18943 22085 25676	18789 22863 27660	$F_{1,48243} = 15, P < 0.001^2$
avhinh8	48245	16349 20383 25211	16766 19957 23589	16358 20371 25166	$F_{1,48243} = 5.7, P = 0.017^2$
meanrnt80	48115	223 268 324	217 256 303	223 268 323	$F_{1,48113} = 27, P < 0.001^2$
mdvalhs9	48245	43929 69394 125500	48500 72700 130600	44000 69400 125600	$F_{1,48243} = 6.1, P = 0.014^2$
meanrnt9	48190	390 491 636	378 471 620	389 491 635	$F_{1,48188} = 6.3, P = 0.012^2$
mdvalhs0	48245	82500 120700 178000	85400 120400 166200	82600 120700 177800	$F_{1,48243} = 0.28, P = 0.6^2$
meanrnt0	48127	520 646 822	515 621 800	520 645 821	$F_{1,48125} = 5, P = 0.025^2$
tothsun8	48245	874 1278 1735	937 1343 1807	875 1280 1737	$F_{1,48243} = 9, P = 0.003^2$
ownocc8	48245	448 748 1089	566 878 1212	450 751 1091	$F_{1,48243} = 60, P < 0.001^2$
owner_occupied80	48245	0.48 0.67 0.79	0.58 0.71 0.80	0.49 0.67 0.79	$F_{1,48243} = 38, P < 0.001^2$
bltlast5yrs80	48245	0.02 0.09 0.22	0.05 0.12 0.20	0.02 0.09 0.22	$F_{1,48243} = 24, P < 0.001^2$
bltlast10yrs80	48245	0.07 0.22 0.45	0.13 0.26 0.40	0.07 0.22 0.45	$F_{1,48243} = 14, P < 0.001^2$
firestoveheat80	48245	0.00 0.01 0.04	0.01 0.03 0.07	0.00 0.01 0.05	$F_{1,48243} = 132, P < 0.001^2$
noaircond80	48245	0.17 0.40 0.66	0.30 0.47 0.68	0.17 0.40 0.66	$F_{1,48243} = 58, P < 0.001^2$
nofullkitchen80	48245	0.00 0.01 0.02	0.01 0.01 0.02	0.00 0.01 0.02	$F_{1,48243} = 20, P < 0.001^2$
zerofullbath80	48245	0.00 0.01 0.03	0.01 0.02 0.03	0.00 0.01 0.03	$F_{1,48243} = 48, P < 0.001^2$
northeast : 0	48245	78% (36651)	62% (611)	77% (37262)	$\chi^2_1 = 132, P < 0.001^1$
1		22% (10609)	38% (374)	23% (10983)	
midwest : 0	48245	77% (36338)	78% (770)	77% (37108)	$\chi^2_1 = 0.89, P = 0.34^1$
1		23% (10922)	22% (215)	23% (11137)	
south : 0	48245	69% (32425)	76% (753)	69% (33178)	$\chi^2_1 = 28, P < 0.001^1$
1		31% (14835)	24% (232)	31% (15067)	
west : 0	48245	77% (36366)	83% (821)	77% (37187)	$\chi^2_1 = 22, P < 0.001^1$
1		23% (10894)	17% (164)	23% (11058)	
meanhs8	48245	38270 52659 73074	38213 49126 64321	38269 52576 72906	$F_{1,48243} = 20, P < 0.001^2$
bedrms02_80	48245	0.32 0.46 0.62	0.33 0.43 0.55	0.32 0.45 0.62	$F_{1,48243} = 10, P = 0.001^2$
bedrms34_80	48245	0.36 0.52 0.65	0.43 0.55 0.63	0.36 0.52 0.65	$F_{1,48243} = 9.7, P = 0.002^2$
detach80	43074	0.45 0.70 0.84	0.57 0.73 0.83	0.46 0.70 0.84	$F_{1,43072} = 16, P < 0.001^2$
bedrms0_80occ	48245	0 0 0	0 0 0	0 0 0	$F_{1,48243} = 0.22, P = 0.64^2$
bedrms1_80occ	48245	0.01 0.03 0.06	0.02 0.03 0.06	0.01 0.03 0.06	$F_{1,48243} = 7.4, P = 0.007^2$
bedrms2_80occ	48245	0.15 0.25 0.36	0.19 0.27 0.35	0.16 0.25 0.36	$F_{1,48243} = 16, P < 0.001^2$
bedrms3_80occ	48245	0.39 0.48 0.57	0.43 0.49 0.55	0.39 0.48 0.57	$F_{1,48243} = 1.2, P = 0.27^2$
bedrms4_80occ	48245	0.09 0.14 0.22	0.10 0.15 0.21	0.09 0.14 0.22	$F_{1,48243} = 0.27, P = 0.61^2$
bedrms5_80occ	48245	0.01 0.02 0.05	0.01 0.03 0.04	0.01 0.02 0.05	$F_{1,48243} = 1.5, P = 0.22^2$
blt0_1yrs80occ	48245	0.00 0.01 0.05	0.01 0.02 0.05	0.00 0.01 0.05	$F_{1,48243} = 44, P < 0.001^2$
blt2_5yrs80occ	48245	0.01 0.06 0.17	0.02 0.09 0.16	0.01 0.06 0.17	$F_{1,48243} = 42, P < 0.001^2$
blt6_10yrs80occ	48245	0.01 0.08 0.19	0.05 0.12 0.19	0.01 0.09 0.19	$F_{1,48243} = 52, P < 0.001^2$
blt10_20yrs80occ	48245	0.07 0.16 0.26	0.12 0.18 0.25	0.07 0.16 0.26	$F_{1,48243} = 29, P < 0.001^2$
blt20_30yrs80occ	48245	0.06 0.14 0.26	0.10 0.16 0.24	0.07 0.14 0.26	$F_{1,48243} = 31, P < 0.001^2$
blt30_40yrs80occ	48245	0.03 0.07 0.14	0.05 0.08 0.13	0.03 0.07 0.14	$F_{1,48243} = 21, P < 0.001^2$
blt40_yrs80occ	48245	0.03 0.14 0.43	0.07 0.18 0.32	0.03 0.14 0.42	$F_{1,48243} = 11, P = 0.001^2$
detach80occ	48245	0.86 0.96 0.99	0.83 0.93 0.98	0.86 0.96 0.99	$F_{1,48243} = 40, P < 0.001^2$
attach80occ	48245	0.00 0.01 0.04	0.00 0.01 0.02	0.00 0.01 0.04	$F_{1,48243} = 40, P < 0.001^2$
mobile80occ	48245	0.00 0.00 0.06	0.00 0.04 0.13	0.00 0.00 0.06	$F_{1,48243} = 238, P < 0.001^2$
occupied80	48245	0.92 0.95 0.97	0.93 0.95 0.97	0.92 0.95 0.97	$F_{1,48243} = 3.4, P = 0.066^2$
bltmore30_80	48245	0.08 0.27 0.56	0.17 0.31 0.46	0.08 0.28 0.55	$F_{1,48243} = 8.8, P = 0.003^2$
nbr_dummy : 0	48245	89% (41989)	56% (551)	88% (42540)	$\chi^2_1 = 1002, P < 0.001^1$
1		11% (5271)	44% (434)	12% (5705)	

$a\ b\ c$ represent the lower quartile a , the median b , and the upper quartile c for continuous variables.

N is the number of non-missing values.

Numbers after percents are frequencies.

Tests used:

¹Pearson test; ²Wilcoxon test

Table 3: Contingency table by HRS test status (over/under 28.5)

	N	FALSE <i>N</i> = 181	TRUE <i>N</i> = 306	Combined <i>N</i> = 487	Test Statistic
hrs_82	487	7.5 16.5 23.1	36.3 42.3 51.9	20.2 34.7 46.0	$F_{1,485} = 1135, P < 0.001^1$
npl1990 : 0	487	87% (158)	1% (3)	33% (161)	$\chi_1^2 = 383, P < 0.001^2$
1		13% (23)	99% (303)	67% (326)	
npl2000 : 0	487	84% (152)	1% (3)	32% (155)	$\chi_1^2 = 361, P < 0.001^2$
1		16% (29)	99% (303)	68% (332)	
pop_den8	487	146 533 1939	146 483 1415	145 504 1568	$F_{1,485} = 0.4, P = 0.53^1$
shrbk8	487	0.00 0.01 0.06	0.00 0.02 0.05	0.00 0.01 0.05	$F_{1,485} = 0.45, P = 0.5^1$
shrhsp8	487	0.00 0.01 0.03	0.00 0.01 0.03	0.00 0.01 0.03	$F_{1,485} = 0.27, P = 0.6^1$
child8	487	0.26 0.30 0.33	0.27 0.30 0.33	0.26 0.30 0.33	$F_{1,485} = 0.01, P = 0.93^1$
shrfor8	487	0.01 0.03 0.05	0.02 0.03 0.06	0.01 0.03 0.06	$F_{1,485} = 4.7, P = 0.03^1$
ffh8	487	0.11 0.15 0.21	0.08 0.13 0.19	0.09 0.14 0.20	$F_{1,485} = 7.4, P = 0.007^1$
smhse8	487	0.52 0.61 0.68	0.48 0.57 0.66	0.50 0.59 0.66	$F_{1,485} = 8.5, P = 0.004^1$
hsdrop8	487	0.07 0.13 0.20	0.06 0.11 0.18	0.07 0.12 0.19	$F_{1,485} = 2.9, P = 0.09^1$
no_hs_diploma8	487	0.30 0.39 0.50	0.24 0.34 0.42	0.26 0.36 0.46	$F_{1,485} = 20, P < 0.001^1$
ba_or_better8	487	0.05 0.08 0.13	0.07 0.11 0.18	0.06 0.10 0.16	$F_{1,485} = 22, P < 0.001^1$
unemprt8	487	0.05 0.07 0.10	0.04 0.06 0.09	0.05 0.07 0.09	$F_{1,485} = 11, P < 0.001^1$
povrat8	487	0.06 0.09 0.14	0.05 0.07 0.13	0.05 0.08 0.13	$F_{1,485} = 3.9, P = 0.048^1$
welfare8	487	0.04 0.07 0.09	0.04 0.05 0.09	0.04 0.06 0.09	$F_{1,485} = 9.7, P = 0.002^1$
favinc8	487	18744 21026 24470	19054 22301 26440	18906 21693 25444	$F_{1,485} = 4.8, P = 0.029^1$
avhhi8	487	16862 19578 22230	17198 20209 23805	16939 19869 23172	$F_{1,485} = 3.9, P = 0.05^1$
meanrnt80	484	208 242 284	218 256 309	214 249 300	$F_{1,482} = 9.3, P = 0.002^1$
mdvalhs9	487	43800 58300 116100	50335 73500 131175	46800 67407 125450	$F_{1,485} = 8.4, P = 0.004^1$
meanrnt9	487	352 412 569	380 470 629	369 449 596	$F_{1,485} = 13, P < 0.001^1$
mdvalhs0	487	73900 101000 145400	87850 121200 161800	82150 114400 156650	$F_{1,485} = 14, P < 0.001^1$
meanrnt0	485	470 560 700	520 618 824	501 594 777	$F_{1,483} = 18, P < 0.001^1$
tothsun8	487	891 1273 1677	905 1304 1753	902 1292 1728	$F_{1,485} = 0.24, P = 0.63^1$
ownocc8	487	571 832 1157	585 872 1210	576 860 1180	$F_{1,485} = 0.12, P = 0.73^1$
owner_occupied80	487	0.61 0.71 0.79	0.61 0.72 0.80	0.61 0.72 0.80	$F_{1,485} = 0.32, P = 0.57^1$
bltlast5yrs80	487	0.02 0.10 0.17	0.05 0.12 0.20	0.04 0.11 0.19	$F_{1,485} = 5.8, P = 0.017^1$
bltlast10yrs80	487	0.09 0.22 0.34	0.14 0.25 0.41	0.12 0.24 0.38	$F_{1,485} = 7.5, P = 0.006^1$
firestoveheat80	487	0.01 0.02 0.07	0.01 0.02 0.06	0.01 0.02 0.06	$F_{1,485} = 0.05, P = 0.82^1$
noaircond80	487	0.34 0.50 0.70	0.29 0.47 0.67	0.31 0.48 0.68	$F_{1,485} = 1.4, P = 0.23^1$
nofullkitchen80	487	0.01 0.01 0.03	0.00 0.01 0.02	0.00 0.01 0.02	$F_{1,485} = 2.6, P = 0.1^1$
zerofullbath80	487	0.01 0.02 0.04	0.01 0.02 0.03	0.01 0.02 0.03	$F_{1,485} = 5.3, P = 0.021^1$
northeast : 0	487	67% (121)	52% (160)	58% (281)	$\chi_1^2 = 9.9, P = 0.002^2$
1		33% (60)	48% (146)	42% (206)	
midwest : 0	487	65% (118)	77% (237)	73% (355)	$\chi_1^2 = 8.7, P = 0.003^2$
1		35% (63)	23% (69)	27% (132)	
south : 0	487	78% (142)	81% (247)	80% (389)	$\chi_1^2 = 0.36, P = 0.55^2$
1		22% (39)	19% (59)	20% (98)	
west : 0	487	90% (162)	90% (274)	90% (436)	$\chi_1^2 = 0, P = 0.99^2$
1		10% (19)	10% (32)	10% (51)	
meanhs8	487	30749 41910 55157	37082 48084 62641	35536 46152 59844	$F_{1,485} = 16, P < 0.001^1$
bedrms02_80	487	0.37 0.46 0.56	0.33 0.43 0.54	0.35 0.44 0.54	$F_{1,485} = 4.7, P = 0.031^1$
bedrms34_80	487	0.42 0.52 0.61	0.44 0.55 0.63	0.43 0.54 0.62	$F_{1,485} = 3.7, P = 0.055^1$
detach80	400	0.55 0.74 0.84	0.58 0.74 0.86	0.57 0.74 0.85	$F_{1,398} = 1.4, P = 0.23^1$
bedrms0_80occ	487	0 0 0	0 0 0	0 0 0	$F_{1,485} = 0.02, P = 0.88^1$
bedrms1_80occ	487	0.02 0.03 0.06	0.02 0.03 0.05	0.02 0.03 0.05	$F_{1,485} = 0.44, P = 0.51^1$
bedrms2_80occ	487	0.22 0.30 0.40	0.19 0.26 0.34	0.20 0.28 0.36	$F_{1,485} = 12, P < 0.001^1$
bedrms3_80occ	487	0.42 0.48 0.54	0.44 0.50 0.56	0.43 0.50 0.55	$F_{1,485} = 1.7, P = 0.2^1$
bedrms4_80occ	487	0.09 0.13 0.17	0.10 0.15 0.21	0.09 0.14 0.20	$F_{1,485} = 13, P < 0.001^1$
bedrms5_80occ	487	0.01 0.02 0.04	0.01 0.03 0.04	0.01 0.02 0.04	$F_{1,485} = 7.2, P = 0.008^1$
blt0_1yrs80occ	487	0.00 0.02 0.04	0.01 0.02 0.05	0.00 0.02 0.04	$F_{1,485} = 4.2, P = 0.04^1$
blt2_5yrs80occ	487	0.01 0.06 0.13	0.02 0.09 0.16	0.02 0.08 0.14	$F_{1,485} = 7.5, P = 0.006^1$
blt6_10yrs80occ	487	0.03 0.09 0.16	0.05 0.12 0.20	0.04 0.11 0.18	$F_{1,485} = 6.6, P = 0.011^1$
blt10_20yrs80occ	487	0.10 0.17 0.23	0.13 0.19 0.26	0.12 0.18 0.25	$F_{1,485} = 7.4, P = 0.007^1$
blt20_30yrs80occ	487	0.09 0.15 0.25	0.11 0.16 0.24	0.10 0.16 0.25	$F_{1,485} = 1.6, P = 0.2^1$
blt30_40yrs80occ	487	0.05 0.09 0.16	0.05 0.08 0.12	0.05 0.08 0.14	$F_{1,485} = 2.1, P = 0.15^1$
blt40_yrs80occ	487	0.11 0.23 0.44	0.08 0.17 0.33	0.09 0.19 0.36	$F_{1,485} = 6.8, P = 0.009^1$
detach80occ	487	0.84 0.91 0.97	0.84 0.94 0.99	0.84 0.93 0.99	$F_{1,485} = 2.5, P = 0.12^1$
attach80occ	487	0.00 0.01 0.02	0.00 0.01 0.01	0.00 0.01 0.02	$F_{1,485} = 0.49, P = 0.49^1$
mobile80occ	487	0.00 0.04 0.12	0.00 0.03 0.12	0.00 0.03 0.12	$F_{1,485} = 0.21, P = 0.65^1$
occupied80	487	0.93 0.95 0.97	0.92 0.95 0.97	0.92 0.95 0.97	$F_{1,485} = 0.03, P = 0.87^1$
bltmore30_80	487	0.24 0.38 0.55	0.16 0.30 0.46	0.19 0.32 0.51	$F_{1,485} = 10, P = 0.001^1$
og82list : 1	487	100% (181)	100% (306)	100% (487)	²
0		0% (0)	0% (0)	0% (0)	
nbr_dummy : 0	487	80% (144)	66% (203)	71% (347)	$\chi_1^2 = 9.7, P = 0.002^2$
1		20% (37)	34% (103)	29% (140)	

a b c represent the lower quartile *a*, the median *b*, and the upper quartile *c* for continuous variables.

N is the number of non-missing values.

Numbers after percents are frequencies.

Table 4: Contingency table by HRS test status (JUST over/under 28.5)

	N	FALSE <i>N</i> = 90	TRUE <i>N</i> = 137	Combined <i>N</i> = 227	Test Statistic
hrs_82	227	19 23 25	32 35 38	24 30 37	$F_{1,225} = 573, P < 0.001^1$
npl1990 : 0	227	78% (70)	1% (2)	32% (72)	$\chi_1^2 = 146, P < 0.001^2$
1		22% (20)	99% (135)	68% (155)	
npl2000 : 0	227	73% (66)	1% (2)	30% (68)	$\chi_1^2 = 134, P < 0.001^2$
1		27% (24)	99% (135)	70% (159)	
pop_den8	227	114 357 1340	142 427 1178	118 417 1192	$F_{1,225} = 0.14, P = 0.71^1$
shrbk8	227	0.00 0.01 0.03	0.00 0.02 0.05	0.00 0.01 0.05	$F_{1,225} = 2.5, P = 0.12^1$
shrhsp8	227	0.00 0.01 0.02	0.00 0.01 0.02	0.00 0.01 0.02	$F_{1,225} = 0.03, P = 0.87^1$
child8	227	0.26 0.30 0.33	0.26 0.30 0.34	0.26 0.30 0.33	$F_{1,225} = 0.05, P = 0.82^1$
shrfor8	227	0.01 0.03 0.05	0.01 0.03 0.06	0.01 0.03 0.05	$F_{1,225} = 0.09, P = 0.76^1$
ffh8	227	0.10 0.15 0.20	0.09 0.13 0.21	0.09 0.14 0.20	$F_{1,225} = 0.32, P = 0.57^1$
smhse8	227	0.51 0.59 0.65	0.48 0.57 0.66	0.50 0.59 0.65	$F_{1,225} = 0.75, P = 0.39^1$
hsdrop8	227	0.07 0.13 0.20	0.06 0.12 0.18	0.07 0.12 0.20	$F_{1,225} = 1.2, P = 0.27^1$
no_hs_diploma8	227	0.30 0.38 0.48	0.24 0.35 0.44	0.29 0.36 0.45	$F_{1,225} = 3.1, P = 0.077^1$
ba_or_better8	227	0.05 0.10 0.13	0.06 0.10 0.17	0.06 0.10 0.16	$F_{1,225} = 2.3, P = 0.13^1$
unemp8	227	0.05 0.07 0.09	0.05 0.06 0.10	0.05 0.06 0.09	$F_{1,225} = 0.54, P = 0.47^1$
povrat8	227	0.05 0.09 0.13	0.05 0.09 0.14	0.05 0.09 0.13	$F_{1,225} = 0, P = 0.95^1$
welfare8	227	0.04 0.06 0.09	0.04 0.05 0.09	0.04 0.06 0.09	$F_{1,225} = 2.7, P = 0.1^1$
favinc8	227	18951 21005 24908	18603 21513 26037	18843 21343 25095	$F_{1,225} = 0.19, P = 0.67^1$
avhhin8	227	17176 19521 22221	16237 19523 23189	16768 19523 22558	$F_{1,225} = 0, P = 0.98^1$
meanrnt80	227	219 245 285	215 244 293	216 245 287	$F_{1,225} = 0, P = 0.97^1$
mdvalhs9	227	45556 64100 121550	44041 68177 118334	44800 66600 120453	$F_{1,225} = 0.06, P = 0.81^1$
meanrnt9	227	358 422 579	365 432 563	364 431 568	$F_{1,225} = 0.03, P = 0.86^1$
mdvalhs0	227	76600 108750 143600	78300 114400 151800	76600 111700 150200	$F_{1,225} = 0.26, P = 0.61^1$
meanrnt0	225	490 577 701	487 550 710	487 568 704	$F_{1,223} = 0.08, P = 0.78^1$
tothsun8	227	901 1280 1693	886 1308 1713	888 1290 1708	$F_{1,225} = 0.01, P = 0.93^1$
ownocc8	227	594 912 1160	558 879 1238	576 900 1198	$F_{1,225} = 0.5, P = 0.48^1$
owner_occupied80	227	0.62 0.73 0.79	0.61 0.73 0.81	0.61 0.73 0.80	$F_{1,225} = 0, P = 0.95^1$
bltlast5yrs80	227	0.05 0.12 0.20	0.05 0.11 0.19	0.05 0.12 0.20	$F_{1,225} = 0.14, P = 0.71^1$
bltlast10yrs80	227	0.13 0.26 0.36	0.14 0.25 0.38	0.13 0.25 0.37	$F_{1,225} = 0.01, P = 0.92^1$
firestoveheat80	227	0.01 0.04 0.09	0.01 0.02 0.06	0.01 0.03 0.07	$F_{1,225} = 0.67, P = 0.41^1$
noaircond80	227	0.34 0.52 0.71	0.34 0.52 0.68	0.34 0.52 0.70	$F_{1,225} = 0.02, P = 0.88^1$
nofullkitchen80	227	0.01 0.01 0.03	0.00 0.01 0.02	0.01 0.01 0.02	$F_{1,225} = 0.96, P = 0.33^1$
zerofullbath80	227	0.01 0.02 0.03	0.01 0.02 0.04	0.01 0.02 0.04	$F_{1,225} = 2.1, P = 0.15^1$
northeast : 0	227	61% (55)	58% (79)	59% (134)	$\chi_1^2 = 0.27, P = 0.6^2$
1		39% (35)	42% (58)	41% (93)	
midwest : 0	227	68% (61)	72% (98)	70% (159)	$\chi_1^2 = 0.37, P = 0.55^2$
1		32% (29)	28% (39)	30% (68)	
south : 0	227	81% (73)	80% (109)	80% (182)	$\chi_1^2 = 0.08, P = 0.78^2$
1		19% (17)	20% (28)	20% (45)	
west : 0	227	90% (81)	91% (125)	91% (206)	$\chi_1^2 = 0.1, P = 0.75^2$
1		10% (9)	9% (12)	9% (21)	
meanhs8	227	33651 44351 55707	34417 46152 61835	34115 45384 59721	$F_{1,225} = 0.82, P = 0.36^1$
bedrms02_80	227	0.37 0.45 0.54	0.33 0.44 0.53	0.35 0.44 0.54	$F_{1,225} = 1.3, P = 0.25^1$
bedrms34_80	227	0.44 0.53 0.59	0.44 0.54 0.63	0.44 0.53 0.62	$F_{1,225} = 0.83, P = 0.36^1$
detach80	179	0.61 0.74 0.84	0.57 0.76 0.85	0.57 0.75 0.85	$F_{1,177} = 0.09, P = 0.76^1$
bedrms0_80occ	227	0 0 0	0 0 0	0 0 0	$F_{1,225} = 0.03, P = 0.86^1$
bedrms1_80occ	227	0.02 0.03 0.06	0.02 0.03 0.05	0.02 0.03 0.06	$F_{1,225} = 1, P = 0.31^1$
bedrms2_80occ	227	0.22 0.30 0.39	0.19 0.27 0.34	0.20 0.29 0.36	$F_{1,225} = 4.2, P = 0.041^1$
bedrms3_80occ	227	0.41 0.47 0.53	0.43 0.50 0.55	0.43 0.48 0.54	$F_{1,225} = 1.5, P = 0.21^1$
bedrms4_80occ	227	0.10 0.14 0.18	0.09 0.15 0.21	0.10 0.14 0.20	$F_{1,225} = 2.4, P = 0.12^1$
bedrms5_80occ	227	0.01 0.02 0.04	0.01 0.03 0.05	0.01 0.03 0.04	$F_{1,225} = 0.68, P = 0.41^1$
blt0_1yrs80occ	227	0.01 0.02 0.04	0.01 0.02 0.04	0.01 0.02 0.04	$F_{1,225} = 0.18, P = 0.68^1$
blt2_5yrs80occ	227	0.02 0.09 0.16	0.02 0.09 0.15	0.02 0.09 0.15	$F_{1,225} = 0.05, P = 0.83^1$
blt6_10yrs80occ	227	0.06 0.12 0.17	0.05 0.11 0.18	0.05 0.11 0.18	$F_{1,225} = 0.17, P = 0.68^1$
blt10_20yrs80occ	227	0.12 0.18 0.24	0.14 0.19 0.24	0.13 0.19 0.24	$F_{1,225} = 0.76, P = 0.38^1$
blt20_30yrs80occ	227	0.10 0.16 0.26	0.12 0.17 0.25	0.11 0.16 0.25	$F_{1,225} = 0.15, P = 0.7^1$
blt30_40yrs80occ	227	0.05 0.08 0.13	0.06 0.08 0.12	0.05 0.08 0.12	$F_{1,225} = 0.01, P = 0.94^1$
blt40_yrs80occ	227	0.11 0.19 0.33	0.11 0.19 0.34	0.11 0.19 0.34	$F_{1,225} = 0.04, P = 0.85^1$
detach80occ	227	0.82 0.91 0.97	0.85 0.93 0.98	0.83 0.92 0.97	$F_{1,225} = 2.8, P = 0.098^1$
attach80occ	227	0.00 0.00 0.01	0.00 0.00 0.01	0.00 0.00 0.01	$F_{1,225} = 0.05, P = 0.82^1$
mobile80occ	227	0.00 0.07 0.13	0.00 0.03 0.12	0.00 0.04 0.13	$F_{1,225} = 1.5, P = 0.23^1$
occupied80	227	0.93 0.95 0.97	0.92 0.95 0.96	0.92 0.95 0.96	$F_{1,225} = 0.09, P = 0.77^1$
bltmore30_80	227	0.21 0.34 0.51	0.21 0.34 0.49	0.21 0.34 0.49	$F_{1,225} = 0.11, P = 0.74^1$
og82list : 1	227	100% (90)	100% (137)	100% (227)	²
0		0% (0)	0% (0)	0% (0)	
nbr_dummy : 0	227	76% (68)	71% (97)	73% (165)	$\chi_1^2 = 0.62, P = 0.43^2$
1		24% (22)	29% (40)	27% (62)	

a b c represent the lower quartile *a*, the median *b*, and the upper quartile *c* for continuous variables.

N is the number of non-missing values.

Numbers after percents are frequencies.

the upperbound 95% C.I. for values below HRS=28.5 and the estimated value above HRS=28.5 overlap, and vice versa for the lowerbound 95% C.I. for values above HRS = 28.5. This has us convinced that the Regression Discontinuity Design is not appropriate around this value. In addition, this lack of discontinuity appears to be consistent across various bandwidth values (tested with values $h = \{4, 8, 16, 20\}$).

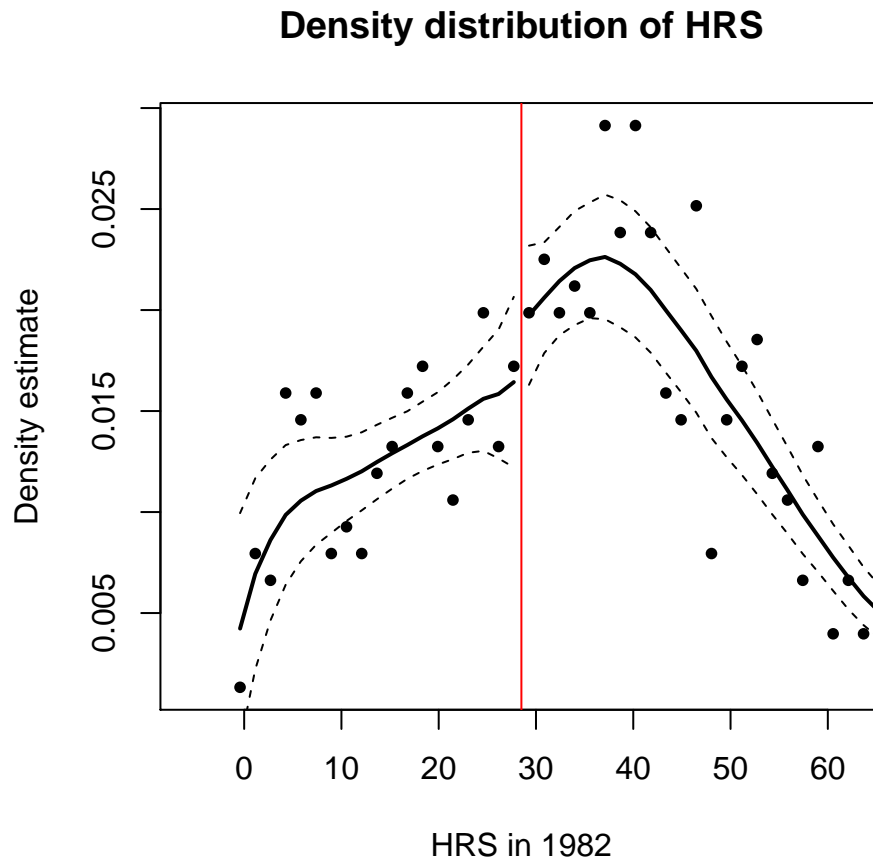


Figure 1: Density distribution histogram for 1982 HRS.

NOTES: The way they picked is good, it means that 28.5 is not some magic number above which things get demonstrably worse but is as good as random. So any discontinuity is due to the vagaries of program design and not endogenous variation.

Part C: RDD First Stage

The first stage equation is $\mathbf{1}\{NPL_{2000}\} = \gamma_1 HRS_{82} + x_i \gamma_2 + u_i$.

Part D: RDD Second Stage

Part E: Synthesis

Part F: Appendix: Code Listings

```

1 # Econometrics helper functions for [R]
2 #
3 # Peter Alstone and Frank Proulx
4 # 2013
5 # version 1
6 # contact: peter.alstone AT gmail.com
7
8 # Category: Data Management -----
9
10
11 # Category: Data Analysis -----
12
13 # Function: Find adjusted R^2 for subset of data
14 # This requires a completed linear model...pull out the relevant y-values and residuals and feed them to
    function
15 # [TODO @Peter] Improve function so it can simply evaluate lm or glm object, add error handling, general
    clean up.
16 adjr2 <- function(y,resid){
17   r2 <- 1-sum(resid^2) / sum((y-mean(y))^2)
18   return(r2)
19 } #end adjr2
20
21
22 # Category: Plots and Graphics -----
23
24 ## Function for arranging ggplots. use png(); arrange(p1, p2, ncol=1); dev.off() to save.
25 require(grid)
26 vp.layout <- function(x, y) viewport(layout.pos.row=x, layout.pos.col=y)
27 arrange_ggplot2 <- function(..., nrow=NULL, ncol=NULL, as.table=FALSE) {
28   dots <- list(...)
29   n <- length(dots)
30   if(is.null(nrow) & is.null(ncol)) { nrow = floor(n/2) ; ncol = ceiling(n/nrow)}
31   if(is.null(nrow)) { nrow = ceiling(n/ncol)}
32   if(is.null(ncol)) { ncol = ceiling(n/nrow)}
33   ## NOTE see n2mfrow in grDevices for possible alternative
34   grid.newpage()
35   pushViewport(viewport(layout=grid.layout(nrow,ncol) ) )
36   ii.p <- 1
37   for(ii.row in seq(1, nrow)){
38     ii.table.row <- ii.row
39     if(as.table) {ii.table.row <- nrow - ii.table.row + 1}
40     for(ii.col in seq(1, ncol)){
41       ii.table <- ii.p
42       if(ii.p > n) break
43       print(dots[[ii.table]], vp=vp.layout(ii.table.row, ii.col))
44       ii.p <- ii.p + 1
45     }
46   }
47 }
48
49 robust <- function(model){ #This calculates the Huber-White Robust standard errors -- code from http://
    thetarzan.wordpress.com/2011/05/28/heteroskedasticity-robust-and-clustered-standard-errors-in-r/
50   s <- summary(model)
51   X <- model.matrix(model)
52   u2 <- residuals(model)^2
53   XDX <- 0
54
55   for(i in 1:nrow(X)) {
56     XDX <- XDX +u2[i]*X[i,]%*%t(X[i,])
57   }
58
59 # inverse(X'X)
60   XX1 <- solve(t(X)%*%X)
61
62 #Compute variance/covariance matrix
63   varcovar <- XX1 %*% XDX %*% XX1
64
65 # Degrees of freedom adjustment
66   dfc <- sqrt(nrow(X))/sqrt(nrow(X)-ncol(X))
67
68   stdh <- dfc*sqrt(diag(varcovar))
69
70   t <- model$coefficients/stdh
71   p <- 2*pnorm(-abs(t))
72   results <- cbind(model$coefficients, stdh, t, p)

```

```

73     dimnames(results) <- dimnames(s$coefficients)
74     results
75 }
76
77 ## Two functions for clustered standard errors below from: http://people.su.se/~ma/clustering.pdf -----
78
79 clx <-
80   function(fm, dfcw, cluster){
81     # R-codes (www.r-project.org) for computing
82     # clustered-standard errors. Mahmood Arai, Jan 26, 2008.
83
84     # The arguments of the function are:
85     # fitted model, cluster1 and cluster2
86     # You need to install libraries 'sandwich' and 'lmtest'
87
88     # reweighting the var-cov matrix for the within model
89     library(sandwich);library(lmtest)
90     M <- length(unique(cluster))
91     N <- length(cluster)
92     K <- fm$rank
93     dfc <- (M/(M-1))*((N-1)/(N-K))
94     uj <- apply(estfun(fm),2, function(x) tapply(x, cluster, sum));
95     vcovCL <- dfc*sandwich(fm, meat=crossprod(uj)/N)*dfcw
96     coeftest(fm, vcovCL) }
97
98 mclx <-
99   function(fm, dfcw, cluster1, cluster2){
100     # R-codes (www.r-project.org) for computing multi-way
101     # clustered-standard errors. Mahmood Arai, Jan 26, 2008.
102     # See: Thompson (2006), Cameron, Gelbach and Miller (2006)
103     # and Petersen (2006).
104     # reweighting the var-cov matrix for the within model
105
106     # The arguments of the function are:
107     # fitted model, cluster1 and cluster2
108     # You need to install libraries 'sandwich' and 'lmtest'
109
110     library(sandwich);library(lmtest)
111     cluster12 = paste(cluster1,cluster2, sep=" ")
112     M1 <- length(unique(cluster1))
113     M2 <- length(unique(cluster2))
114     M12 <- length(unique(cluster12))
115     N <- length(cluster1)
116     K <- fm$rank
117     dfc1 <- (M1/(M1-1))*((N-1)/(N-K))
118     dfc2 <- (M2/(M2-1))*((N-1)/(N-K))
119     dfc12 <- (M12/(M12-1))*((N-1)/(N-K))
120     u1j <- apply(estfun(fm), 2, function(x) tapply(x, cluster1, sum))
121     u2j <- apply(estfun(fm), 2, function(x) tapply(x, cluster2, sum))
122     u12j <- apply(estfun(fm), 2, function(x) tapply(x, cluster12, sum))
123     vc1 <- dfc1*sandwich(fm, meat=crossprod(u1j)/N )
124     vc2 <- dfc2*sandwich(fm, meat=crossprod(u2j)/N )
125     vc12 <- dfc12*sandwich(fm, meat=crossprod(u12j)/N)
126     vcovMCL <- (vc1 + vc2 - vc12)*dfcw
127     coeftest(fm, vcovMCL)}
128
129 ## Function to compute ols standard errors , robust, clustered...
130 ## Based on http://diffuseprior.wordpress.com/2012/06/15/standard-robust-and-clustered-standard-errors-computed-in-r/
131 ols.hetero <- function(form, data, robust=FALSE, cluster=NULL,digits=3){
132   r1 <- lm(form, data)
133   if(length(cluster)!=0){
134     data <- na.omit(data[,c(colnames(r1$model),cluster)])
135     r1 <- lm(form, data)
136   }
137   X <- model.matrix(r1)
138   n <- dim(X)[1]
139   k <- dim(X)[2]
140   if(robust==FALSE & length(cluster)==0){
141     se <- sqrt(diag(solve(crossprod(X)) * as.numeric(crossprod(resid(r1))/(n-k))))
142     res <- cbind(coef(r1),se)
143   }
144   if(robust==TRUE){
145     u <- matrix(resid(r1))
146     meat1 <- t(X) %*% diag(diag(crossprod(t(u)))) %*% X

```



```

147 dfc <- n/(n-k)
148 se <- sqrt(dfc*diag(solve(crossprod(X)) %*% meat1 %*% solve(crossprod(X))))
149 res <- cbind(coef(r1),se)
150 }
151 if(length(cluster)!=0){
152   clus <- cbind(X,data[,cluster],resid(r1))
153   colnames(clus)[(dim(clus)[2]-1):dim(clus)[2]] <- c(cluster,"resid")
154   m <- dim(table(clus[,cluster]))
155   dfc <- (m/(m-1))*((n-1)/(n-k))
156   uclust <- apply(resid(r1)*X,2, function(x) tapply(x, clus[,cluster], sum))
157   se <- sqrt(diag(solve(crossprod(X)) %*% (t(uclust) %*% uclust) %*% solve(crossprod(X)))*dfc)
158   res <- cbind(coef(r1),se)
159 }
160 res <- cbind(res,res[,1]/res[,2],(1-pnorm(abs(res[,1]/res[,2])))*2)
161 res1 <- matrix(as.numeric(sprintf(paste("%. ",paste(digits,"f",sep=""),sep=""),res)),nrow=dim(res)[1])
162 rownames(res1) <- rownames(res)
163 colnames(res1) <- c("Estimate","Std. Error","t value","Pr(>|t|)")
164 return(res1)
165 }

```

../util/are213-func.R