TECHNICAL REPORT 2011-2

Computing Value per Square Foot of Vacant Parcels and Aggregating to Model Zone Level**

Huiling Zhang*#
Richard Arnott*

August 2011

Abstract: Average value per square foot of vacant parcels within a model zone has been of interest. Given the fact that a parcel's assessed value is a fixed fraction of its last-sale price, all values should be expressed in 2000 year dollars in order to be comparable. OLS regression of natural logarithm of value per square foot of vacant parcels on accessibility variables, city dummy, planned land use dummy, and last-sale year dummy permits imputing missing values.

** This report was prepared in conjunction with the University of California MRPI Project LA-Plan.
* Department of Economics, University of California, Riverside, CA 92506#
# Please address questions and comments to the primary author, Huiling Zhang, at hzhan017@ucr.edu.

Computing value per square foot of vacant parcels and aggregating to model zone level

A model zone's average value per square foot of its vacant parcels equals to total value of its vacant parcels divided by total area of its vacant parcels. Area of any parcel can be easily found with the help of a GIS software, but parcel value, which was collected and processed separately by assessor offices of each county, contains lots of missing data. Simply averaging over parcels that have land value data will do the job, but a lot of data will be discarded. This sub-project tried to make the best use of available datasets by running a regression on parcels with complete data and imputing values for parcels with missing data.

A regression reveals how value per square foot of vacant parcels was determined by various factors. In this project, accessibility measures, including distances to the nearest freeway, coast, sub-centers and CBD, planned land use, year of last sale, and the belonging city of a vacant parcel acted as explanatory variables.

Planned land use is special to vacant parcels compared to other types of parcels. A cropland that is going to be transformed into residential houses will be more valuable than if it is to remain as cropland. And transforming into residential housing would be more valuable than transforming into public parking lot. So planned land use as a categorical explanatory variable should be in the regression equation.

Values should all be discounted to year 2000 for them to be comparable.[1] Since the value used was "TOTVAL07", whose value was calculated by county assessor offices by multiplying a constant fraction on the last sale price. So it was largely affected by the year when its last sale occurred. A piece of vacant land that has earlier last sale date would be more severely underestimated in value. So inflating or deflating the assessed values to a reference year, in this project 2000, is a must. This is why last sale year should enter the regression equation as a dummy explanatory variable.

Vacant land's value has also been affected by the city it was located in. Cities vary in their infrastructure level, economic policies, public services, environment quality and etc. Two pieces of vacant land with all qualities the same except for the city they were located in may possibly differ in value per square foot. So city should be one of the categorical dummy variables too.

This report has five sections. Section I documents data source and data preparation methods. Section II provides regression results and imputation methods, including how to discount value per square foot into year 2000. Section III documents how to aggregate parcel information into model zone level. Section IV documents how to present results on a map, and Section V concludes.

[1] TOTVAL07 is the *assessed* value in 2007. Due to Proposition 13 (California's property tax revolt Proposition) assessed value is *not* the assessor's estimate of true market value in 2007, but instead the property tax base of the parcel in 2007. The property tax base of vacant parcels in 2007 is calculated as the most recent sales price compounded annually by the maximum of 2% and an administratively-decided inflation from the date of the most recent sale to 2007 (the procedure is more complicated for developed properties since account is taken of improvements). Since TOTVAL07 is therefore a function only of the most recent sales price and the year of the most recent sale, a property's market value in 2000 can be estimated by using TOTVAL07 and a time dummy for the year of most recent sale.

1. Data preparation

All data preparation work was done in ArcCatalog.

1.1 Data input

Five primary data sources contributed as data input to this sub-project. The first three are about parcels, and the last two are useful in calculating accessibility measures.

1. Parcels with model zone code shape file

   (ftp://mrpi.geog.ucsb.edu/data2010/parcel/MZparcel_imputed_GIS/)

   Useful attribute fields[2] are SCAGXYID, Shape_Area, X-Y coordinates, MZ and APN.

2. Assessed value of parcels table

   (ftp://mrpi.geog.ucsb.edu/data2010/parcel/attribute_whole/)

   Useful attribute fields are SCAGXYID, APN, TOTVAL07, City_name, and SCAG_GP_CO.

3. Latest transaction records of parcels.

   (ftp://mrpi.geog.ucsb.edu/data2010/parcel/raw/)

   Useful attribute fields are APN, and DT_SALE.

4. Freeway and coastline shape files.

5. Employment sub-centers coordinates and CBD coordinates

In the regression, dependent variable is natural logarithm of value per square foot, which equals assessed value (TOTVAL07) scaled by area (Shape_Area). Independent variables are accessibility variables, which are calculated from the X-Y coordinates of parcels, sub-

[2] To ease calculation burden, it is recommended to export only useful attributes of any file, no matter it is shape file or dbf table or csv table.

centers, and CBD; and shape files of freeway and coastline. SCAGXYID and APN were keywords in matching parcels from different data sources. Model zone codes (MZ) were used in identifying parcels that are from the same model zone.

1.2 Data preparation

1.2.1 Select vacant parcels out

Vacant parcels in this sub project refers to parcels that have land use code[3], either LU08 or LU_08, that falls into one of the three major categories: 1700, 1800, and 2000. Data inputs of this project share the characteristic that data size is huge. Because only vacant parcels are of interest in this sub project, selecting vacant parcels out was done before any process was taken to avoid unnecessary calculations.

In data source 1, parcel model zone shape file, land use code is LU_08, while for data source 2, assessed value table file, land use code is LU08. [4]

LU08 and LU_08 were prepared in different methods, it was consensus of the project team that LU08 should be relied upon when deciding the land use type of a certain parcel. But random sample comparison revealed that the two codes were not significantly different in identifying the same parcel, so for the sake of easing calculation burden, both codes were used.

---

[3] For detailed interpretations of land use classification and code system employed in this sub-project, please refer to ftp://mrpi.geog.ucsb.edu/data/11_Land_use/LU_CODE/

[4] Query syntax in ArcGIS is:
"LU_08" >=1700 AND "LU_08" < 3000 AND "LU_08" <>1900.
"LU08" >=1700 AND "LU08" < 3000 AND "LU08" <>1900.
Notice that both codes system assign same number to same type of parcel.

1.2.2 Calculate accessibility measures

Four kinds of accessibility measures used in this sub-project can be grouped into two according to their calculation methods.

1. Distance to the nearest freeway and to the nearest coast:

   They are point to line distances, and can be done only in shape files. “near” function in proximity of analysis tools of ArcMap was employed.

   LA_MZ.dbf → LA_MZ_events.shp → LA_MZ2.shp → LA_MZ3.shp → LA_MZ_dist.dbf

2. Distance to the nearest sub-center and to CBD

   They are point to point distances, so the calculations are done in R codes, detail of which can be found in Appendix I.

1.2.3 Combine parcels’ information from different data sources

Data source 1 → LA_MZ_dist.dbf

(scagxyid, shape_area, x-y coordinates, apn, fsub, cbd, freeway, ocean.)

Data source 2 → LAX_ATT.dbf

(scagxyid, apn, totval07, city_name, and scag_gp_co)

Data source 3 → last_sale_LA.dbf

(apn, dt_sale)

“Join” function of ArcCatalog was employed. Join 2 to 1 using SCAGXYID, and join 3 to 1 using APN.

Output: LA_join2.dbf

(scagxyid, shape_area, x-y coordinates, apn, fsub, cbd, freeway, ocean, totval07, city_name, scag_gp_co, and dt_sale.)

1.2.4 Merge six counties' data

"Merge" function of ArcCatalog was employed.

Notice one small thing about extracting "last_sale_year" from dt_sale. Different counties have different format recording last-sale date.

1.2.5 Blanks and zeros in datasets

In this sub-project, datasets used are flawed in many different ways. So blanks and zeros were all treated as missing values. But this should not significantly alter regression and imputation results on the aggregated model zone level.

2. Regression and Imputation

2.1 Ordinary Least Square Linear Regression

Response variable:

Natural logarithm of value per square foot of a vacant parcel (lgvsqft)

Explanatory variable:

Accessibility variables: fsub, CBD, freeway, and ocean

City dummies, default Los Angeles

Last-sale year dummies, default 2000

Planned land use dummies: scag_gp_co, default single family residential (1100)[5]

Regression sample:

Parcels that have data on lgvsqft, accessibility variables, and last-sale year. Notice that Imperial County has no data on last-sale year, therefore not a parcel of it was included in the regression.

2.2 Discount to year 2000

For parcels that have data on both last-sale year and assessed value totval07, subtracting regression coefficients of its last-sale year from lgvsqft yields the natural logarithm of value in 2000 dollars.

2.3 Imputation

Impute value per square foot in 2000 dollars for parcels with missing last-sale year or assessed value totval07. Set all last-sale year dummies to zero and apply regression coefficients produces predicted value.

This part was done in STATA, and codes can be found in Appendix II.

Output: lgvsqft_adj

[5] For documentation on correspondence between planned land use and planned land use code assigned, please refer to ftp://mrpi.geog.ucsb.edu/data/10_Parcel/GP_LU_Correspondent.doc

3. Aggregate to model zone level[6]

Average value per square foot in 2000 dollars of vacant parcels of a model zone is calculated in this way:

First, get the value in 2000 dollars of every vacant parcel of a model zone. If the land value and last-sale year of a vacant parcel is available in the database, then the value here is raw or true data. Otherwise, imputed values were applied.

Second, add up adjusted values of all vacant parcels belonging to one model zone.

Third, add up area of all vacant parcels belonging to one model zone.

Finally, total adjusted values scaled by total area would yield adjusted value per square foot of vacant parcels in a model zone.

Results:

Table 1: average value per square foot of vacant parcels within a model zone

Model Zone (ID)	Model Zone Name	vacant parcels (count#)	Sum_Area (sqmt)	Sum_value_2000 ($)	$/sqft per model zone ($/sqft)
0		1197	259454783	2633038474	0.94
1	Downtown Los Angeles	363	2376068	230374173	9.01
2	Westside	65	833935	57990680	6.46
3	Glendale	165	5951176	199154116	3.11
4	East Los Angeles	118	2221676	78152036	3.27
5	Maywood	48	376854	69878604	17.23
6	Florence	63	551460	19387934	3.27
7	Baldwin Hills	218	4809134	384933833	7.44
8	Beverly Hills	85	2094572	117916709	5.23
9	El Segundo	814	4740379	904476210	17.73
10	Santa Monica	102	1536391	156593250	9.47
11	Marina del Rey	99	972913	65300881	6.24
12	Westwod	7	611811	41859392	6.36

[6] This part was done in ArcMap using function "summarize" by model zone in field calculator of attribute table.

13	East Santa Monica Mtns	165	3229748	313339092	9.01
14	Reseda - van Nuys	96	6924837	168221485	2.26
15	East van Nuys	174	1659512	93517234	5.24
16	Burbank	130	3022165	124426740	3.82
17	Pasadena	119	3697575	166192000	4.18
18	East Pasadena	125	3164412	114360854	3.36
19	Rosemead	301	7233003	163849724	2.10
20	Pico Rivera	245	2465748	224538385	8.46
21	South Gate	151	1738273	181063854	9.68
22	West Compton	172	2320723	64754707	2.59
23	Torrance	135	1595735	190502522	11.09
24	Palos Verdes	353	8327166	1497696828	16.71
25	Carson	250	4514197	124385147	2.56
26	Long Beach	70	152475	59502899	36.26
27	Signal Hill	269	6963660	1347734746	17.98
28	Compton	293	2478440	362722850	13.60
29	Hawaiian Gardens	130	4256269	262501906	5.73
30	Cerritos	24	345929	5506084	1.48
31	Norwalk	264	5232099	405333130	7.20
32	Industry	272	11828011	219104854	1.72
33	Diamond Bar	290	8463315	231762825	2.54
34	North El Monte	80	5420550	512901917	8.79
35	West Covina	47	511421	35337927	6.42
36	Glendora	358	3723964	38141575	0.95
37	La Verne - Azusa	1827	35738220	594771193	1.55
38	Altadena	356	11762972	243620634	1.92
39	North Hills - Sylmar	223	3416559	182192567	4.95
40	Chatsworth	494	3422824	166974817	4.53
41	Calabasas	217	3807096	160641908	3.92
42	Malibu - Point Dume	183	5294536	291861612	5.12
43	Agoura Hills	171	5551079	106610389	1.78
44	Lake Los Angeles	2118	78873852	138295235	0.16
45	Lancaster - Palmdale	6792	123513990	983087678	0.74
46	Santa Clarita	3424	145405662	748741499	0.48
47	Ventura North County	3955	2685124384	9317705307	0.32
48	Thousand Oaks	3048	215399201	2686014939	1.16
49	Oxnard -	2354	205660596	2336964136	1.06

	Camarillo				
50	Seal Beach - Los Alamitos	170	2013132	402869487	18.59
51	Cypress	94	1338993	53632478	3.72
52	South Buena Park	65	1135707	23955466	1.96
53	Buena Park - La Habra	561	6085794	164628942	2.51
54	Placentia	152	1400885	103356570	6.85
55	Yorba Linda	728	5403576	163578908	2.81
56	Huntington Beach	505	6130170	913581574	13.85
57	Garden Grove	166	1697172	79605313	4.36
58	Anaheim	126	1769323	39051718	2.05
59	North Tustin	616	21687975	604440698	2.59
60	Costa Mesa	135	3433346	158818956	4.30
61	Santa Ana	375	7883164	298257704	3.51
62	Tustin	1069	1451114	371239426	23.77
63	Newport Coast	1237	13812867	669483366	4.50
64	Irvine	645	10192328	780223228	7.11
65	East Orange County	3403	67304436	1935235348	2.67
66	San Juan Capistrano	3101	35645657	1210452929	3.15
67	Montclair - Chino	2200	81214409	1118528292	1.28
68	Ontario	113	893337	28823107	3.00
69	Rancho Cucamonga	723	3186366	231307546	6.74
70	Upland	2101	8800706	516636059	5.45
71	Fontana	599	4515273	175219352	3.61
72	Colton	483	8666117	131392018	1.41
73	San Bernardino	93	899857	39422120	4.07
74	Redlands - Highland	620	9937787	249439726	2.33
75	Crestline	582	7682861	190236060	2.30
76	Victorville	2693	60104914	400548326	0.62
77	Lucerne Valley	444	32815224	105145821	0.30
78	San Bernardino Mountains	2142	27944645	420638166	1.40
79	Northwest Mojave	380	58977214	34118950	0.05
80	Northeast Mojave	790	443925384	471077635	0.10
81	Corona	5375	38687939	1090952686	2.62

82	East Riverside	2120	45338323	796196247	1.63
83	Indio	5996	38925036	1056368320	2.52
84	East Mojave	7385	3217800511	2296591402	0.07
85	Lake Elsinore	4439	73224352	1351075096	1.71
86	Riverside	200	8287651	104673056	1.17
87	Moreno Valley	919	21803556	257012510	1.10
88	Perris	6883	88919914	1362573280	1.42
89	Banning	3804	160348758	1276133581	0.74
90	Hemet	9314	190773550	2418936435	1.18
91	Temecula	4699	59223786	1182028725	1.85
92	Palm Springs	2010	18608637	348372408	1.74
93	La Quinta	3232	147726351	1056352839	0.66
94	Cathedral City	1174	8735964	240207709	2.55
95	Palm Desert	1470	23630541	669905670	2.63
96	Imperial Valley	5378	1697634335	1428770480	0.08
97	El Centro	3508	321459347	509785442	0.15

Note: 1. "Vacant Parcels" counts the number of vacant parcels that were used in this sub-project for every model zone. A parcel can be useful either in regression or in imputation.

2. "Sum_Area" is the total area of all vacant parcels within a model zone and being counted.

3. "Sum_value_2000" is the total value in 2000 dollars of all vacant parcels within a model zone and being counted.

4. "Average Value/ sqft" equals to "Sum_value_2000" divided by "Sum_Area".

5. Model zone with ID 0 includes any parcel whose belonging model zone is unknown.

4. Mapping[7]

To provide an intuitive presentation of average value per square foot of vacant parcels within a model zone, colored map of Los Angeles Metropolitan Area was used. The

[7] Four steps were taken before creating the map.
Export: parcel model zone shape files are too large in size, so select fields from attribute table is a good way to speed up calculation time. In this case, scagxyid and model zone code are the only two fields that are necessary.
Dissolve, Merge, and then a final Dissolve.

darker a model zone is on the map, the higher value per square foot of its vacant parcels has on average.[8]

Blank areas in the map represent parcels that were lost in the process of producing model-zone-based map from parcel-based map, which was done by tool “dissolve” in ArcGIS software. Fortunately, only some model zone in Los Angeles County suffered this problem, and there is no model zone that lost all of its parcels.

This problem may take a while to be fixed, due to some unknown technical reason. As the data loss occurred only at the phase of producing maps, it did not affect regression and imputation results at all. Therefore, it was left for future treatment.

[8] This part was done in ArcMap in “Symbology” Panel of “Layer Properties”.

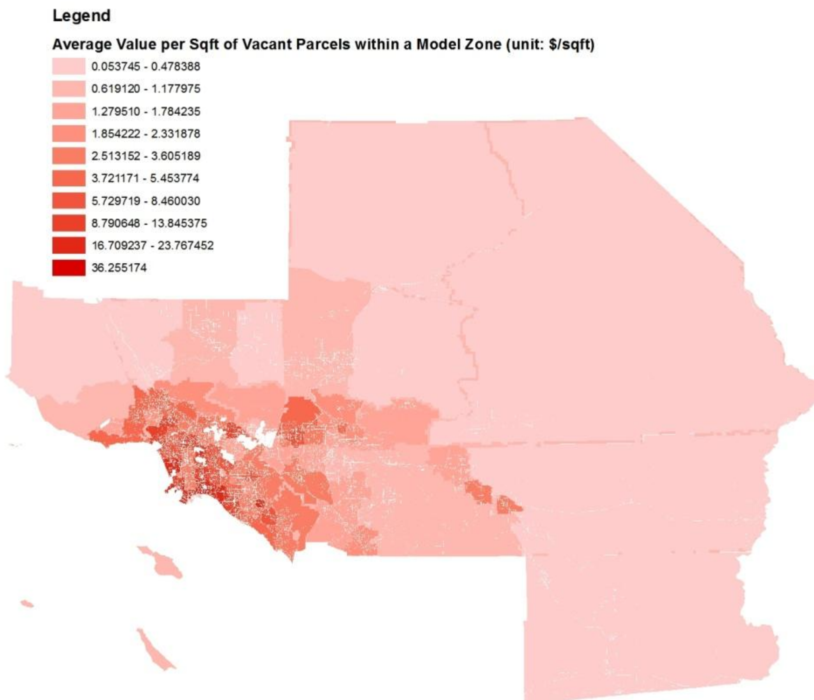

Figure 1: Average Value per Square Foot of Vacant Parcels within a Model Zone. Unit is in dollar per square foot. The darker a model zone is on the map, the higher value per square foot of its vacant parcels has on average.

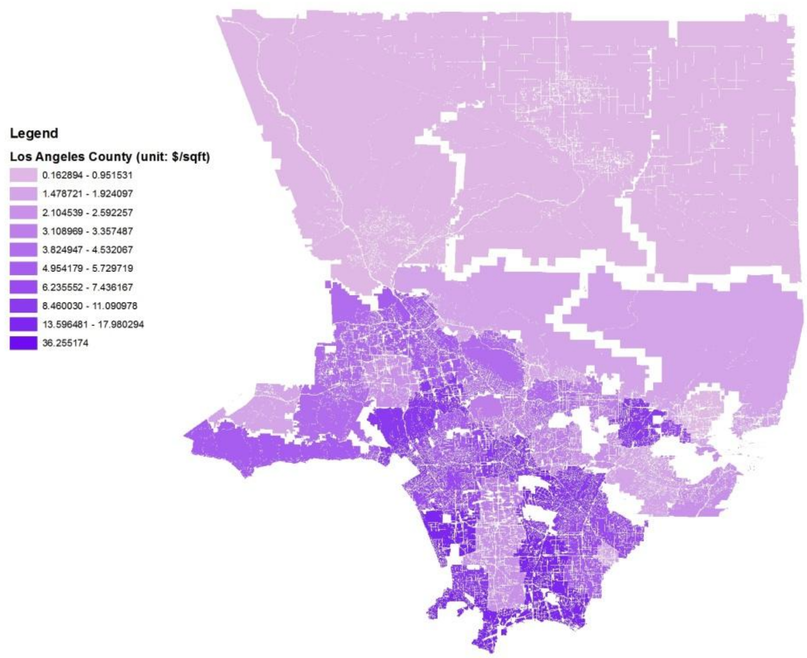

Figure 2: Model Zones in Los Angeles County, colored by average value per square foot of their vacant parcels. Units on the map are dollar per square foot. Darker color is associated with higher value per square foot.

5. Conclusion

Places where improvement can be achieved given more time:

5.1 Detect and adjust spatial autocorrelation of parcel data.

Spatial autocorrelation should be taken care of if regression data is spatial. If an autocorrelation pattern is detected, all the regression results and imputed aggregated average value per square foot for model zone may be false. But it would just be a change of parameters and a simple re-run of ready-made codes.

5.2 Make use of last-sale price data

Price of last-sale is the ideal variable for measuring *value* of a parcel, but as a result of the low quality of its data, assessed value "totval07" was used instead. Orange County and Riverside County have data on both variables, which provides an opportunity to compare the results using two different dependent variables.

Comparing last-sale-price and assessed value does not make much sense. All model zone "values" can be transformed into "relative values" compared to a common model zone. Then the "relative values" using two variables become comparable.

Acknowledgements

The authors would like to thank the following persons for their constant support: Wenwen Li, for her prompt and detailed answers to whatever technical questions and data questions; Yizhen Gu for his specialized knowledge in the data; and Jifei Ban for his well-developed procedures and codes for solving the problems.

Appendix I: Calculating distances to nearest sub-centers and CBD in R

R codes:

```
#========== begin public ============
CBD<-t(as.matrix(c(-118.446305110092,34.0615632358611)))
geodist<-function(center_coor,coordinates)
  {
    a<-57.2958
   dist_center<-3963*acos( outer(sin(center_coor[,2]/a),sin(coordinates[,2]/a))+
   outer(cos(center_coor[,2]/a),cos(coordinates[,2]/a))*cos(outer(-
center_coor[,1]/a,coordinates[,1]/a,"+")))
  return(dist_center)  }
con<-1609.344
```

```
library(rgdal)
library(foreign)

coor<-read.csv(file="subcoord.csv")
subid<-as.numeric(as.matrix(as.data.frame(table(coor$subcenterid))$Var1))[-1]
subcoor<-matrix(0,nrow=51,ncol=3)
for (k in 1:length(subid))
{
  for(i in 1:dim(coor)[1])
    {
     if (coor$subcenterid[i]==subid[k])
       subcoor[k,]<-subcoor[k,]+
c(coor$EMP03[i]*coor$longitude[i],coor$EMP03[i]*coor$latitud[i],coor$EMP03[i])
      }
}
subcoor1<-cbind(subcoor[,1]/subcoor[,3],subcoor[,2]/subcoor[,3])
#========== end public =============

#======== San Bernardino county ================
parcel_sb<-read.dbf("san_bernardino_county.dbf")
parcel_sb1<-subset(parcel_sb,LU_08>=1700 & LU_08<3000 & LU_08!=1900)

xy<-cbind(parcel_sb1$X,parcel_sb1$Y)
xy1<-project(xy, "+proj=utm +zone=11 ellps=WGS84",inv=T)

subdist<-geodist(subcoor1,xy1)
parcel_sb1$fsub<- apply(subdist,2,min)
parcel_sb1$CBD<-as.vector(geodist(CBD,xy1))

## ArcGIS can only read comma separated file.
write.csv (parcel_sb1,"parcel_sb2.csv")
```

Discussion:

The essence of the above codes was borrowed from R codes written by Jifei Ban. The same procedure applies to six counties, therefore only codes on processing San Bernardino data were pasted here.

Appendix II: Regression and Imputation in STATA

Part I: STATA codes:

```
// input distance vars, totval07, last-sale-year
// output scagid, value per square foot discounted to year 2000

clear
log close _all
log using Aug22_1

cd "D:\summer, 2011\zone\join2_backup"
insheet using "D:\summer, 2011\zone\join2_backup\FIVE_merge.csv"

foreach var of varlist fsub cbd freeway ocean shape_area {
        drop if missing(`var')
}


replace  scag_gp_co = 1 if  scag_gp_co == 0
replace  scag_gp_co = 1 if  scag_gp_co == .

replace saleyr = . if saleyr == 1899
replace saleyr = . if saleyr == 0
drop if missing(saleyr)


gen scagxyid = scag_xyid

duplicates tag  scagxyid, gen (dup_SCAGID)
drop if  dup_SCAGID >1

replace  totvalue07 = . if  dup_SCAGID == 1
gen lgvsq = ln( totvalue07/ shape_area*0.09290304)
gen year = string(saleyr)


gen freeway_mile = freeway * 0.00062137
gen ocean_mile = ocean * 0.00062137

replace freeway = freeway_mile
replace ocean = ocean_mile

char  scag_gp_co [omit] 1110
char  city_name [omit] "Los Angeles"
char  year [omit] "2000"
```

```
xi: reg  lgvsq  fsub cbd freeway ocean  i.scag_gp_co  i.city_name i.year

predict lgvsq_p
gen lgvsq_int = lgvsq
replace lgvsq_int = lgvsq_p if missing(lgvsq)

gen lgvsq_adj = .

foreach var of varlist _Iyear* {
        gen b`var' = _b[`var']
        replace lgvsq_adj =  lgvsq_int - b`var' if (`var' == 1)
}

// as year 2000 is not in the varlist above
replace lgvsq_adj =  lgvsq_int if (saleyr == 2000)


gen vsq_adj = exp(lgvsq_adj)
gen scagxyid_st = string(scagxyid,"%14.0f")

gen val_adj =  vsq_adj * shape_area * 10.7639104

outsheet  scagxyid_st vsq_adj shape_area val_adj mz using 8_22_1.csv, comma
```

Part II: Regression results table:

```
. xi: reg  lgvsq  fsub cbd freeway ocean  i.scag_gp_co  i.city_name i.year
i.scag_gp_co      _Iscag_gp_c_1-4000  (naturally coded; _Iscag_gp_c_1110 omitted)
i.city_name       _Icity_name_1-170   (_Icity_name_87 for cit~e==Los Angeles omitted)
i.year            _Iyear_1-69         (_Iyear_61 for year==2000 omitted)
note: _Icity_name_78 omitted because of collinearity
note: _Icity_name_147 omitted because of collinearity
note: _Iyear_2 omitted because of collinearity
note: _Iyear_12 omitted because of collinearity

      Source |       SS       df       MS              Number of obs =   53887
-------------+------------------------------           F(273, 53613) =  172.58
       Model |  233206.139   273  854.234942           Prob > F      =  0.0000
    Residual |  265377.133 53613  4.94986538           R-squared     =  0.4677
-------------+------------------------------           Adj R-squared =  0.4650
       Total |  498583.272 53886  9.25255672           Root MSE      =  2.2248

------------------------------------------------------------------------------
       lgvsq |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
        fsub |  -.0421477   .0019803   -21.28   0.000    -.0460291   -.0382662
         cbd |  -.0147708   .0015745    -9.38   0.000    -.0178568   -.0116848
```

freeway	.0006728	.0050802	0.13	0.895	-.0092844	.01063
ocean	-.0037231	.0019986	-1.86	0.062	-.0076403	.0001941
scag_gp_co==1	-.1464293	.0511574	-2.86	0.004	-.2466983	-.0461604
scag_gp_co==1100	-.0166764	1.018471	-0.02	0.987	-2.012887	1.979534
scag_gp_co==1120	.0668991	.0469469	1.42	0.154	-.0251172	.1589154
scag_gp_co==1130	-1.619473	.042456	-38.14	0.000	-1.702687	-1.536259
scag_gp_co==1200	-.1375123	.1444795	-0.95	0.341	-.4206932	.1456687
scag_gp_co==1210	.5805213	.2858613	2.03	0.042	.0202308	1.140812
scag_gp_co==1220	-1.164887	.1370823	-8.50	0.000	-1.433569	-.8962042
scag_gp_co==1230	-.3294244	.1167385	-2.82	0.005	-.5582328	-.100616
scag_gp_co==1233	.0764382	.3416174	0.22	0.823	-.5931347	.7460111
scag_gp_co==1240	-1.176254	.5794177	-2.03	0.042	-2.311918	-.0405908
scag_gp_co==1250	-1.243793	.3803609	-3.27	0.001	-1.989303	-.4982822
scag_gp_co==1260	-.9184947	.1591718	-5.77	0.000	-1.230473	-.6065167
scag_gp_co==1270	-1.257101	.4182459	-3.01	0.003	-2.076866	-.4373352
scag_gp_co==1280	-.9768996	1.289385	-0.76	0.449	-3.504105	1.550306
scag_gp_co==1300	-1.064545	.1484479	-7.17	0.000	-1.355504	-.7735862
scag_gp_co==1310	-1.378398	.1269218	-10.86	0.000	-1.627165	-1.12963
scag_gp_co==1320	-.6022273	.1106701	-5.44	0.000	-.8191415	-.385313
scag_gp_co==1330	-1.19002	.4327169	-2.75	0.006	-2.038149	-.3418916
scag_gp_co==1340	-1.457068	.3735264	-3.90	0.000	-2.189183	-.7249535
scag_gp_co==1400	.088946	2.227936	0.04	0.968	-4.277828	4.45572
scag_gp_co==1410	.5092401	.3437187	1.48	0.138	-.1644514	1.182932
scag_gp_co==1420	-1.449534	.2349611	-6.17	0.000	-1.910059	-.989008
scag_gp_co==1430	-2.911922	1.287223	-2.26	0.024	-5.43489	-.3889551
scag_gp_co==1500	-.5079029	.1171458	-4.34	0.000	-.7375097	-.2782961
scag_gp_co==1600	.2882788	.0711363	4.05	0.000	.148851	.4277066
scag_gp_co==1800	-1.826786	.0771109	-23.69	0.000	-1.977924	-1.675648
scag_gp_co==1810	-.7653916	.1666912	-4.59	0.000	-1.092108	-.4386755
scag_gp_co==1820	-1.667788	.1277519	-13.05	0.000	-1.918183	-1.417393
scag_gp_co==1830	-2.716105	.3667136	-7.41	0.000	-3.434867	-1.997344
scag_gp_co==1840	-1.741041	.3976674	-4.38	0.000	-2.520473	-.9616098
scag_gp_co==1850	-2.553584	.1186234	-21.53	0.000	-2.786086	-2.321081
scag_gp_co==1870	-5.088242	1.309276	-3.89	0.000	-7.654434	-2.52205
scag_gp_co==1880	-3.204772	.225629	-14.20	0.000	-3.647006	-2.762537
scag_gp_co==2000	-1.992928	.0682436	-29.20	0.000	-2.126686	-1.85917
scag_gp_co==3000	-2.457077	2.252223	-1.09	0.275	-6.871453	1.957299
scag_gp_co==4000	-3.662869	.4395821	-8.33	0.000	-4.524453	-2.801284
Adelanto	-1.716058	.8499406	-2.02	0.043	-3.381949	-.0501675
Agoura Hills	-3.923359	.38083	-10.30	0.000	-4.669789	-3.176929
Alhambra	.1940342	1.576683	0.12	0.902	-2.896278	3.284347
Aliso Viejo	-1.651841	2.231052	-0.74	0.459	-6.02472	2.721038
Apple Valley	-1.062856	.2902236	-3.66	0.000	-1.631697	-.4940152
Artesia	1.642569	.9981562	1.65	0.100	-.3138255	3.598963
Avalon	-8.451604	1.309798	-6.45	0.000	-11.01882	-5.884389
Azusa	-4.074342	.3521576	-11.57	0.000	-4.764574	-3.38411

Baldwin Park	2.7915	.6376722	4.38	0.000	1.541657	4.041343
Banning	.3625474	.3307624	1.10	0.273	-.2857495	1.010844
Barstow	1.562803	.4042354	3.87	0.000	.7704984	2.355108
Beaumont	-7.870084	.1697647	-46.36	0.000	-8.202825	-7.537344
Bell Gardens	2.899516	.5833467	4.97	0.000	1.756152	4.04288
Bellflower	2.765529	1.289922	2.14	0.032	.2372719	5.293786
Beverly Hills	1.191835	.9996853	1.19	0.233	-.7675566	3.151226
Big Bear Lake	2.255896	.3752132	6.01	0.000	1.520475	2.991317
Blythe	.220949	.2149719	1.03	0.304	-.2003976	.6422956
Bradbury	-1.798325	.9405263	-1.91	0.056	-3.641765	.0451139
Brea	.1177677	.304049	0.39	0.699	-.4781708	.7137063
Burbank	1.135294	.7509388	1.51	0.131	-.3365522	2.60714
Calabasas	-6.355357	.4074027	-15.60	0.000	-7.153869	-5.556844
Calimesa	-.2278868	.4295748	-0.53	0.596	-1.069857	.6140834
Camarillo	-.0462185	.5656846	-0.08	0.935	-1.154965	1.062528
Canyon Lake	-3.09126	1.292981	-2.39	0.017	-5.625514	-.5570056
Carson	-1.459445	.3317511	-4.40	0.000	-2.10968	-.8092098
Cathedral City	.934358	.1698843	5.50	0.000	.6013834	1.267333
Cerritos	-1.49009	.5669967	-2.63	0.009	-2.601408	-.3787719
Chino	.0222496	.1637981	0.14	0.892	-.298796	.3432952
Chino Hills	-.2767785	.3057329	-0.91	0.365	-.8760175	.3224606
Claremont	-.7875974	.3207198	-2.46	0.014	-1.416211	-.1589839
Coachella	.8390784	.1372439	6.11	0.000	.5700792	1.108077
Colton	-2.41041	.4146444	-5.81	0.000	-3.223116	-1.597703
Commerce	1.291364	.8449661	1.53	0.126	-.3647767	2.947504
Compton	-.4288485	.2666454	-1.61	0.108	-.9514756	.0937786
Corona	-.1212344	.1444643	-0.84	0.401	-.4043857	.1619169
Costa Mesa	.0007743	.3404924	0.00	0.998	-.6665937	.6681422
Covina	-.149549	.9139468	-0.16	0.870	-1.940892	1.641794
Cudahy	.4256977	1.288191	0.33	0.741	-2.099168	2.950563
Culver City	2.037914	1.295196	1.57	0.116	-.5006817	4.576509
Cypress	-.2030668	2.233153	-0.09	0.928	-4.580065	4.173931
Dana Point	2.814204	.289734	9.71	0.000	2.246323	3.382085
Desert Hot Springs	1.45155	.15072	9.63	0.000	1.156138	1.746962
Diamond Bar	-.954929	.61011	-1.57	0.118	-2.15075	.2408917
Downey	.3235541	.7472975	0.43	0.665	-1.141155	1.788263
Duarte	.6756844	.5647619	1.20	0.232	-.4312537	1.782622
El Monte	-1.080595	1.000424	-1.08	0.280	-3.041434	.8802441
El Segundo	-.8788791	.8504742	-1.03	0.301	-2.545816	.7880573
Fillmore	-.6769337	.6042969	-1.12	0.263	-1.861361	.5074931
Fontana	.8421409	.106062	7.94	0.000	.6342585	1.050023
Fullerton	-2.695205	1.589728	-1.70	0.090	-5.811086	.4206749
Garden Grove	.2193001	.6934282	0.32	0.752	-1.139825	1.578425
Gardena	-1.136493	.5029317	-2.26	0.024	-2.122243	-.1507424
Glendale	.3640386	.436438	0.83	0.404	-.4913834	1.219461
Glendora	-1.663287	.5300512	-3.14	0.002	-2.702192	-.6243824

Grand Terrace	-1.146475	1.290213	-0.89	0.374	-3.675303	1.382353
Hawthorne	-.8980696	1.124447	-0.80	0.424	-3.101996	1.305857
Hemet	-.6289247	.1361016	-4.62	0.000	-.895685	-.3621644
Hermosa Beach	2.195194	1.3464	1.63	0.103	-.4437608	4.834149
Hesperia	-.7347361	.1417982	-5.18	0.000	-1.012662	-.4568105
Hidden Hills	-3.131138	1.292935	-2.42	0.015	-5.665301	-.5969755
Highland	-.7671475	.3572822	-2.15	0.032	-1.467423	-.0668715
Huntington Beach	1.255458	1.005411	1.25	0.212	-.7151558	3.226072
Huntington Park	3.056485	.7564521	4.04	0.000	1.573832	4.539137
Indian Wells	1.079695	.2151908	5.02	0.000	.6579191	1.501471
Indio	.7545664	.1161356	6.50	0.000	.5269396	.9821931
Industry	.1670392	.5563666	0.30	0.764	-.923444	1.257522
Inglewood	.3105675	.1616245	1.92	0.055	-.0062179	.6273529
Irvine	.9362458	.2117766	4.42	0.000	.5211619	1.35133
Irwindale	1.579129	1.010276	1.56	0.118	-.4010196	3.559278
La Canada Flintridge	-2.306388	.5016824	-4.60	0.000	-3.289689	-1.323086
La Habra	.971905	.7493969	1.30	0.195	-.4969191	2.440729
La Habra Heights	-1.311967	1.175397	-1.12	0.264	-3.615755	.9918204
La Mirada	-2.535684	.8561944	-2.96	0.003	-4.213832	-.857536
La Puente	-3.540649	1.135586	-3.12	0.002	-5.766406	-1.314892
La Quinta	-.4700658	.1478574	-3.18	0.001	-.7598674	-.1802641
La Verne	-1.098478	.5627098	-1.95	0.051	-2.201394	.0044376
Laguna Hills	.4639422	.4327363	1.07	0.284	-.3842246	1.312109
Laguna Niguel	(omitted)					
Laguna Woods	.9452447	.9200002	1.03	0.304	-.8579633	2.748453
Lake Elsinore	-.0843311	.1304653	-0.65	0.518	-.3400441	.1713819
Lake Forest	.403359	.3039289	1.33	0.184	-.1923441	.999062
Lancaster	1.444875	.0990451	14.59	0.000	1.250746	1.639004
Loma Linda	.8091642	.2063915	3.92	0.000	.4046352	1.213693
Lomita	2.141451	1.585326	1.35	0.177	-.9658018	5.248703
Long Beach	1.552173	.2185092	7.10	0.000	1.123893	1.980452
Los Alamitos	.6689117	1.121108	0.60	0.551	-1.528468	2.866292
Lynwood	1.629342	.3992543	4.08	0.000	.8468001	2.411884
Malibu	1.625292	.262703	6.19	0.000	1.110391	2.140192
Manhattan Beach	-.5409719	1.134602	-0.48	0.634	-2.764801	1.682857
Maywood	-1.673243	.9984325	-1.68	0.094	-3.630179	.2836925
Menifee	.2703286	.1110034	2.44	0.015	.052761	.4878961
Mission Viejo	-.3748707	.3105144	-1.21	0.227	-.9834814	.23374
Monrovia	.9911387	1.289577	0.77	0.442	-1.536442	3.518719
Montclair	.6972921	.4425825	1.58	0.115	-.1701733	1.564758
Montebello	.9551281	.3467865	2.75	0.006	.2754237	1.634832
Monterey Park	.0325669	.7898199	0.04	0.967	-1.515487	1.58062
Moorpark	1.329307	.5037445	2.64	0.008	.3419636	2.31665
Moreno Valley	.0506624	.2014464	0.25	0.801	-.3441742	.4454989
Murrieta	1.103819	.1225861	9.00	0.000	.8635491	1.344088
Needles	4.511532	.8087291	5.58	0.000	2.926416	6.096648

Newport Beach	.8411421	.6830409	1.23	0.218	-.4976236	2.179908
Norco	.0066771	.2140256	0.03	0.975	-.4128149	.4261691
Norwalk	.8773232	2.230346	0.39	0.694	-3.494174	5.24882
Ojai	1.360021	.8475738	1.60	0.109	-.3012306	3.021273
Ontario	-1.30487	.1203792	-10.84	0.000	-1.540814	-1.068925
Orange	.2274293	.9148849	0.25	0.804	-1.565753	2.020611
Oxnard	.8962331	.5207169	1.72	0.085	-.1243763	1.916842
Palm Desert	.8535784	.1538243	5.55	0.000	.5520815	1.155075
Palm Springs	.3836968	.134731	2.85	0.004	.1196228	.6477707
Palmdale	1.465493	.1078999	13.58	0.000	1.254008	1.676977
Palos Verdes Estates	2.862821	.8465647	3.38	0.001	1.203548	4.522095
Paramount	1.162738	.4361924	2.67	0.008	.3077974	2.017679
Pasadena	.8560164	.4421565	1.94	0.053	-.010614	1.722647
Perris	.2507769	.1090611	2.30	0.021	.0370161	.4645376
Pico Rivera	.2408299	.649404	0.37	0.711	-1.032007	1.513667
Pomona	.849	.1005225	8.45	0.000	.651975	1.046025
Port Hueneme	-.846992	1.289042	-0.66	0.511	-3.373525	1.679541
Rancho Cucamonga	.8726938	.1151398	7.58	0.000	.6470188	1.098369
Rancho Mirage	1.048332	.1502263	6.98	0.000	.753887	1.342777
Rancho Palos Verdes	-.9446344	.5661761	-1.67	0.095	-2.054344	.1650754
Rancho Santa Margarita	-.5863706	.3953793	-1.48	0.138	-1.361317	.1885761
Redlands	.377205	.1459294	2.58	0.010	.0911821	.6632278
Redondo Beach	1.551211	.7093083	2.19	0.029	.1609606	2.941461
Rialto	1.095632	.2429797	4.51	0.000	.6193903	1.571875
Riverside	-.6420216	.1456505	-4.41	0.000	-.9274978	-.3565455
Rolling Hills Estates	-1.835819	.6935069	-2.65	0.008	-3.195098	-.4765399
Rosemead	.1095699	.9235897	0.12	0.906	-1.700674	1.919813
San Bernardino	.4811807	.1723241	2.79	0.005	.143424	.8189374
San Buenaventura	1.028169	.3842456	2.68	0.007	.2750448	1.781294
San Clemente	1.079982	1.293198	0.84	0.404	-1.454697	3.614661
San Dimas	-6.613101	.2082378	-31.76	0.000	-7.021249	-6.204953
San Fernando	.8246525	1.29623	0.64	0.525	-1.715969	3.365275
San Gabriel	.3752048	.999483	0.38	0.707	-1.58379	2.3342
San Jacinto	.3085134	.1162388	2.65	0.008	.0806843	.5363424
San Juan Capistrano	.0429162	.9194233	0.05	0.963	-1.759161	1.844994
Santa Ana	-1.270053	2.228446	-0.57	0.569	-5.637825	3.097719
Santa Clarita	-1.132297	.1344744	-8.42	0.000	-1.395868	-.8687264
Santa Fe Springs	.3737121	.5932028	0.63	0.529	-.7889703	1.536395
Santa Monica	1.051039	.648805	1.62	0.105	-.2206239	2.322702
Santa Paula	-.764497	.7506723	-1.02	0.308	-2.235821	.706827
Seal Beach	1.514604	.3636871	4.16	0.000	.8017746	2.227434
Sierra Madre	-1.966768	2.226031	-0.88	0.377	-6.329808	2.396271
Signal Hill	.1134567	.6062788	0.19	0.852	-1.074855	1.301768
Simi Valley	-1.357902	.3086611	-4.40	0.000	-1.962881	-.7529241
South El Monte	-.9424039	1.117078	-0.84	0.399	-3.131887	1.247079
South Gate	(omitted)					

South Pasadena	.310281	.9165381	0.34	0.735	-1.486141	2.106703
Temecula	.1890873	.1362577	1.39	0.165	-.077979	.4561535
Thousand Oaks	-.8131907	.5952963	-1.37	0.172	-1.979976	.3535949
Torrance	.5394213	.4635041	1.16	0.245	-.3690506	1.447893
Tustin	1.47725	.2325885	6.35	0.000	1.021375	1.933126
Twentynine Palms	1.156293	.2428888	4.76	0.000	.6802288	1.632357
Upland	.995949	.1228303	8.11	0.000	.7552006	1.236697
Victorville	1.804593	.1052601	17.14	0.000	1.598283	2.010904
Walnut	-1.903353	1.120951	-1.70	0.090	-4.100425	.2937203
West Covina	-.8637398	.4092792	-2.11	0.035	-1.66593	-.0615492
West Hollywood	1.843925	1.294611	1.42	0.154	-.6935227	4.381373
Westlake Village	-.9583395	.6061543	-1.58	0.114	-2.146407	.2297279
Westminster	1.265169	.852094	1.48	0.138	-.4049419	2.935281
Whittier	-2.195017	.5010674	-4.38	0.000	-3.177113	-1.212921
Wildomar	.8223127	.1478746	5.56	0.000	.5324773	1.112148
Yorba Linda	-1.026421	2.228095	-0.46	0.645	-5.393506	3.340664
Yucaipa	.8303627	.1219497	6.81	0.000	.5913402	1.069385
Yucca Valley	.4246333	.2894577	1.47	0.142	-.1427062	.9919727
unincorporated_la	-.426316	.0861342	-4.95	0.000	-.5951397	-.2574922
unincorporated_or	.607757	.2376748	2.56	0.011	.1419125	1.073602
unincorporated_rv	.2113233	.0975543	2.17	0.030	.0201161	.4025305
unincorporated_sb	.1943895	.0956553	2.03	0.042	.0069043	.3818747
unincorporated_vn	-.1251242	.1111317	-1.13	0.260	-.3429432	.0926948
year==1929	-.9709112	2.228695	-0.44	0.663	-5.339172	3.39735
year==1934	(omitted)					
year==1937	.6281862	2.227968	0.28	0.778	-3.73865	4.995022
year==1941	.4195066	2.227908	0.19	0.851	-3.947212	4.786225
year==1942	.959063	2.227931	0.43	0.667	-3.4077	5.325825
year==1943	-.3406889	2.227882	-0.15	0.878	-4.707357	4.025979
year==1945	-2.406284	2.228738	-1.08	0.280	-6.77463	1.962061
year==1946	-3.08786	2.228711	-1.39	0.166	-7.456153	1.280432
year==1947	-.9986829	2.25829	-0.44	0.658	-5.42495	3.427585
year==1948	-1.038041	1.577214	-0.66	0.510	-4.129393	2.053312
year==1949	-2.048896	2.228717	-0.92	0.358	-6.4172	2.319409
year==1950	(omitted)					
year==1951	.0955578	2.22794	0.04	0.966	-4.271224	4.462339
year==1953	.3098938	.6807202	0.46	0.649	-1.024323	1.644111
year==1954	.7670384	1.577447	0.49	0.627	-2.324771	3.858848
year==1955	.5871645	1.181184	0.50	0.619	-1.727966	2.902295
year==1956	-1.219465	1.577644	-0.77	0.440	-4.311659	1.872729
year==1957	1.007718	.9153245	1.10	0.271	-.7863258	2.801761
year==1958	.5662551	.7182032	0.79	0.430	-.8414291	1.973939
year==1959	.1955383	.7970593	0.25	0.806	-1.366704	1.757781
year==1960	-1.747229	.9179932	-1.90	0.057	-3.546503	.0520457
year==1961	.2878084	.8575566	0.34	0.737	-1.39301	1.968626
year==1962	.0798211	.7605954	0.10	0.916	-1.410952	1.570594

year==1963	1.097368	.6847408	1.60	0.109	-.24473	2.439465
year==1964	.2413569	.348702	0.69	0.489	-.4421018	.9248157
year==1965	-.0202599	.3703538	-0.05	0.956	-.7461565	.7056367
year==1966	.4275663	.3105715	1.38	0.169	-.1811564	1.036289
year==1967	-.3949606	.3004209	-1.31	0.189	-.983788	.1938669
year==1968	.0171673	.2466018	0.07	0.945	-.4661742	.5005087
year==1969	-.0982733	.2261728	-0.43	0.664	-.5415739	.3450272
year==1970	-.0167127	.2508507	-0.07	0.947	-.5083823	.4749568
year==1971	-.0519337	.2310043	-0.22	0.822	-.5047041	.4008366
year==1972	-.4486995	.2358487	-1.90	0.057	-.910965	.0135659
year==1973	-.7311156	.1640329	-4.46	0.000	-1.052622	-.4096098
year==1974	-.2334568	.2178544	-1.07	0.284	-.6604532	.1935396
year==1975	-.1239583	.2070723	-0.60	0.549	-.5298217	.281905
year==1976	-.5023716	.2089782	-2.40	0.016	-.9119706	-.0927726
year==1977	-.7620763	.1888442	-4.04	0.000	-1.132212	-.3919402
year==1978	-.2862527	.1686401	-1.70	0.090	-.6167886	.0442832
year==1979	-.2349156	.168738	-1.39	0.164	-.5656434	.0958122
year==1980	.0490812	.1860532	0.26	0.792	-.3155847	.413747
year==1981	.0121268	.1343508	0.09	0.928	-.251202	.2754555
year==1982	.1661368	.1359626	1.22	0.222	-.1003511	.4326248
year==1983	.090021	.1688841	0.53	0.594	-.2409932	.4210352
year==1984	-.4139582	.1602791	-2.58	0.010	-.7281066	-.0998098
year==1985	.1427875	.1679844	0.85	0.395	-.1864632	.4720383
year==1986	.141733	.1571866	0.90	0.367	-.1663541	.44982
year==1987	.2361162	.1585752	1.49	0.136	-.0746926	.546925
year==1988	.4926776	.1530305	3.22	0.001	.1927366	.7926186
year==1989	.6481617	.1516879	4.27	0.000	.3508521	.9454712
year==1990	.6921378	.15533	4.46	0.000	.3876897	.996586
year==1991	.638099	.1689351	3.78	0.000	.3069849	.9692131
year==1992	.3211483	.1611608	1.99	0.046	.0052719	.6370248
year==1993	-.10865	.1709062	-0.64	0.525	-.4436275	.2263275
year==1994	-.0895674	.1748224	-0.51	0.608	-.4322207	.2530859
year==1995	-.1216701	.1634817	-0.74	0.457	-.4420955	.1987553
year==1996	-.1533448	.1756711	-0.87	0.383	-.4976615	.190972
year==1997	.1678412	.1689957	0.99	0.321	-.1633918	.4990741
year==1998	-.1523902	.1484255	-1.03	0.305	-.4433054	.1385249
year==1999	-.4518479	.1357197	-3.33	0.001	-.7178597	-.1858361
year==2001	.1033051	.1312584	0.79	0.431	-.1539624	.3605726
year==2002	-.0309675	.1149156	-0.27	0.788	-.256203	.1942681
year==2003	-.0757776	.1100515	-0.69	0.491	-.2914794	.1399241
year==2004	.0264866	.1055937	0.25	0.802	-.180478	.2334511
year==2005	1.869328	.102339	18.27	0.000	1.668743	2.069914
year==2006	1.470469	.1027241	14.31	0.000	1.269128	1.671809
year==2007	1.221694	.1050698	11.63	0.000	1.015757	1.427632
year==2008	1.137493	.2531848	4.49	0.000	.641249	1.633738
_cons	2.742461	.1172426	23.39	0.000	2.512665	2.972258
