


 This repository

[Pull requests](#) [Issues](#) [Gist](#)


 [rgilman33 / applied_econometrics](#)

[Unwatch](#) [1](#) [★ Star](#) [0](#) [Fork](#) [0](#)

[Code](#) [Issues 0](#) [Pull requests 0](#) [Wiki](#) [Pulse](#) [Graphs](#) [Settings](#)

Branch: [master](#) [applied_econometrics / PS4_Gilman.ipynb](#)

[Find file](#) [Copy path](#)

 [rgilman33](#) ff a70ea3d 18 seconds ago

1 contributor

2066 lines (2065 sloc) 493 KB [Raw](#) [Blame](#) [History](#)  

```
In [3]: # %load PS4_Gilman.py
#!/usr/bin/env python

#####
# Applied Econometrics, PS4
# Rudy Gilman
# April 28, 2016
#####

import pandas as pd
import numpy as np
from pandas import DataFrame
import statsmodels.formula.api as smf
import statsmodels.api as sm
import matplotlib.pyplot as plt
import os, copy
from scipy import stats
from scipy.stats import ttest_ind
from sklearn.tree import DecisionTreeClassifier, export_graphviz, DecisionTreeRegressor
from sklearn.ensemble import RandomForestClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.cross_validation import cross_val_score
import seaborn as sns

path = "/home/rudebeans/Desktop/school_spring2016/applied_econometrics/"

#df = pd.read_stata(path+"poll7080.dta", convert_categoricals=False) dta not loading

df = pd.read_csv(path+"poll7080.csv")

df['intercept'] = 1 # Adding constant

"""
Problem Set 4

This exercise examines the following research question: What is the relationship between change
s in air pollution and housing prices? For background on the topic and the data source refer to
the paper, "Does Air Quality Matter? Evidence from the Housing Market," by Kenneth Chay and Mic
hael Greenstone, Journal of Political Economy, April 2005, 376-424. Please include a concise s
ummary of your empirical results when appropriate. We will analyze the following data set:

Data Source: poll7080.dta
This STATA data extract is from a combination of the 1972 and 1983 City and County Data Books,
the EPA's Air Quality Subsystem data file, and the Code of Federal Regulations. The data is mea
sured at the county-level in the United States.

Data Notes:
1. There are 1,000 observations at the U.S. county level. These are the counties with particu
lates pollution monitors both at the beginning and end of the 1970s and contain the vast majori
ty of the U.S. population (over 80%).

2. The key variables are:
dlhouse = change in log-housing values from 1970 to 1980 (1980 log-price minus 1970 log-price).
dgtsp = change in the annual geometric mean of total suspended particulates pollution (TSPs) fr
om 1969-72 to 1977-80 (1977-80 TSPs minus 1969-72 TSPs).
tsp75 = indicator equal to one if the county was regulated by the Environmental Protection Agen
cy (EPA) in 1975 and equal to zero, otherwise.
tsp7576 = indicator equal to one if the county was regulated by the Environmental Protection Ag
ency (EPA) in either 1975 or 1976 and equal to zero, otherwise.
mtspgm74 = annual geometric mean of TSPs in 1974.
mtspgm75 = annual geometric mean of TSPs in 1975.

3. The other relevant variables are:
ddens = 1970-80 change in population density,
dmnfcg = change in % manufacturing employment,
dwhite = change in fraction of population that is white,
dfeml = change in fraction female,
dage65 = change in fraction over 65 years old,
dhs = change in fraction with at least a high school degree,
dcoll = change in fraction with at least a college degree,
durban = change in fraction living in urban area,
dunemp = change in unemployment rate,
dincome = change in income per-capita,
dpover = change in poverty rate,
vacant70 and vacant80 = housing vacancy rate in 1970 and 1980,
vacrnt70 = rental vacancy rate in 1970,
downer = change in fraction of houses that are owner-occupied,
dplumb = change in fraction of houses with plumbing,
drevnu = change in government revenue per-capita,
dtaxprop = change in property taxes per-capita,
depend = change in general expenditures per-capita,
deduc = change in fraction of spending on education,
dhghwy = change in % spending on highways,
dwelfr = change in % spending on public welfare,
dhlth = change in % spending on health.
```

```
blt1080 = % of houses built in the last 10 years as of 1980,
blt2080 = % of houses built in the last 20 years as of 1980,
bltold80 = % of houses built more than 20 years ago as of 1980.
```

The remaining variables in the data set are polynomials and interactions of the control variables.

Research Question: Does Air Quality Get Capitalized into Housing Prices?

The outcome of interest is the change in county housing prices during the 1970s. We want to estimate the "causal" effect of air pollution changes on housing price changes. According to hedonic price theory, the housing market may be used to estimate the implicit prices of clean air and the economic value of pollution reductions to individuals (if you're interested in hedonic pricing, see this article: Rosen, Sherwin, "The Theory of Equalizing Differences," Chapter 12 in Handbook of Labor Economics, Volume 1, 1986, pp. 641-92.). A statistically significant negative relationship between changes in property values and pollution levels across counties is interpreted as evidence that clean air has economic benefits.

A basic model for the change in housing prices at the county level could be:

Change in housing price = $g(\text{economic shocks, changes in county characteristics, change in air pollution})$.

```
print "a. Estimate the relationship between changes in air pollution and housing prices: 1) not
adjusting for any control variables; 2) adjusting for the main effects of the control variables
listed on the previous page; and 3) adjusting for the main effects, polynomials and interaction
s of the control variables included in the data set. What do your estimates imply and do they m
ake sense? Describe the potential omitted variables biases. What is the likely relationship bet
ween economic shocks and pollution and housing price changes? Using the observable measures of
economic shocks (dincome, dunemp, dmnfcg, ddens, durban, blt1080), provide evidence on this.\n
\n"
```

```
print "Answer: Model 1) with no controls shows a positive correlation btwn increases in polluti
on and increases in house prices. Adding controls drives this relationship in the direction we
would expect--towards a negative correlation. Our estimates make sense when we consider the eff
ects of economic shocks. As we can see in the scatterplot matrix below, increased unemployment
and decreased incomes are associated with lower levels of pollution as well as lower house pric
es. Without controlling for economic shocks, our estimate was biased downwards (ie being confou
nded by omitted variables working in the opposite direction). It probably still is, as we've on
ly used observable manifestations of economic shock. Model 3) with all the controls is difficul
t to interpret.\n\n"
```

```
### Creating Xs for linear models
```

```
# X_1
```

```
X_1 = df[['dgtsp', 'intercept']]
```

```
# X_2
```

```
# bag of words from which to draw control variables of interest
```

```
p = "intercept dgtsp tsp75 = indicator equal to one if the county was regulated by the Environm
ental Protection Agency (EPA) in 1975 and equal to zero, otherwise. tsp7576 = indicator equal t
o one if the county was regulated by the Environmental Protection Agency (EPA) in either 1975 o
r 1976 and equal to zero, otherwise. mtspgm74 = annual geometric mean of TSPs in 1974. mtspgm75
= annual geometric mean of TSPs in 1975. 3. The other relevant variables are: ddens = 1970-80 c
hange in population density, dmnfcg = change in % manufacturing employment, dwhite = change i
n fraction of population that is white, dfeml = change in fraction female, dage65 = change in
fraction over 65 years old, dhs = change in fraction with at least a high school degree, dcol
l = change in fraction with at least a college degree, durban = change in fraction living in u
rban area, dunemp = change in unemployment rate, dincome = change in income per-capita, dpov
erty = change in poverty rate, vacant70 and vacant80 = housing vacancy rate in 1970 and 1980,
vacrnt70 = rental vacancy rate in 1970, downer = change in fraction of houses that are owner-o
ccupied, dplumb = change in fraction of houses with plumbing, drevenue = change in government
revenue per-capita, dtaxprop = change in property taxes per-capita, depend = change in genera
l expenditures per-capita, deduc = change in fraction of spending on education, dhghwy = chan
ge in % spending on highways, dwelfr = change in % spending on public welfare, dhlth = change
in % spending on health, blt1080 = % of houses built in the last 10 years as of 1980, blt2080
= % of houses built in the last 20 years as of 1980, bltold80 = % of houses built more than 20
years ago as of 1980"
```

```
p = p.split() # list of words
```

```
X_2_cols = (df.columns[df.columns.isin(p)==True]) # basic control variables
```

```
X_2 = df[X_2_cols]
```

```
# X_3
```

```
X_3 = df[df.columns[df.columns != 'dlhouse']]
```

```
# Returns df with variables and importance, descending
```

```
def get_imp(X,y):
```

```
    #rf = RandomForestClassifier()
```

```
    rf = DecisionTreeRegressor(random_state=9)
```

```
    rf.fit(X, y)
```

```
    imp_var = rf.feature_importances_
```

```
    imp_var = pd.DataFrame({'variable':X.columns, 'imp':imp_var}).sort('imp', ascending=False)
```

```
    return(imp_var)
```

```

var = get_imp(X_3.fillna(0), df.dlhouse)
imp_var = var[var.imp > 0.0005] # only keeping variables w some explanatory power

kill = ['lhouse80', 'house80'] # combined w numbers for 70, these perfectly predict dlhouse
X_3 = X_3[imp_var.variable]
X_3 = X_3[X_3.columns[X_3.columns.isin(kill)==False]]
X_3['intercept'] = 1 # adding back in intercept and dgtsp, as both were removed in Imp filter
X_3['dgtsp'] = df.dgtsp

print "X_1"
print "\n"
lm = sm.OLS(df.dlhouse, X_1, missing='drop').fit()
print lm.summary()
print "1) dgtsp coefficient: "+str(lm.params['dgtsp'])
print "\n\n\n"

print "X_2"
print "\n"
lm = sm.OLS(df.dlhouse, X_2, missing='drop').fit()
print lm.summary()
print "2) dgtsp coefficient: "+str(lm.params['dgtsp'])
print "\n\n\n"

print "X_3"
print "\n"
lm = sm.OLS(df.dlhouse, X_3, missing='drop').fit()
print lm.summary()
print "3) dgtsp coefficient: "+str(lm.params['dgtsp'])
print "\n\n\n"

cols = ['dincome', 'dunemp', 'dgtsp', 'dmnfcg', 'dlhouse']

pp = df[cols].dropna()
sns.set(style="ticks", color_codes=True)
#iris = sns.load_dataset("iris")

g = sns.PairGrid(pp)
g = g.map_upper(plt.scatter, alpha=.5)
g = g.map_lower(sns.kdeplot, cmap="Blues_d")
g = g.map_diag(sns.distplot)
#g = sns.pairplot(pp, kind='reg')

# Rescaling axis. Why doesn't Seaborn do this for me automatically?
axes = g.axes
for i in range(len(cols)):
    axes[i,i].set_ylim(np.min(pp[cols[i]]), np.max(pp[cols[i]]))
    axes[i,i].set_xlim(np.min(pp[cols[i]]), np.max(pp[cols[i]]))
#g.set(ylim=(0, 9))
#g.set(xlim=(0, 9)) sets all axes to this extent

plt.show()

print "b. Suppose that federal EPA pollution regulation is a potential instrumental variable for pollution changes during the 1970s. What are the assumptions required for 1975-1976 regulatory status, tsp7576, to be a valid instrument for pollution changes when the outcome of interest is housing price changes? Provide evidence on the relationship between the regulatory status indicator and the observable economic shock measures. Interpret your findings.\n\n"

print "Answer: tsp7576 must be strong, ie correlated w dgtsp, and valid, ie not correlated w dlhouse except through dgtsp. As we can see in the correlation matrix below, tsp7576 is only slightly correlated w our economic shock variables, making it potentially a good IV.\n\n"

shock_cols = ['tsp7576', 'dincome', 'dunemp', 'dmnfcg', 'ddens', 'durban', 'blt1080']

d = df[shock_cols]
cor = d.corr()
print cor

#lm = sm.OLS(df.tsp7576, df[shock_cols], missing='drop').fit()
#print lm.summary()
#print "\n\n"

print "\n\n c. Document the “first-stage” relationship between regulation (tsp7576) and air pollution changes and the “reduced-form” relationship between regulation and housing price changes, using the same three specifications you used in part a). Interpret your findings. How does two-stage least squares use these two equations? Now estimate the effect of air quality changes on housing price changes using two-stage least squares and the tsp7576 indicator as an instrument for the three specifications. Interpret the results. Now do the same using the 1975 regulatory indicator, tsp75, as an instrumental variable. Compare the findings.\n\n"

print "Answer: the negative effect of regulation on air pollution decreases as we add controls (relationship gets less negative). The positive effect of regulation on changes in house prices decreases as we add controls. In terms of IV, our 7576 and 75 results are similar, both around -.003 (elasticity of -0.3) for uncontrolled and basically controlled regressions. As we showed before, the IV is only slightly correlated with economic shock variables, so the model isn't particularly sensitive to control specification. Estimates for model w all interactions + higher-order terms remains difficult to interpret. The reduced form results show that house prices in treated counties are 2.4% higher than they would be otherwise. First stage results suggest that

```

created counties are 2-4% higher than they would be otherwise. First-stage results suggest that treatment results in pollution decreases of 5-10%.\n\n"

```
# For 7576
X_1 = df[['intercept', 'tsp7576']]
kill = ['dgtsp', 'tsp75']
X_2 = X_2[X_2.columns[X_2.columns.isin(kill)==False]]
X_3 = X_3[X_3.columns[X_3.columns.isin(kill)==False]]
X_3['tsp7576'] = df.tsp7576

Xs=[X_1, X_2, X_3]
Xs_str=['X_1', 'X_2', 'X_3']

for i in range(len(Xs)):
    print Xs_str[i]
    X = Xs[i]
    first = sm.OLS(df.dgtsp, X, missing="drop").fit()
    print first.summary()
    print '\n'
    print Xs_str[i]+": first stage tsp7576 coefficient:"
    print first.params['tsp7576']
    reduced = sm.OLS(df.dlhouse, X, missing="drop").fit()
    print reduced.summary()
    print '\n'
    print Xs_str[i]+": reduced form tsp7576 coefficient:"
    print reduced.params['tsp7576']
    # IV
    dgtsp_hat = first.predict(X)
    X['dgtsp_hat'] = dgtsp_hat
    X = X.drop(['tsp7576'], axis=1)
    IV = sm.OLS(df.dlhouse, X, missing="drop").fit()
    print Xs_str[i]+ ": IV estimate: "+ str(IV.params['dgtsp_hat'])
    print IV.summary()
    print '\n'
```

```
# for 75
X_1 = df[['intercept', 'tsp75']]
kill = ['dgtsp', 'tsp7576']
X_2 = X_2[X_2.columns[X_2.columns.isin(kill)==False]]
X_2['tsp75'] = df.tsp75
X_3 = X_3[X_3.columns[X_3.columns.isin(kill)==False]]
X_3['tsp75'] = df.tsp75

Xs=[X_1, X_2, X_3]
Xs_str=['X_1', 'X_2', 'X_3']
```

```
for i in range(len(Xs)):
    print Xs_str[i]
    X = Xs[i]
    first = sm.OLS(df.dgtsp, X, missing="drop").fit()
    print first.summary()
    print '\n'
    print Xs_str[i]+": first stage tsp75 coefficient:"
    print first.params['tsp75']
    reduced = sm.OLS(df.dlhouse, X, missing="drop").fit()
    print reduced.summary()
    print '\n'
    print Xs_str[i]+": reduced form tsp75 coefficient:"
    print reduced.params['tsp75']
    # IV
    dgtsp_hat = first.predict(X)
    X['dgtsp_hat'] = dgtsp_hat
    X = X.drop(['tsp75'], axis=1)
    IV = sm.OLS(df.dlhouse, X, missing="drop").fit()
    print Xs_str[i]+ ": IV estimate: "+ str(IV.params['dgtsp_hat'])
    print IV.summary()
    print '\n'
```

print("d. In principle, the 1975 regulation indicator variable, tsp75, should be a discrete function of pollution levels in 1974. Specifically, the EPA is supposed to regulate those counties in 1975 who had either an annual geometric mean of TSPs above 75 units ($\mu\text{g}/\text{m}^3$) or a 2nd highest daily concentration above 260 units in 1974. Describe how one could use this discontinuity in treatment assignment to derive alternative estimates of the capitalization of pollution changes. Under what conditions will these estimates be valid? Describe the graphical analysis you would use to examine the validity of these conditions.\n\n")

```
print "Answer: We could take only the section of the dataframe + and - a certain delta around the threshold value of pollution in 1974. Then we could construct a Wald Estimator with it, i.e. find the difference in price changes and pollution changes for a group just under the threshold, as well as for a group just over the threshold, then divide the differences to find change in dlhouse per change in TSPs. I'd want to see that the discontinuity wasn't fuzzy, so a graph like that below would be helpful. I'd want to verify that group means were similar in below-threshold and above-threshold groups. \n\n"
```

```

y = 'tsp75'
x = 'mtspgm74'
fig = plt.figure()
ax = fig.add_subplot(111)
ax.scatter(df[x], df[y], c='blue', alpha=0.25)
ax.set_title(str(x)+' '+str(y))
ax.set_ylabel(str(y))
ax.set_xlabel(str(x))
#ax.set_ylim([0,7])
#ax.set_xlim([500,1500])
#ax.legend([y, y2])
plt.show()
fig.clf()
print '\n'

```

print "e. Describe (in words) the theoretical reasons why the effects of pollution changes on housing price changes may be heterogeneous. Under what assumptions will two-stage least squares identify the average treatment effect (ATE)? What is the economic interpretation of ATE in the context of hedonic theory? If ATE is not identified, describe what may be identifiable with two-stage least squares estimation. Under what conditions is this effect identified? Give some intuition on what this effect may represent when one uses EPA regulation as an instrument.\n\n"

print "Answer: Small, unnoticeable changes in pollution might have no effect on changes in price, while larger changes in pollution may have large effects on price changes, perhaps increasing at an increasing rate as pollution changes become noticeable, then at a diminishing rate when jumps in pollution are extreme. 2SLS will identify the ATE if effects of pollution changes on price changes are homogenous. The ATE in the context of the hedonic theory represents the amount people have revealed themselves willing to pay for clean air. \nIn this case, however, we've only identified the LATE, as our results are only applicable around the pollution threshold. The LATE is the effect of pollution changes on house price changes in the small window around the regulatory threshold for those cities which were induced into cleaning up as a result of regulations, but wouldn't have done so otherwise. We should also be aware of selection effects: People in the highly-polluted areas eligible for treatment may be less sensitive to pollution, so we're measuring the effect amongst a demographic that may not be representative of the greater population.\n\n"

print "f. Now provide a concise synthesis/summary of your results. Discuss the "credibility" of the research designs underlying the results.\n\n"

print "Answer: In our simple OLS models, we measured a slightly positive effect of changes in pollution on changes in house price. On the face of it, this runs counter to what we expect the relationship to be. When we consider the omitted variable of economic shocks, however, we see how this paradoxical result came about--negative economic shocks decrease both pollution and house prices. Controlling for a few manifestations of economic shocks (unemployment, changes in income, etc) helped ameliorate OVB to some extent. \nTo more thoroughly purge our model of OVB, we used an IV approach, (hopefully) capturing only the variation in dgtsp uncorrelated with our confounding omitted variable. Using this approach, we captured a more expected result: A 1% increase in pollution is associated with an approximate .3% decrease in price. This result was robust to our selection of control variables, probably bc our IV was uncorrelated with the OV. This strikes me as a credible approach. \n\n"

a. Estimate the relationship between changes in air pollution and housing prices: 1) not adjusting for any control variables; 2) adjusting for the main effects of the control variables listed on the previous page; and 3) adjusting for the main effects, polynomials and interactions of the control variables included in the data set. What do your estimates imply and do they make sense? Describe the potential omitted variables biases. What is the likely relationship between economic shocks and pollution and housing price changes? Using the observable measures of economic shocks (dincome, dunemp, dnmfcg, ddens, durban, blt1080), provide evidence on this.

Answer: Model 1) with no controls shows a positive correlation between increases in pollution and increases in house prices. Adding controls drives this relationship in the direction we would expect--towards a negative correlation. Our estimates make sense when we consider the effects of economic shocks. As we can see in the scatterplot matrix below, increased unemployment and decreased incomes are associated with lower levels of pollution as well as lower house prices. Without controlling for economic shocks, our estimate was biased downwards (ie being confounded by omitted variables working in the opposite direction). It probably still is, as we've only used observable manifestations of economic shock. Model 3) with all the controls is difficult to interpret.

```

/usr/local/lib/python2.7/dist-packages/ipykernel/_main_.py:118: FutureWarning: sort(columns=...) is deprecated, use sort_values(by=...)

```

X_1

OLS Regression Results

```

=====
Dep. Variable:          dlhouse      R-squared:                0.017
Model:                  OLS          Adj. R-squared:           0.016
Method:                 Least Squares   F-statistic:             16.85
Date:                  Thu, 28 Apr 2016   Prob (F-statistic):       4.38e-05
Time:                  19:09:25         Log-Likelihood:          346.20

```

```

No. Observations:      1000    AIC:                -688.4
Df Residuals:          998    BIC:                -678.6
Df Model:              1

```

```

=====
              coef      std err          t      P>|t|      [95.0% Conf. Int.]
-----
dgtsp         0.0010      0.000       4.105      0.000       0.001      0.001
intercept     0.2822      0.006      49.133      0.000       0.271      0.293
=====
Omnibus:              66.452    Durbin-Watson:              1.023
Prob(Omnibus):        0.000    Jarque-Bera (JB):           99.410
Skew:                 0.527    Prob(JB):                   2.59e-22
Kurtosis:             4.129    Cond. No.                    25.1
=====

```

1) dgtsp coefficient: 0.000995299882288

X_2

OLS Regression Results

```

=====
Dep. Variable:          dlhouse    R-squared:              0.573
Model:                 OLS        Adj. R-squared:         0.559
Method:                Least Squares    F-statistic:           40.30
Date:                  Thu, 28 Apr 2016    Prob (F-statistic):    6.30e-149
Time:                  19:09:25          Log-Likelihood:        740.06
No. Observations:      962          AIC:                  -1416.
Df Residuals:          930          BIC:                  -1260.
Df Model:              31
=====

```

```

=====
              coef      std err          t      P>|t|      [95.0% Conf. Int.]
-----
ddens         -7.721e-06    1.74e-05     -0.443      0.658     -4.19e-05    2.65e-05
dmnfcg        -0.0874      0.111     -0.787      0.431     -0.305      0.131
dwhite        -0.5255      0.091     -5.777      0.000     -0.704     -0.347
dfeml         -0.7631      0.502     -1.519      0.129     -1.749      0.223
dage65        -1.7964      0.372     -4.833      0.000     -2.526     -1.067
dhs           0.4133      0.141      2.924      0.004      0.136      0.691
dcoll         0.1756      0.204      0.861      0.389     -0.224      0.576
durban        -0.1159      0.053     -2.180      0.029     -0.220     -0.012
dunemp        -0.9476      0.230     -4.124      0.000     -1.399     -0.497
dincome       6.6e-05    8.44e-06      7.824      0.000      4.94e-05    8.26e-05
dpoverly      -0.6197      0.163     -3.797      0.000     -0.940     -0.299
downer        -0.1407      0.093     -1.515      0.130     -0.323      0.042
dplumb        -0.1593      0.183     -0.868      0.386     -0.519      0.201
drevenue      1.807e-05    2.34e-05      0.774      0.439     -2.78e-05    6.39e-05
dtaxprop      -6.672e-05    3.15e-05     -2.121      0.034     -0.000     -4.99e-06
depend       -3.023e-05    2.46e-05     -1.229      0.220     -7.85e-05    1.81e-05
deduc         0.1101      0.049      2.228      0.026      0.013      0.207
dhghwy        -0.1694      0.119     -1.426      0.154     -0.403      0.064
dwelfr        -0.3150      0.101     -3.108      0.002     -0.514     -0.116
dhlth         -0.0513      0.067     -0.764      0.445     -0.183      0.080
vacant70      -1.0210      0.518     -1.973      0.049     -2.037     -0.005
vacant80       0.5242      0.142      3.698      0.000      0.246      0.802
vacrnt70      -0.1276      0.146     -0.872      0.383     -0.415      0.159
blt1080       0.3265      0.073      4.463      0.000      0.183      0.470
blt2080      -0.9466      0.128     -7.386      0.000     -1.198     -0.695
bltold80      -0.2222      0.069     -3.231      0.001     -0.357     -0.087
tsp7576       0.0387      0.021      1.882      0.060     -0.002      0.079
tsp75        -0.0221      0.021     -1.040      0.299     -0.064      0.020
dgtsp         0.0005      0.000      2.846      0.005      0.000      0.001
mtspgm74      0.0018      0.000      4.628      0.000      0.001      0.003
mtspgm75     -0.0018      0.000     -4.826      0.000     -0.003     -0.001
intercept     0.2858      0.062      4.588      0.000      0.164      0.408
=====

```

```

=====
Omnibus:              78.680    Durbin-Watson:              1.423
Prob(Omnibus):        0.000    Jarque-Bera (JB):           147.728
Skew:                 0.540    Prob(JB):                   8.34e-33
Kurtosis:             4.587    Cond. No.                    1.90e+05
=====

```

Warnings:

[1] The condition number is large, 1.9e+05. This might indicate that there are strong multicollinearity or other numerical problems.

2) dgtsp coefficient: 0.000505352938748

X_3

OLS Regression Results

```

=====

```

```

Dep. Variable:          dlhouse    R-squared:                0.868
Model:                  OLS        Adj. R-squared:           0.812
Method:                 Least Squares    F-statistic:             15.51
Date:                   Thu, 28 Apr 2016    Prob (F-statistic):      1.28e-63
Time:                   19:09:25    Log-Likelihood:          434.67
No. Observations:      331    AIC:                     -671.3
Df Residuals:          232    BIC:                     -294.9
Df Model:               98

```

	coef	std err	t	P> t	[95.0% Conf. Int.]	
region	0.0280	0.005	5.864	0.000	0.019	0.037
inchs	-0.0002	0.000	-0.437	0.662	-0.001	0.001
dlincome	0.5145	0.802	0.642	0.522	-1.065	2.094
lhouse70	-0.5841	0.124	-4.696	0.000	-0.829	-0.339
incage	-0.0002	0.001	-0.221	0.826	-0.002	0.002
age6570	0.4662	0.555	0.840	0.402	-0.627	1.559
hs3	-6.4999	27.908	-0.233	0.816	-61.486	48.486
owner70	-0.6593	0.139	-4.758	0.000	-0.932	-0.386
welfr70	0.4128	0.206	2.005	0.046	0.007	0.818
TOTOB570	1.862e-05	2.65e-05	0.703	0.483	-3.36e-05	7.08e-05
MAX1V80	2.641e-05	3.83e-05	0.690	0.491	-4.9e-05	0.000
built202	-10.6199	7.297	-1.455	0.147	-24.997	3.757
XAROB574	0.0004	0.001	0.648	0.518	-0.001	0.002
revnue70	1.226e-05	7.97e-05	0.154	0.878	-0.000	0.000
MTSPGM83	-0.0009	0.001	-0.713	0.476	-0.003	0.002
vacant70	-3.0959	1.313	-2.359	0.019	-5.682	-0.510
built102	-1.3039	0.564	-2.314	0.022	-2.414	-0.194
dage65	0.4599	1.040	0.442	0.659	-1.589	2.509
urban80	-0.0732	0.058	-1.272	0.205	-0.187	0.040
age3	306.6796	379.571	0.808	0.420	-441.167	1054.526
XAROB572	-0.0001	0.000	-0.313	0.755	-0.001	0.001
dgtsp	-0.0004	0.000	-0.896	0.371	-0.001	0.001
MAX1V78	-3.72e-06	5.11e-05	-0.073	0.942	-0.000	9.69e-05
dpoverly	-0.0253	0.399	-0.063	0.950	-0.812	0.761
pctghw2	1.8554	2.285	0.812	0.418	-2.647	6.358
pctwelf3	21.8911	10.348	2.116	0.035	1.503	42.279
whtage	-3.2526	13.740	-0.237	0.813	-30.324	23.819
dwelfr	-0.2065	0.265	-0.779	0.437	-0.729	0.316
hospbed2	-3.177e-08	2.56e-08	-1.241	0.216	-8.22e-08	1.87e-08
dunemp	-0.6233	0.468	-1.333	0.184	-1.545	0.298
built203	14.9999	10.057	1.491	0.137	-4.815	34.815
white70	0.5644	0.248	2.277	0.024	0.076	1.053
pop7080	-1.421e-07	1.12e-07	-1.272	0.205	-3.62e-07	7.8e-08
coll2	-1.4325	6.656	-0.215	0.830	-14.547	11.682
vacrnt70	-0.4619	0.300	-1.537	0.126	-1.054	0.130
pcteduc2	-0.2356	0.596	-0.395	0.693	-1.411	0.939
vacant80	-0.3919	0.362	-1.083	0.280	-1.105	0.321
XGMOBS82	0.0004	0.000	1.938	0.054	-7.04e-06	0.001
feml80	-0.4440	0.763	-0.582	0.561	-1.948	1.060
epend2	-5.219e-08	3.46e-08	-1.506	0.133	-1.2e-07	1.61e-08
house70	5.731e-06	2.5e-06	2.290	0.023	8e-07	1.07e-05
dfeml	-0.1312	1.459	-0.090	0.928	-3.006	2.744
XAROB583	-0.0003	0.000	-1.247	0.214	-0.001	0.000
XAROB577	-0.0001	0.000	-0.339	0.735	-0.001	0.001
pophs	0.0017	0.001	1.363	0.174	-0.001	0.004
MTSPAR73	-0.0006	0.002	-0.364	0.716	-0.004	0.003
educ80	0.0171	0.136	0.126	0.900	-0.251	0.285
unemp70	-0.0341	0.495	-0.069	0.945	-1.010	0.942
TOTOB574	-1.176e-05	5.36e-05	-0.219	0.827	-0.000	9.39e-05
XGMOBS77	0.0001	0.000	0.474	0.636	-0.000	0.001
XTSPAR74	-0.0002	0.000	-0.614	0.540	-0.001	0.000
MAX1V76	1.83e-05	3.07e-05	0.596	0.552	-4.22e-05	7.88e-05
hlth80	0.1057	0.112	0.940	0.348	-0.116	0.327
hs70	0.5997	0.189	3.180	0.002	0.228	0.971
MTSPGM84	0.0004	0.001	0.373	0.709	-0.002	0.003
gtsp7780	0.0030	0.002	1.577	0.116	-0.001	0.007
TOTOB572	-3.799e-06	2.79e-05	-0.136	0.892	-5.88e-05	5.12e-05
XGMOBS73	-0.0002	0.000	-1.142	0.255	-0.001	0.000
polic80	0.0849	0.742	0.114	0.909	-1.376	1.546
linc70	0.0569	0.532	0.107	0.915	-0.991	1.105
femal3	0.0371	1.960	0.019	0.985	-3.824	3.898
age6580	0.7636	0.669	1.142	0.255	-0.554	2.081
MAX2V70	-1.366e-05	5.73e-05	-0.238	0.812	-0.000	9.93e-05
plumb80	-0.2223	0.600	-0.370	0.711	-1.405	0.960
femal2	11.2191	65.314	0.172	0.864	-117.466	139.904
poverty3	-5.2729	27.105	-0.195	0.846	-58.676	48.130
povrty80	0.1479	0.366	0.404	0.687	-0.574	0.870
MTSPGM74	0.0007	0.001	0.874	0.383	-0.001	0.002
fstate	-0.0005	0.000	-1.164	0.245	-0.001	0.000
dhghwy	0.2872	0.320	0.896	0.371	-0.344	0.918
dincome	3.698e-05	0.000	0.328	0.743	-0.000	0.000
XAROB571	-0.0002	0.000	-1.284	0.200	-0.001	0.000
epend70	-7.222e-05	7.1e-05	-1.017	0.310	-0.000	6.77e-05
inccoll	-7.208e-05	0.001	-0.127	0.899	-0.001	0.001
XGMOBS72	0.0002	0.000	0.617	0.538	-0.000	0.001
revenue2	7.452e-08	2.12e-08	3.517	0.001	3.28e-08	1.16e-07
TOTOB576	2.427e-05	2.61e-05	0.930	0.342	-3.60e-05	8.00e-05

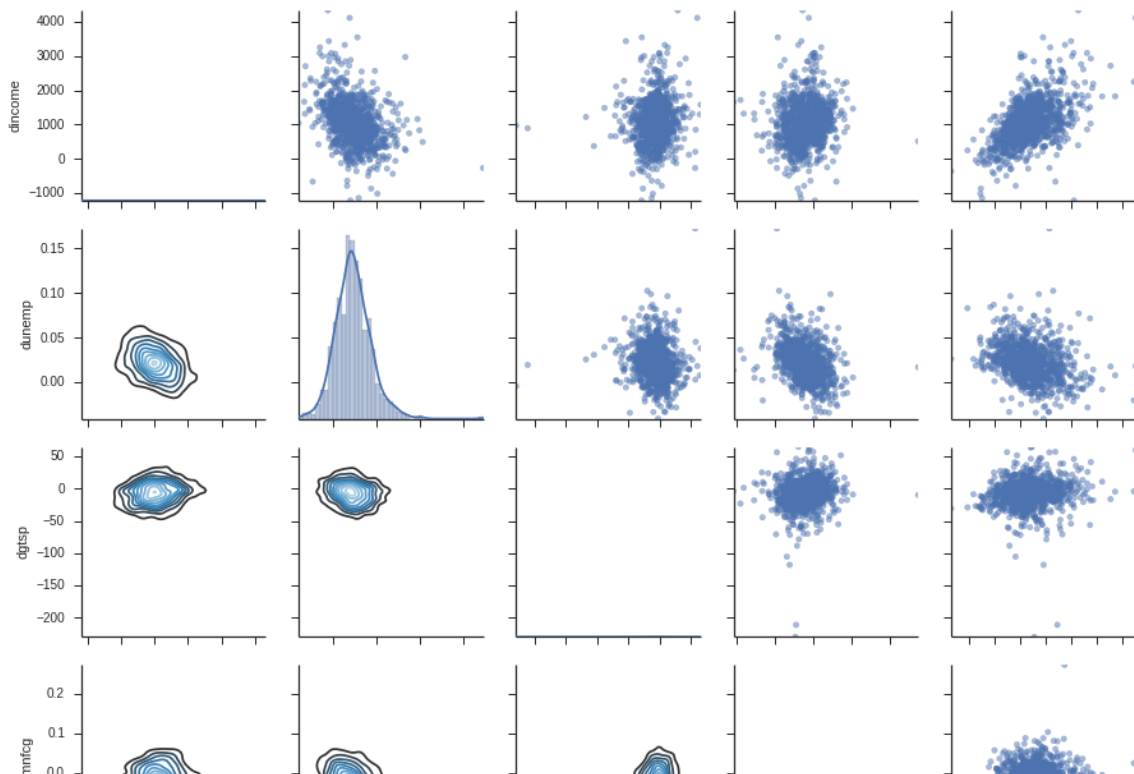

```

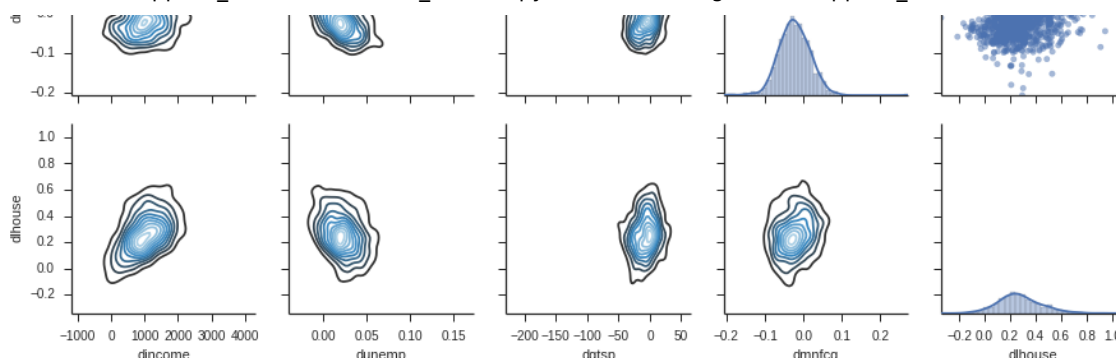
TOTOBS76  3.427e-05  3.01e-05  0.349  0.343  -3.09e-05  0.000
blt1080    1.1429    0.425    2.692    0.008    0.306    1.980
TOTOBS75  -6.509e-06  5.25e-05  -0.124    0.901    -0.000    9.69e-05
lrent80     0.5133    0.096    5.335    0.000    0.324    0.703
mnfcg80     0.1930    0.102    1.895    0.059    -0.008    0.394
income80   -1.048e-07  5.53e-05  -0.002    0.998    -0.000    0.000
MTSPAR78   -0.0005    0.001    -0.421    0.674    -0.003    0.002
TOTOBS71  -1.551e-05  2.43e-05  -0.639    0.523    -6.34e-05  3.23e-05
hs2         5.5901    6.791    0.823    0.411    -7.789    18.970
MTSPGM73   -0.0007    0.002    -0.362    0.718    -0.004    0.003
manwhite   -7.9499    4.380    -1.815    0.071    -16.580    0.680
MAX1V73    -3.89e-05  4.17e-05  -0.933    0.352    -0.000    4.32e-05
MAX2V71    -2.456e-05  3.59e-05  -0.683    0.495    -9.54e-05  4.63e-05
downer     -0.1102    0.238    -0.462    0.644    -0.580    0.359
dmnfcg     -1.0173    0.388    -2.619    0.009    -1.783    -0.252
MTSPAR69   -5.153e-05  0.000    -0.431    0.667    -0.000    0.000
hospbed3    9.9e-12    1.07e-11  0.927    0.355    -1.11e-11  3.09e-11
blt2080     2.1959    1.710    1.284    0.200    -1.174    5.566
bltold80    0.1344    0.146    0.920    0.359    -0.154    0.422
XGMOBS75    0.0002    0.000    0.844    0.400    -0.000    0.001
txprop80    4.18e-05  6.47e-05  0.646    0.519    -8.58e-05  0.000
rent70     -0.0003    0.000    -1.037    0.301    -0.001    0.000
drevenue   -0.0001    6.07e-05  -2.193    0.029    -0.000    -1.35e-05
mnfcg2     -1.4452    4.144    -0.349    0.728    -9.610    6.719
hghwy70    0.3014    0.264    1.140    0.256    -0.220    0.822
pctpol3    -30.3144    32.551    -0.931    0.353    -94.448    33.819
MTSPGM77   -0.0007    0.001    -0.647    0.518    -0.003    0.001
educ70     0.0419    0.121    0.345    0.730    -0.197    0.281
MAX1V77    -1.119e-05  1.48e-05  -0.754    0.452    -4.04e-05  1.81e-05
poptot80   3.007e-07  2.17e-07  1.383    0.168    -1.28e-07  7.29e-07
crime82    -2.92e-10  3.03e-10  -0.962    0.337    -8.9e-10  3.06e-10
XAROBS84   -0.0002    0.000    -0.805    0.422    -0.001    0.000
MAX1V75    -2.248e-05  4.37e-05  -0.515    0.607    -0.000    6.36e-05
ddens      -0.0003    0.000    -1.517    0.131    -0.001    7.91e-05
XTSPGM75   3.349e-05  0.000    0.102    0.919    -0.001    0.001
white80    -0.4527    0.254    -1.779    0.077    -0.954    0.049
XGMOBS74   -0.0002    0.001    -0.384    0.701    -0.001    0.001
povrty70   0.2343    0.302    0.775    0.439    -0.361    0.830
XAROBS76   -0.0001    0.000    -0.592    0.554    -0.000    0.000
intercept  2.4191    3.975    0.609    0.543    -5.412    10.250
=====
Omnibus:                0.507    Durbin-Watson:          1.628
Prob(Omnibus):          0.776    Jarque-Bera (JB):       0.291
Skew:                   -0.005    Prob(JB):               0.864
Kurtosis:               3.145    Cond. No.:              nan
=====

```

Warnings:

[1] The smallest eigenvalue is -0.00931. This might indicate that there are strong multicollinearity problems or that the design matrix is singular.
 3) dgtsp coefficient: -0.000424930439339





b. Suppose that federal EPA pollution regulation is a potential instrumental variable for pollution changes during the 1970s. What are the assumptions required for 1975-1976 regulatory status, `tsp7576`, to be a valid instrument for pollution changes when the outcome of interest is housing price changes? Provide evidence on the relationship between the regulatory status indicator and the observable economic shock measures. Interpret your findings.

Answer: `tsp7576` must be strong, ie correlated w `dgtsps`, and valid, ie not correlated w `dlhouse` except through `dgtsps`. As we can see in the correlation matrix below, `tsp7576` is only slightly correlated w our economic shock variables, making it potentially a good IV.

	<code>tsp7576</code>	<code>dincome</code>	<code>dunemp</code>	<code>dmnfcg</code>	<code>ddens</code>	<code>durban</code>	<code>blt1080</code>
<code>tsp7576</code>	1.000000	0.033421	0.006804	-0.005299	-0.021966	-0.004475	-0.029616
<code>dincome</code>	0.033421	1.000000	-0.355727	0.120453	0.202457	0.243080	0.452957
<code>dunemp</code>	0.006804	-0.355727	1.000000	-0.368449	-0.104737	-0.095059	-0.189928
<code>dmnfcg</code>	-0.005299	0.120453	-0.368449	1.000000	0.040436	-0.056728	0.124982
<code>ddens</code>	-0.021966	0.202457	-0.104737	0.040436	1.000000	0.045735	0.257792
<code>durban</code>	-0.004475	0.243080	-0.095059	-0.056728	0.045735	1.000000	0.325309
<code>blt1080</code>	-0.029616	0.452957	-0.189928	0.124982	0.257792	0.325309	1.000000

c. Document the "first-stage" relationship between regulation (`tsp7576`) and air pollution changes and the "reduced-form" relationship between regulation and housing price changes, using the same three specifications you used in part a). Interpret your findings. How does two-stage least squares use these two equations? Now estimate the effect of air quality changes on housing price changes using two-stage least squares and the `tsp7576` indicator as an instrument for the three specifications. Interpret the results. Now do the same using the 1975 regulation indicator, `tsp75`, as an instrumental variable. Compare the findings.

Answer: the negative effect of regulation on air pollution decreases as we add controls (relationship gets less negative). The positive effect of regulation on changes in house prices decreases as we add controls. In terms of IV, our 7576 and 75 results are similar, both around -.003 (elasticity of -.03) for uncontrolled and basically controlled regressions. As we showed before, the IV is only slightly correlated with economic shock variables, so the model isn't particularly sensitive to control specification. Estimates for model w all interactions + higher-order terms remains difficult to interpret. The reduced form results show that house prices in treated counties are 2-4% higher than they would be otherwise. First-stage results suggest that treatment results in pollution decreases of 5-10%.

X_1

OLS Regression Results

Dep. Variable:	<code>dgtsps</code>	R-squared:	0.039
Model:	OLS	Adj. R-squared:	0.038
Method:	Least Squares	F-statistic:	40.72
Date:	Thu, 28 Apr 2016	Prob (F-statistic):	2.68e-10
Time:	19:09:49	Log-Likelihood:	-4505.5
No. Observations:	1000	AIC:	9015.
Df Residuals:	998	BIC:	9025.
Df Model:	1		

	coef	std err	t	P> t	[95.0% Conf. Int.]
intercept	-5.1013	0.817	-6.243	0.000	-6.705 -3.498
<code>tsp7576</code>	-9.8540	1.544	-6.382	0.000	-12.884 -6.824

Omnibus:	521.430	Durbin-Watson:	1.900
Prob(Omnibus):	0.000	Jarque-Bera (JB):	13678.349
Skew:	-1.838	Prob(JB):	0.00
Kurtosis:	20.742	Cond. No.	2.44

X_1: first stage `tsp7576` coefficient:
-9.85395322927

OLS Regression Results

Dep. Variable:	<code>dlhouse</code>	R-squared:	0.009
Model:	OLS	Adj. R-squared:	0.008

```

Method: Least Squares      F-statistic: 9.026
Date: Thu, 28 Apr 2016     Prob (F-statistic): 0.00273
Time: 19:09:49            Log-Likelihood: 342.33
No. Observations: 1000    AIC: -680.7
Df Residuals: 998         BIC: -670.8
Df Model: 1

```

	coef	std err	t	P> t	[95.0% Conf. Int.]
intercept	0.2642	0.006	41.214	0.000	0.252 0.277
tsp7576	0.0364	0.012	3.004	0.003	0.013 0.060

```

Omnibus: 69.692 Durbin-Watson: 1.047
Prob(Omnibus): 0.000 Jarque-Bera (JB): 113.534
Skew: 0.518 Prob(JB): 2.22e-25
Kurtosis: 4.286 Cond. No. 2.44

```

X_1: reduced form tsp7576 coefficient:
0.0363932219048

/usr/local/lib/python2.7/dist-packages/ipykernel/_main_.py:216: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: <http://pandas.pydata.org/pandas-docs/stable/indexing.html#indexing-view-versus-copy>

X_1: IV estimate: -0.00369326107584

OLS Regression Results

```

Dep. Variable: dlhouse      R-squared: 0.009
Model: OLS                Adj. R-squared: 0.008
Method: Least Squares     F-statistic: 9.026
Date: Thu, 28 Apr 2016    Prob (F-statistic): 0.00273
Time: 19:09:49           Log-Likelihood: 342.33
No. Observations: 1000    AIC: -680.7
Df Residuals: 998         BIC: -670.8
Df Model: 1

```

	coef	std err	t	P> t	[95.0% Conf. Int.]
intercept	0.2453	0.011	22.126	0.000	0.224 0.267
dgtsp_hat	-0.0037	0.001	-3.004	0.003	-0.006 -0.001

```

Omnibus: 69.692 Durbin-Watson: 1.047
Prob(Omnibus): 0.000 Jarque-Bera (JB): 113.534
Skew: 0.518 Prob(JB): 2.22e-25
Kurtosis: 4.286 Cond. No. 18.6

```

X_2

OLS Regression Results

```

Dep. Variable: dgtsp      R-squared: 0.119
Model: OLS                Adj. R-squared: 0.091
Method: Least Squares     F-statistic: 4.333
Date: Thu, 28 Apr 2016    Prob (F-statistic): 5.81e-13
Time: 19:09:49           Log-Likelihood: -4280.1
No. Observations: 962     AIC: 8620.
Df Residuals: 932         BIC: 8766.
Df Model: 29

```

	coef	std err	t	P> t	[95.0% Conf. Int.]
ddens	0.0009	0.003	0.281	0.779	-0.005 0.007
dmnfcg	52.1047	20.384	2.556	0.011	12.100 92.109
dwhite	-11.9107	16.772	-0.710	0.478	-44.827 21.005
dfeml	86.3239	92.598	0.932	0.351	-95.401 268.049
dage65	72.0942	68.490	1.053	0.293	-62.318 206.506
dhs	-13.3483	26.069	-0.512	0.609	-64.508 37.812
dcoll	67.1590	37.494	1.791	0.074	-6.423 140.740
durban	-10.1453	9.783	-1.037	0.300	-29.345 9.055
dunemp	20.1578	42.375	0.476	0.634	-63.004 103.320
dincome	0.0024	0.002	1.523	0.128	-0.001 0.005
dpoverly	-13.4282	30.082	-0.446	0.655	-72.465 45.609
downer	9.9094	17.135	0.578	0.563	-23.719 43.538
dplumb	-17.2102	33.829	-0.509	0.611	-83.601 49.180
drevenue	0.0030	0.004	0.696	0.486	-0.005 0.011
dtaxprop	-0.0154	0.006	-2.660	0.008	-0.027 -0.004
depend	-0.0029	0.005	-0.647	0.518	-0.012 0.006
deduc	-1.0129	9.095	-0.111	0.911	-18.861 16.835
dhighwy	-4.4420	21.911	-0.203	0.839	-47.443 38.559
dwelfr	-12.5714	18.689	-0.673	0.501	-49.248 24.105
dhlth	-7.8801	12.375	-0.637	0.524	-32.166 16.406
vacant70	164.2036	95.315	1.723	0.085	-22.852 351.260
vacant80	16.8748	26.121	0.646	0.518	-34.387 68.137

```

vacrnt70      14.6256    26.977    0.542    0.588    -38.317    67.568
blt1080       18.5584    13.471    1.378    0.169    -7.878    44.994
blt2080      -11.8607    23.635   -0.502    0.616   -58.246    34.524
bltold80       6.2804    12.679    0.495    0.620   -18.603    31.164
tsp7576       -6.5183     2.107   -3.093    0.002   -10.654   -2.383
mtspgm74      -0.2715     0.070   -3.901    0.000    -0.408   -0.135
mtspgm75       0.1596     0.068    2.338    0.020     0.026     0.294
intercept     -9.9169    11.475   -0.864    0.388   -32.437    12.604
=====
Omnibus:                514.119    Durbin-Watson:                1.916
Prob(Omnibus):          0.000    Jarque-Bera (JB):            15770.558
Skew:                   -1.848    Prob(JB):                     0.00
Kurtosis:               22.488    Cond. No.                     1.89e+05
=====

```

Warnings:

[1] The condition number is large, 1.89e+05. This might indicate that there are strong multicollinearity or other numerical problems.

X_2: first stage tsp7576 coefficient:
-6.51828681598

OLS Regression Results

```

=====
Dep. Variable:          dlhouse    R-squared:                0.569
Model:                  OLS        Adj. R-squared:           0.556
Method:                 Least Squares    F-statistic:             42.43
Date:                   Thu, 28 Apr 2016    Prob (F-statistic):      1.28e-148
Time:                   19:09:49          Log-Likelihood:          735.33
No. Observations:      962            AIC:                    -1411.
Df Residuals:          932            BIC:                    -1265.
Df Model:               29
=====
               coef    std err          t      P>|t|      [95.0% Conf. Int.]
-----
ddens         -6.938e-06    1.75e-05    -0.397    0.692    -4.12e-05    2.74e-05
dmnfcg        -0.0547     0.111    -0.493    0.622    -0.272     0.163
dwhite        -0.5296     0.091    -5.802    0.000    -0.709    -0.350
dfeml        -0.7348     0.504    -1.458    0.145    -1.724     0.254
dage65       -1.7494     0.373    -4.694    0.000    -2.481    -1.018
dhs           0.4084     0.142     2.879    0.004     0.130     0.687
dcoll         0.2186     0.204     1.071    0.284    -0.182     0.619
durban       -0.1241     0.053    -2.331    0.020    -0.229    -0.020
dunemp       -0.9334     0.231    -4.047    0.000    -1.386    -0.481
dincome      6.722e-05    8.46e-06     7.947    0.000     5.06e-05    8.38e-05
dpoverthy    -0.6205     0.164    -3.790    0.000    -0.942    -0.299
downer       -0.1349     0.093    -1.446    0.148    -0.318     0.048
dplumb       -0.1652     0.184    -0.897    0.370    -0.527     0.196
drevenue     1.955e-05    2.34e-05     0.834    0.404    -2.64e-05    6.55e-05
dtaxprop     -7.503e-05    3.15e-05    -2.385    0.017    -0.000    -1.33e-05
depend      -3.154e-05    2.47e-05    -1.277    0.202     -8e-05    1.69e-05
deduc         0.1134     0.049     2.290    0.022     0.016     0.210
dhghwy       -0.1713     0.119    -1.437    0.151    -0.405     0.063
dwelfr       -0.3207     0.102    -3.153    0.002    -0.520    -0.121
dhlth        -0.0532     0.067    -0.790    0.430    -0.185     0.079
vacant70     -0.9395     0.519    -1.811    0.070    -1.958     0.078
vacant80      0.5380     0.142     3.785    0.000     0.259     0.817
vacrnt70     -0.1216     0.147    -0.828    0.408    -0.410     0.167
blt1080      0.3329     0.073     4.542    0.000     0.189     0.477
blt2080     -0.9507     0.129    -7.391    0.000    -1.203    -0.698
bltold80     -0.2211     0.069    -3.204    0.001    -0.356    -0.086
tsp7576       0.0177     0.011     1.540    0.124    -0.005     0.040
mtspgm74      0.0016     0.000     4.173    0.000     0.001     0.002
mtspgm75     -0.0017     0.000    -4.494    0.000    -0.002    -0.001
intercept     0.2831     0.062     4.533    0.000     0.161     0.406
=====
Omnibus:                73.169    Durbin-Watson:                1.414
Prob(Omnibus):          0.000    Jarque-Bera (JB):            137.848
Skew:                   0.507    Prob(JB):                     1.17e-30
Kurtosis:               4.553    Cond. No.                     1.89e+05
=====

```

Warnings:

[1] The condition number is large, 1.89e+05. This might indicate that there are strong multicollinearity or other numerical problems.

X_2: reduced form tsp7576 coefficient:
0.0176592751237

X_2: IV estimate: -0.00270918964173

OLS Regression Results

```

=====
Dep. Variable:          dlhouse    R-squared:                0.569
Model:                  OLS        Adj. R-squared:           0.556
Method:                 Least Squares    F-statistic:             42.43
Date:                   Thu, 28 Apr 2016    Prob (F-statistic):      1.28e-148
Time:                   19:09:49          Log-Likelihood:          735.33

```

```

No. Observations:      962      AIC:      -1411.
Df Residuals:         932      BIC:      -1265.
Df Model:              29
=====
              coef      std err          t      P>|t|      [95.0% Conf. Int.]
-----
ddens      -4.492e-06    1.75e-05    -0.257    0.797    -3.88e-05  2.98e-05
dmnfcg      0.0864      0.142      0.607    0.544    -0.193    0.366
dwhite     -0.5619      0.093     -6.047    0.000    -0.744    -0.380
dfeml     -0.5009      0.526     -0.953    0.341    -1.532    0.531
dage65     -1.5541      0.390     -3.987    0.000    -2.319    -0.789
dhs        0.3723      0.143      2.595    0.010    0.091    0.654
dcoll      0.4005      0.231      1.736    0.083    -0.052    0.853
durban     -0.1516      0.057     -2.674    0.008    -0.263    -0.040
dunemp     -0.8788      0.233     -3.775    0.000    -1.336    -0.422
dincome    7.363e-05    9.18e-06    8.024    0.000    5.56e-05  9.16e-05
dpoverly   -0.6569      0.169     -3.890    0.000    -0.988    -0.326
downer     -0.1080      0.095     -1.133    0.257    -0.295    0.079
dplumb     -0.2118      0.188     -1.127    0.260    -0.581    0.157
drevenue   2.767e-05    2.42e-05    1.145    0.252    -1.97e-05  7.51e-05
dtaxprop   -0.0001      4.13e-05    -2.826    0.005    -0.000    -3.56e-05
depend    -3.949e-05    2.55e-05    -1.549    0.122    -8.95e-05  1.06e-05
deduc      0.1106      0.050      2.233    0.026    0.013    0.208
dhghwy     -0.1834      0.120     -1.533    0.126    -0.418    0.051
dwelfr     -0.3548      0.104     -3.417    0.001    -0.558    -0.151
dhlth      -0.0745      0.069     -1.087    0.278    -0.209    0.060
vacant70   -0.4947      0.617     -0.802    0.423    -1.705    0.716
vacant80   -0.5838      0.144     -4.057    0.000    -0.301    -0.866
vacant70   -0.0820      0.147     -0.557    0.578    -0.371    0.207
blt1080    0.3832      0.079      4.827    0.000    0.227    0.539
blt2080    -0.9828      0.129     -7.603    0.000    -1.236    -0.729
bltold80   -0.2040      0.070     -2.910    0.004    -0.342    -0.066
mtspgm74   0.0008      0.001      1.201    0.230    -0.001    0.002
mtspgm75   -0.0012      0.000     -2.844    0.005    -0.002    -0.000
intercept  0.2563      0.063      4.078    0.000    0.133    0.380
dgtsp_hat  -0.0027      0.002     -1.540    0.124    -0.006    0.001
=====
Omnibus:      73.169      Durbin-Watson:      1.414
Prob(Omnibus): 0.000      Jarque-Bera (JB):    137.848
Skew:         0.507      Prob(JB):            1.17e-30
Kurtosis:     4.553      Cond. No.            2.31e+05
=====

```

Warnings:

[1] The condition number is large, 2.31e+05. This might indicate that there are strong multicollinearity or other numerical problems.

X_3

OLS Regression Results

```

=====
Dep. Variable:      dgtsp      R-squared:      0.849
Model:              OLS      Adj. R-squared:    0.786
Method:             Least Squares      F-statistic:    13.35
Date:               Thu, 28 Apr 2016      Prob (F-statistic): 1.43e-57
Time:               19:09:50      Log-Likelihood: -1197.4
No. Observations:   331      AIC:      2593.
Df Residuals:       232      BIC:      2969.
Df Model:           98
=====
              coef      std err          t      P>|t|      [95.0% Conf. Int.]
-----
region      -0.1653      0.661     -0.250    0.803    -1.467    1.137
inchs       0.0584      0.053      1.112    0.267    -0.045    0.162
dlincome   -89.9238     111.138     -0.809    0.419   -308.892   129.044
lhouse70    5.3509      17.224      0.311    0.756   -28.585    39.287
incage      0.0856      0.134      0.641    0.522    -0.178    0.349
age6570     63.5019      77.067      0.824    0.411   -88.339   215.342
hs3        -1687.4154    3863.464     -0.437    0.663  -9299.373  5924.543
owner70     32.5558      19.110      1.704    0.090    -5.095    70.207
welfr70     -15.8921      28.543     -0.557    0.578   -72.129   40.345
TOTOB570    0.0169      0.004      4.821    0.000      0.010     0.024
MAX1V80     0.0026      0.005      0.482    0.631    -0.008    0.013
built202    908.1756     1011.346      0.898    0.370  -1084.421  2900.772
XAROB574    -0.0223      0.081     -0.275    0.784    -0.182    0.138
revnue70    -0.0014      0.011     -0.129    0.898    -0.023    0.020
MTSPGM83    0.0377      0.169      0.223    0.824    -0.296    0.371
vacant70    138.0168     181.642      0.760    0.448   -219.861   495.895
built102    -81.4795      78.479     -1.038    0.300   -236.103   73.144
dage65     -127.0932     143.606     -0.885    0.377   -410.031   155.845
urban80     2.2782       7.975      0.286    0.775   -13.435    17.991
age3       -4297.1617     5.26e+04     -0.082    0.935   -1.08e+05  9.93e+04
XAROB572    0.0550      0.045      1.223    0.222    -0.034    0.143
MAX1V78     -0.0041      0.007     -0.567    0.572    -0.018    0.010
dpoverly   -53.5883      55.638     -0.963    0.336   -163.209    56.032
pctghw2     7.0780      319.139      0.022    0.982   -621.703   635.859
pctwelf3    -979.4367     1436.845     -0.682    0.496  -3810.369  1851.496
whtane     -760.3433     1907.234     -0.400    0.690   -4508.204   2987.517
=====

```

dwelfr	15.0630	36.941	0.408	0.684	-57.719	87.846
hospbed2	-4.436e-06	3.53e-06	-1.255	0.211	-1.14e-05	2.53e-06
dunemp	-29.2411	64.856	-0.451	0.653	-157.024	98.542
built203	-1007.9768	1393.720	-0.723	0.470	-3753.943	1737.989
white70	0.4033	34.400	0.012	0.991	-67.373	68.180
pop7080	-1.117e-05	1.54e-05	-0.723	0.470	-4.16e-05	1.93e-05
coll2	335.8045	922.352	0.364	0.716	-1481.452	2153.061
vacrnt70	12.8388	41.608	0.309	0.758	-69.139	94.817
pcteduc2	61.7698	82.496	0.749	0.455	-100.767	224.307
vacant80	73.7602	50.108	1.472	0.142	-24.964	172.485
XGMOBS82	-0.0210	0.030	-0.701	0.484	-0.080	0.038
feml80	-62.5351	105.655	-0.592	0.555	-270.702	145.632
epend2	-3.997e-06	4.79e-06	-0.834	0.405	-1.34e-05	5.45e-06
house70	0.0001	0.000	0.381	0.704	-0.001	0.001
dfeml	-7.9380	203.211	-0.039	0.969	-408.313	392.437
XAR0BS83	-0.0274	0.033	-0.822	0.412	-0.093	0.038
XAR0BS77	0.0163	0.047	0.345	0.731	-0.077	0.110
pophs	0.0360	0.171	0.211	0.833	-0.300	0.372
MTSPAR73	0.1245	0.230	0.541	0.589	-0.329	0.578
educ80	4.1129	18.855	0.218	0.828	-33.036	41.261
unemp70	-35.0823	68.726	-0.510	0.610	-170.490	100.325
TOT0BS74	-0.0110	0.007	-1.494	0.137	-0.026	0.004
XGMOBS77	-0.0158	0.041	-0.382	0.703	-0.097	0.066
XTSPAR74	-0.0147	0.036	-0.410	0.682	-0.085	0.056
MAX1V76	-0.0061	0.004	-1.438	0.152	-0.015	0.002
hlth80	-25.8147	15.484	-1.667	0.097	-56.322	4.693
hs70	20.8747	26.094	0.800	0.425	-30.537	72.286
MTSPGM84	-0.0401	0.155	-0.258	0.797	-0.346	0.266
gtsp7780	1.0271	0.257	4.004	0.000	0.522	1.533
TOT0BS72	0.0038	0.004	0.979	0.328	-0.004	0.011
XGMOBS73	0.0461	0.025	1.829	0.069	-0.004	0.096
polic80	21.6946	102.688	0.211	0.833	-180.625	224.014
linc70	-43.6459	73.622	-0.593	0.554	-188.698	101.406
femal3	68.9136	300.586	0.229	0.819	-523.314	661.142
age6580	-60.8976	92.947	-0.655	0.513	-244.025	122.230
MAX2V70	-0.0902	0.005	-17.039	0.000	-0.101	-0.080
plumb80	124.3085	82.797	1.501	0.135	-38.822	287.438
femal2	1887.8294	9047.588	0.209	0.835	-1.59e+04	1.97e+04
poverty3	-746.3027	3753.398	-0.199	0.843	-8141.406	6648.800
povrty80	-84.1690	50.630	-1.662	0.098	-183.921	15.583
MTSPGM74	-0.2250	0.109	-2.065	0.040	-0.440	-0.010
fstate	0.1008	0.064	1.566	0.119	-0.026	0.228
dhghwy	22.0220	44.389	0.496	0.620	-65.435	109.479
dincome	-0.0085	0.016	-0.543	0.588	-0.039	0.022
XAR0BS71	0.0643	0.025	2.614	0.010	0.016	0.113
epend70	0.0127	0.010	1.296	0.196	-0.007	0.032
inccoll	0.0452	0.079	0.575	0.566	-0.110	0.200
XGMOBS72	-0.0583	0.050	-1.174	0.242	-0.156	0.040
revenue2	6.979e-07	2.94e-06	0.238	0.812	-5.08e-06	6.48e-06
TOT0BS76	0.0021	0.005	0.412	0.681	-0.008	0.012
blt1080	-8.1680	59.306	-0.138	0.891	-125.016	108.680
TOT0BS75	0.0003	0.007	0.042	0.967	-0.014	0.015
lrent80	-16.1082	13.281	-1.213	0.226	-42.275	10.058
mnfcg80	4.3119	14.128	0.305	0.760	-23.524	32.147
income80	0.0006	0.008	0.082	0.935	-0.014	0.016
MTSPAR78	0.0437	0.168	0.261	0.795	-0.287	0.374
TOT0BS71	-0.0016	0.003	-0.476	0.634	-0.008	0.005
hs2	281.3381	940.605	0.299	0.765	-1571.881	2134.557
MTSPGM73	-0.5084	0.253	-2.008	0.046	-1.007	-0.009
manwhite	621.2448	605.507	1.026	0.306	-571.750	1814.240
MAX1V73	0.0152	0.006	2.673	0.008	0.004	0.026
MAX2V71	-0.0187	0.005	-3.861	0.000	-0.028	-0.009
downer	-5.0839	33.014	-0.154	0.878	-70.130	59.962
dmnfcg	98.6471	53.460	1.845	0.066	-6.682	203.976
MTSPAR69	-0.0837	0.016	-5.359	0.000	-0.114	-0.053
hospbed3	1.247e-09	1.48e-09	0.841	0.401	-1.67e-09	4.17e-09
blt2080	-278.8630	236.819	-1.178	0.240	-745.453	187.727
bltol80	-65.3324	19.863	-3.289	0.001	-104.467	-26.198
XGMOBS75	0.0050	0.031	0.162	0.871	-0.056	0.066
txprop80	0.0061	0.009	0.685	0.494	-0.012	0.024
rent70	-0.0384	0.038	-1.009	0.314	-0.113	0.037
drevenue	0.0028	0.008	0.334	0.739	-0.014	0.019
mnfcg2	680.6806	573.541	1.187	0.237	-449.334	1810.695
hghwy70	-33.0704	36.628	-0.903	0.368	-105.236	39.095
pctpol3	-528.0439	4511.827	-0.117	0.907	-9417.434	8361.346
MTSPGM77	-0.0886	0.144	-0.615	0.539	-0.372	0.195
educ70	-7.1610	16.788	-0.427	0.670	-40.237	25.915
MAX1V77	0.0018	0.002	0.872	0.384	-0.002	0.006
poptot80	2.045e-05	3.01e-05	0.680	0.497	-3.88e-05	7.97e-05
crime82	5.314e-08	4.22e-08	1.260	0.209	-2.99e-08	1.36e-07
XAR0BS84	0.0732	0.036	2.042	0.042	0.003	0.144
MAX1V75	0.0072	0.006	1.201	0.231	-0.005	0.019
ddens	-0.0078	0.024	-0.321	0.748	-0.055	0.040
XTSPGM75	0.0220	0.045	0.485	0.628	-0.067	0.111
white80	-3.6965	35.362	-0.105	0.917	-73.367	65.974
XGMOBS74	0.0304	0.081	0.374	0.709	-0.130	0.191
povrty70	-31.5016	41.833	-0.753	0.452	-113.922	50.919

```

XAR0BS76      -0.0397      0.024      -1.690      0.092      -0.086      0.007
intercept      462.7005      549.670      0.842      0.401      -620.282      1545.683
tsp7576        0.4082        2.048        0.199        0.842        -3.627        4.444
=====
Omnibus:                41.017      Durbin-Watson:                2.046
Prob(Omnibus):          0.000      Jarque-Bera (JB):            206.790
Skew:                   0.318      Prob(JB):                    1.25e-45
Kurtosis:               6.820      Cond. No.:                   nan
=====

```

Warnings:

[1] The smallest eigenvalue is -0.00827. This might indicate that there are strong multicollinearity problems or that the design matrix is singular.

X_3: first stage tsp7576 coefficient:
0.408180519449

OLS Regression Results

```

=====
Dep. Variable:          dlhouse      R-squared:                0.869
Model:                  OLS          Adj. R-squared:          0.813
Method:                 Least Squares  F-statistic:            15.67
Date:                  Thu, 28 Apr 2016  Prob (F-statistic):      4.79e-64
Time:                  19:09:52      Log-Likelihood:         436.17
No. Observations:      331          AIC:                   -674.3
Df Residuals:          232          BIC:                   -297.9
Df Model:              98
=====

```

```

=====
              coef      std err          t      P>|t|      [95.0% Conf. Int.]
-----
region          0.0277      0.005      5.829      0.000      0.018      0.037
inchs          -0.0001      0.000     -0.343      0.732     -0.001      0.001
dlincome        0.4630      0.799      0.580      0.563     -1.111      2.037
lhouse70       -0.5845      0.124     -4.721      0.000     -0.828     -0.341
incage         -0.0003      0.001     -0.331      0.741     -0.002      0.002
age6570         0.4133      0.554      0.746      0.456     -0.678      1.505
hs3            -5.4369     27.771     -0.196      0.845    -60.153     49.279
owner70        -0.6889      0.137     -5.015      0.000     -0.960     -0.418
welfr70         0.4402      0.205      2.146      0.033      0.036      0.844
TOT0BS70       8.436e-06     2.52e-05     0.335      0.738    -4.12e-05     5.81e-05
MAX1V80        3.004e-05     3.82e-05     0.787      0.432    -4.51e-05     0.000
built202       -11.9030      7.270     -1.637      0.103    -26.226      2.420
XAR0BS74        0.0004      0.001      0.702      0.483     -0.001      0.002
revnue70       1.081e-05     7.94e-05     0.136      0.892     -0.000      0.000
MTSPGM83       -0.0010      0.001     -0.781      0.435     -0.003      0.001
vacant70       -3.0813      1.306     -2.360      0.019     -5.654     -0.509
built102       -1.3906      0.564     -2.465      0.014     -2.502     -0.279
dage65         0.5930      1.032      0.574      0.566     -1.441      2.627
urban80        -0.0697      0.057     -1.215      0.226     -0.183      0.043
age3           302.9151     377.864      0.802      0.424   -441.569    1047.399
XAR0BS72       -6.273e-05     0.000     -0.194      0.846     -0.001      0.001
MAX1V78       -1.597e-05     5.15e-05     -0.310      0.757     -0.000      8.54e-05
dpoverly       -0.0915      0.400     -0.229      0.819     -0.879      0.696
pctghw2         1.3445      2.294      0.586      0.558     -3.175      5.864
pctwelf3       20.8003     10.328      2.014      0.045      0.451     41.149
whtage        -2.8147     13.674     -0.206      0.837    -29.755     24.125
dwelfr         -0.1588      0.266     -0.598      0.550     -0.682      0.364
hospbed2       -3.123e-08     2.54e-08     -1.229      0.220    -8.13e-08     1.88e-08
dunemp         -0.5605      0.466     -1.202      0.231     -1.479      0.358
built203       16.4704     10.018      1.644      0.102     -3.268     36.209
white70        0.5922      0.247      2.395      0.017      0.105      1.079
pop7080       -1.381e-07     1.11e-07     -1.244      0.215    -3.57e-07     8.07e-08
coll2         -1.1123      6.630     -0.168      0.867    -14.175     11.950
vacrnt70       -0.4770      0.299     -1.595      0.112     -1.066      0.112
pcteduc2       -0.2490      0.593     -0.420      0.675     -1.417      0.919
vacant80       -0.4828      0.360     -1.340      0.181     -1.192      0.227
XGMOBS82       0.0004      0.000      2.016      0.045      9.84e-06      0.001
feml80         -0.4328      0.759     -0.570      0.569     -1.929      1.063
epend2         -4.93e-08     3.44e-08     -1.431      0.154    -1.17e-07     1.86e-08
house70        5.789e-06     2.49e-06     2.323      0.021      8.8e-07     1.07e-05
dfeml         -0.3929      1.461     -0.269      0.788     -3.271      2.485
XAR0BS83       -0.0003      0.000     -1.193      0.234     -0.001      0.000
XAR0BS77       -0.0002      0.000     -0.482      0.630     -0.001      0.001
pophs          0.0017      0.001      1.402      0.162     -0.001      0.004
MTSPAR73       -0.0009      0.002     -0.526      0.600     -0.004      0.002
educ80         0.0244      0.136      0.180      0.857     -0.243      0.291
unemp70        0.0400      0.494      0.081      0.936     -0.933      1.013
TOT0BS74       -7.715e-06     5.32e-05     -0.145      0.885     -0.000      9.7e-05
XGMOBS77       0.0002      0.000      0.551      0.582     -0.000      0.001
XTSPAR74       -0.0002      0.000     -0.914      0.362     -0.001      0.000
MAX1V76        1.359e-05     3.07e-05     0.442      0.659    -4.69e-05     7.41e-05
hlth80         0.1215      0.111      1.092      0.276     -0.098      0.341
hs70           0.5808      0.188      3.096      0.002      0.211      0.950
MTSPGM84       0.0006      0.001      0.510      0.611     -0.002      0.003
gtsp7780       0.0023      0.002      1.221      0.223     -0.001      0.006
TOT0BS72       -5.911e-06     2.77e-05     -0.213      0.831    -6.05e-05     4.87e-05
XGMOBS73       -0.0002      0.000     -1.132      0.259     -0.001      0.000
=====

```

police	0.0087	0.138	0.093	0.920	-1.380	1.523
linc70	0.0639	0.529	0.121	0.904	-0.979	1.107
femal3	-0.3438	2.161	-0.159	0.874	-4.601	3.913
age6580	0.8377	0.668	1.254	0.211	-0.479	2.154
MAX2V70	2.564e-05	3.8e-05	0.674	0.501	-4.93e-05	0.000
plumb80	-0.3191	0.595	-0.536	0.592	-1.492	0.854
femal2	13.4227	65.035	0.206	0.837	-114.713	141.558
poverty3	-5.0142	26.980	-0.186	0.853	-58.171	48.143
povrty80	0.1268	0.364	0.348	0.728	-0.590	0.844
MTSPGM74	0.0005	0.001	0.658	0.511	-0.001	0.002
fstate	-0.0006	0.000	-1.299	0.195	-0.002	0.000
dghwy	0.2545	0.319	0.798	0.426	-0.374	0.883
dincome	4.832e-05	0.000	0.431	0.667	-0.000	0.000
XAR0BS71	-0.0002	0.000	-1.350	0.178	-0.001	0.000
epend70	-7.859e-05	7.05e-05	-1.115	0.266	-0.000	6.02e-05
inccoll	-0.0002	0.001	-0.324	0.746	-0.001	0.001
XGMOBS72	0.0001	0.000	0.419	0.675	-0.001	0.001
revenue2	7.354e-08	2.11e-08	3.486	0.001	3.2e-08	1.15e-07
TOT0BS76	4.622e-05	3.67e-05	1.260	0.209	-2.61e-05	0.000
blt1080	1.2423	0.426	2.914	0.004	0.402	2.082
TOT0BS75	-1.289e-05	5.24e-05	-0.246	0.806	-0.000	9.03e-05
lrent80	0.5195	0.095	5.442	0.000	0.331	0.708
mnfcg80	0.1803	0.102	1.776	0.077	-0.020	0.380
income80	-9.234e-07	5.5e-05	-0.017	0.987	-0.000	0.000
MTSPAR78	-0.0004	0.001	-0.299	0.765	-0.003	0.002
TOT0BS71	-1.727e-05	2.42e-05	-0.714	0.476	-6.5e-05	3.04e-05
hs2	5.1582	6.761	0.763	0.446	-8.163	18.479
MTSPGM73	-0.0001	0.002	-0.081	0.936	-0.004	0.003
manwhite	-8.4516	4.352	-1.942	0.053	-17.027	0.124
MAX1V73	-4.523e-05	4.09e-05	-1.107	0.270	-0.000	3.53e-05
MAX2V71	-1.292e-05	3.47e-05	-0.372	0.710	-8.14e-05	5.55e-05
downer	-0.1132	0.237	-0.477	0.634	-0.581	0.354
dmnfcg	-1.0920	0.384	-2.842	0.005	-1.849	-0.335
MTSPAR69	-2.201e-05	0.000	-0.196	0.845	-0.000	0.000
hospbed3	1.01e-11	1.06e-11	0.948	0.344	-1.09e-11	3.11e-11
blt2080	2.5384	1.702	1.491	0.137	-0.816	5.892
bltold80	0.1853	0.143	1.298	0.196	-0.096	0.467
XGMOBS75	0.0002	0.000	0.940	0.348	-0.000	0.001
txprop80	3.772e-05	6.44e-05	0.586	0.559	-8.91e-05	0.000
rent70	-0.0002	0.000	-0.887	0.376	-0.001	0.000
drevenue	-0.0001	6.06e-05	-2.342	0.020	-0.000	-2.25e-05
mnfcg2	-1.2469	4.123	-0.302	0.763	-9.370	6.876
hghwy70	0.3450	0.263	1.310	0.191	-0.174	0.864
pctpol3	-27.7296	32.432	-0.855	0.393	-91.628	36.169
MTSPGM77	-0.0005	0.001	-0.449	0.653	-0.003	0.002
educ70	0.0429	0.121	0.355	0.723	-0.195	0.281
MAX1V77	-1.28e-05	1.48e-05	-0.867	0.387	-4.19e-05	1.63e-05
poptot80	2.919e-07	2.16e-07	1.351	0.178	-1.34e-07	7.18e-07
crime82	-2.554e-10	3.03e-10	-0.843	0.400	-8.52e-10	3.42e-10
XAR0BS84	-0.0003	0.000	-0.981	0.328	-0.001	0.000
MAX1V75	-2.824e-05	4.34e-05	-0.651	0.516	-0.000	5.72e-05
ddens	-0.0003	0.000	-1.564	0.119	-0.001	7.05e-05
XTSPGM75	1.297e-05	0.000	0.040	0.968	-0.001	0.001
white80	-0.4882	0.254	-1.920	0.056	-0.989	0.013
XGMOBS74	-0.0003	0.001	-0.514	0.608	-0.001	0.001
povrty70	0.2740	0.301	0.911	0.363	-0.318	0.866
XAR0BS76	-0.0001	0.000	-0.676	0.500	-0.000	0.000
intercept	2.3069	3.951	0.584	0.560	-5.478	10.092
tsp7576	0.0252	0.015	1.710	0.089	-0.004	0.054

```

=====
Omnibus:                0.855    Durbin-Watson:                1.639
Prob(Omnibus):          0.652    Jarque-Bera (JB):          0.612
Skew:                   0.057    Prob(JB):                  0.736
Kurtosis:               3.177    Cond. No.:                 nan
=====

```

Warnings:

[1] The smallest eigenvalue is -0.00827. This might indicate that there are strong multicollinearity problems or that the design matrix is singular.

X_3: reduced form tsp7576 coefficient:

0.0251801195173

X_3: IV estimate: 0.0616905607797

OLS Regression Results

```

=====
Dep. Variable:          dlhouse    R-squared:                0.869
Model:                  OLS        Adj. R-squared:           0.813
Method:                 Least Squares
Date:                   Thu, 28 Apr 2016
Time:                   19:09:54    Prob (F-statistic):       4.79e-64
No. Observations:      331        Log-Likelihood:           436.17
Df Residuals:          232        AIC:                     -674.3
Df Model:               98         BIC:                     -297.9
=====

```

	coef	std err	t	P> t	[95.0% Conf. Int.]
region	0.0379	0.007	5.075	0.000	0.023 0.053

inchs	-0.0037	0.002	-1.773	0.078	-0.008	0.000
dlincome	6.0103	3.290	1.827	0.069	-0.471	12.492
lhouse70	-0.9146	0.228	-4.005	0.000	-1.364	-0.465
incage	-0.0056	0.003	-1.711	0.088	-0.012	0.001
age6570	-3.6083	2.392	-1.508	0.133	-8.322	1.105
hs3	98.6646	67.087	1.471	0.143	-33.512	230.842
owner70	-2.6973	1.191	-2.264	0.025	-5.045	-0.350
welfr70	1.4206	0.620	2.291	0.023	0.199	2.642
TOTOB570	-0.0010	0.001	-1.690	0.092	-0.002	0.000
MAX1V80	-0.0001	9.72e-05	-1.313	0.190	-0.000	6.39e-05
built202	-67.9282	34.061	-1.994	0.047	-135.036	-0.821
XAROB574	0.0018	0.001	1.780	0.076	-0.000	0.004
revnue70	9.847e-05	9.39e-05	1.049	0.295	-8.64e-05	0.000
MTSPGM83	-0.0033	0.002	-1.769	0.078	-0.007	0.000
vacant70	-11.5958	5.106	-2.271	0.024	-21.655	-1.537
built102	3.6358	2.923	1.244	0.215	-2.123	9.394
dage65	8.3294	4.723	1.764	0.079	-0.976	17.634
urban80	-0.2102	0.098	-2.144	0.033	-0.403	-0.017
age3	568.0123	407.177	1.395	0.164	-234.225	1370.249
XAROB572	-0.0035	0.002	-1.750	0.081	-0.007	0.000
MAX1V78	0.0002	0.000	1.591	0.113	-5.58e-05	0.001
dpoverity	3.2015	1.919	1.668	0.097	-0.580	6.983
pctghw2	0.9078	2.341	0.388	0.698	-3.704	5.519
pctwelf3	81.2230	35.959	2.259	0.025	10.376	152.070
whtage	44.0928	30.706	1.436	0.152	-16.405	104.591
dwelfr	-1.0881	0.576	-1.889	0.060	-2.223	0.047
hospbed2	2.424e-07	1.61e-07	1.504	0.134	-7.53e-08	5.6e-07
dunemp	1.2434	1.180	1.054	0.293	-1.081	3.568
built203	78.6524	38.293	2.054	0.041	3.207	154.098
white70	0.5673	0.247	2.299	0.022	0.081	1.053
pop7080	5.511e-07	4.18e-07	1.320	0.188	-2.72e-07	1.37e-06
coll2	-21.8270	13.570	-1.608	0.109	-48.564	4.910
vacrnt70	-1.2690	0.556	-2.282	0.023	-2.364	-0.174
pcteduc2	-4.0595	2.298	-1.766	0.079	-8.588	0.469
vacant80	-5.0331	2.719	-1.851	0.065	-10.390	0.324
XGMOBS82	0.0017	0.001	2.188	0.030	0.000	0.003
feml80	3.4248	2.372	1.444	0.150	-1.248	8.097
epend2	1.973e-07	1.49e-07	1.325	0.187	-9.61e-08	4.91e-07
house70	-2.351e-06	5.31e-06	-0.442	0.659	-1.28e-05	8.12e-06
dfeml	0.0964	1.459	0.066	0.947	-2.777	2.970
XAROB583	0.0014	0.001	1.379	0.169	-0.001	0.003
XAROB577	-0.0012	0.001	-1.672	0.096	-0.003	0.000
pophs	-0.0005	0.002	-0.284	0.776	-0.004	0.003
MTSPAR73	-0.0085	0.005	-1.745	0.082	-0.018	0.001
educ80	-0.2293	0.197	-1.164	0.246	-0.617	0.159
unemp70	2.2043	1.390	1.586	0.114	-0.535	4.943
TOTOB574	0.0007	0.000	1.678	0.095	-0.000	0.001
XGMOBS77	0.0011	0.001	1.750	0.082	-0.000	0.002
XTSPAR74	0.0007	0.001	1.237	0.217	-0.000	0.002
MAX1V76	0.0004	0.000	1.789	0.075	-3.98e-05	0.001
hlth80	1.7140	0.941	1.822	0.070	-0.139	3.567
hs70	-0.7070	0.782	-0.905	0.367	-2.247	0.833
MTSPGM84	0.0030	0.002	1.611	0.108	-0.001	0.007
gtsp7780	-0.0611	0.037	-1.639	0.103	-0.135	0.012
TOTOB572	-0.0002	0.000	-1.715	0.088	-0.001	3.56e-05
XGMOBS73	-0.0031	0.002	-1.838	0.067	-0.006	0.000
police80	-1.2697	1.079	-1.177	0.240	-3.395	0.856
linc70	2.7563	1.655	1.666	0.097	-0.503	6.016
femal3	0.5394	3.246	0.166	0.868	-5.857	6.935
age6580	4.6987	2.340	2.008	0.046	0.089	9.308
MAX2V70	0.0056	0.003	1.718	0.087	-0.001	0.012
plumb80	-7.9877	4.549	-1.756	0.080	-16.949	0.974
femal2	-103.1854	92.927	-1.110	0.268	-286.275	79.904
poverty3	41.0255	38.089	1.077	0.283	-34.019	116.070
povrty80	5.3320	3.028	1.761	0.080	-0.634	11.298
MTSPGM74	0.0144	0.008	1.799	0.073	-0.001	0.030
fstate	-0.0068	0.004	-1.856	0.065	-0.014	0.000
dhghwy	-1.1040	0.869	-1.271	0.205	-2.815	0.607
dincome	0.0006	0.000	1.732	0.085	-7.86e-05	0.001
XAROB571	-0.0042	0.002	-1.817	0.071	-0.009	0.000
epend70	-0.0009	0.000	-1.858	0.064	-0.002	5.23e-05
inccoll	-0.0030	0.002	-1.674	0.095	-0.006	0.001
XGMOBS72	0.0037	0.002	1.803	0.073	-0.000	0.008
revenue2	3.048e-08	3.32e-08	0.920	0.359	-3.48e-08	9.58e-08
TOTOB576	-8.363e-05	7.73e-05	-1.082	0.281	-0.000	6.87e-05
blt1080	1.7462	0.549	3.181	0.002	0.665	2.828
TOTOB575	-3.176e-05	5.43e-05	-0.585	0.559	-0.000	7.51e-05
lrent80	1.5132	0.588	2.571	0.011	0.354	2.673
mnfcg80	-0.0857	0.191	-0.449	0.654	-0.462	0.291
income80	-3.95e-05	5.96e-05	-0.663	0.508	-0.000	7.79e-05
MTSPAR78	-0.0031	0.002	-1.604	0.110	-0.007	0.001
TOTOB571	8.169e-05	6.14e-05	1.330	0.185	-3.93e-05	0.000
hs2	-12.1989	12.345	-0.988	0.324	-36.521	12.123
MTSPGM73	0.0312	0.019	1.678	0.095	-0.005	0.068
manwhite	-46.7766	22.963	-2.037	0.043	-92.019	-1.534
MAX1V73	-0.0010	0.001	-1.788	0.075	-0.002	0.000
MAX2V71	0.0011	0.001	1.683	0.094	-0.000	0.002

```

downer      0.2005      0.298      0.673      0.502      -0.387      0.788
dmnfcg     -7.1776      3.598     -1.995      0.047     -14.266     -0.089
MTSPAR69    0.0051      0.003      1.704      0.090      -0.001      0.011
hospbed3   -6.675e-11    4.57e-11    -1.459      0.146     -1.57e-10    2.34e-11
blt2080     19.7414     10.329      1.911      0.057     -0.610     40.093
bltold80     4.2157      2.374      1.776      0.077     -0.462      8.894
XGMOBS75   -0.0001      0.000     -0.361      0.719     -0.001      0.000
txprop80    -0.0003      0.000     -1.473      0.142     -0.001      0.000
rent70      0.0021      0.001      1.490      0.137     -0.001      0.005
drevenue    -0.0003      0.000     -2.588      0.010     -0.001     -7.53e-05
mnfcg2     -43.2382     24.616     -1.757      0.080     -91.737      5.261
hghwy70     2.3851      1.238      1.926      0.055     -0.055      4.825
pctpol3     4.8461     38.299      0.127      0.899     -70.613     80.305
MTSPGM77    0.0050      0.003      1.449      0.149     -0.002      0.012
educ70      0.4846      0.284      1.706      0.089     -0.075      1.044
MAX1V77     -0.0001      6.67e-05    -1.847      0.066     -0.000      8.21e-06
poptot80   -9.695e-07    7.69e-07    -1.261      0.208     -2.48e-06    5.45e-07
crime82    -3.533e-09    1.91e-09    -1.854      0.065     -7.29e-09    2.22e-10
XAR0BS84    -0.0048      0.003     -1.793      0.074     -0.010      0.000
MAX1V75     -0.0005      0.000     -1.783      0.076     -0.001      4.98e-05
ddens       0.0002      0.000      0.639      0.524     -0.000      0.001
XTSPGM75    -0.0013      0.001     -1.556      0.121     -0.003      0.000
white80     -0.2602      0.277     -0.940      0.348     -0.806      0.285
XGMOBS74    -0.0022      0.001     -1.708      0.089     -0.005      0.000
povrty70     2.2045      1.187      1.858      0.064     -0.134      4.543
XAR0BS76     0.0023      0.001      1.639      0.102     -0.000      0.005
intercept   -26.2368     17.104     -1.534      0.126     -59.935      7.461
dgtsp_hat    0.0617      0.036      1.710      0.089     -0.009      0.133
=====
Omnibus:                0.858    Durbin-Watson:                1.639
Prob(Omnibus):          0.651    Jarque-Bera (JB):             0.615
Skew:                   0.058    Prob(JB):                     0.735
Kurtosis:               3.177    Cond. No.:                    nan
=====

```

Warnings:

[1] The smallest eigenvalue is -0.0103. This might indicate that there are strong multicollinearity problems or that the design matrix is singular.

X_1

OLS Regression Results

```

=====
Dep. Variable:          dgtsp    R-squared:                0.042
Model:                  OLS      Adj. R-squared:           0.041
Method:                 Least Squares    F-statistic:             43.05
Date:                   Thu, 28 Apr 2016    Prob (F-statistic):      8.64e-11
Time:                   19:09:56    Log-Likelihood:         -4380.5
No. Observations:      975    AIC:                    8765.
Df Residuals:          973    BIC:                    8775.
Df Model:               1
=====
               coef      std err          t      P>|t|      [95.0% Conf. Int.]
-----
intercept    -5.1772      0.798     -6.484      0.000     -6.744     -3.610
tsp75       -10.5599      1.609     -6.562      0.000     -13.718     -7.402
=====
Omnibus:                505.183    Durbin-Watson:                1.859
Prob(Omnibus):          0.000    Jarque-Bera (JB):            14285.473
Skew:                  -1.793    Prob(JB):                    0.00
Kurtosis:              21.406    Cond. No.:                   2.49
=====

```

X_1: first stage tsp75 coefficient:
-10.5599254927

OLS Regression Results

```

=====
Dep. Variable:          dlhouse    R-squared:                0.008
Model:                  OLS      Adj. R-squared:           0.007
Method:                 Least Squares    F-statistic:             8.153
Date:                   Thu, 28 Apr 2016    Prob (F-statistic):      0.00439
Time:                   19:09:56    Log-Likelihood:         328.84
No. Observations:      975    AIC:                    -653.7
Df Residuals:          973    BIC:                    -643.9
Df Model:               1
=====
               coef      std err          t      P>|t|      [95.0% Conf. Int.]
-----
intercept     0.2653      0.006    41.612      0.000      0.253      0.278
tsp75         0.0367      0.013     2.855      0.004      0.011      0.062
=====
Omnibus:                70.215    Durbin-Watson:                1.057
Prob(Omnibus):          0.000    Jarque-Bera (JB):            114.236
Skew:                   0.531    Prob(JB):                    1.56e-25
Kurtosis:              4.298    Cond. No.:                   2.49
=====

```

X_1: reduced form tsp75 coefficient:

0.0366977705017

X_1: IV estimate: -0.00347519218078

OLS Regression Results

```
=====
Dep. Variable:          dlhouse      R-squared:                0.008
Model:                  OLS          Adj. R-squared:           0.007
Method:                 Least Squares  F-statistic:              8.153
Date:                   Thu, 28 Apr 2016  Prob (F-statistic):      0.00439
Time:                   19:09:56      Log-Likelihood:           328.84
No. Observations:      975           AIC:                    -653.7
Df Residuals:          973           BIC:                    -643.9
Df Model:               1
=====
```

	coef	std err	t	P> t	[95.0% Conf. Int.]
intercept	0.2474	0.011	22.558	0.000	0.226 0.269
dgtsp_hat	-0.0035	0.001	-2.855	0.004	-0.006 -0.001

```
=====
Omnibus:                70.215      Durbin-Watson:           1.057
Prob(Omnibus):          0.000      Jarque-Bera (JB):        114.236
Skew:                   0.531      Prob(JB):                1.56e-25
Kurtosis:               4.298      Cond. No.:               18.0
=====
```

X_2

/usr/local/lib/python2.7/dist-packages/ipykernel/_main_.py:251: SettingWithCopyWarning:

A value is trying to be set on a copy of a slice from a DataFrame.

Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: <http://pandas.pydata.org/pandas-docs/stable/indexing.html#indexing-view-versus-copy>

OLS Regression Results

```
=====
Dep. Variable:          dgtsp      R-squared:                0.119
Model:                  OLS          Adj. R-squared:           0.090
Method:                 Least Squares  F-statistic:              4.184
Date:                   Thu, 28 Apr 2016  Prob (F-statistic):      1.23e-12
Time:                   19:09:56      Log-Likelihood:           -4280.1
No. Observations:      962           AIC:                    8622.
Df Residuals:          931           BIC:                    8773.
Df Model:               30
=====
```

	coef	std err	t	P> t	[95.0% Conf. Int.]
ddens	3.647e-06	0.003	0.001	0.999	-0.006 0.006
dmnfcg	0.2319	35.525	0.007	0.995	-69.486 69.950
dwhite	-0.0588	18.136	-0.003	0.997	-35.650 35.532
dfeml	0.4287	106.336	0.004	0.997	-208.257 209.114
dage65	0.3180	78.870	0.004	0.997	-154.465 155.101
dhs	-0.0655	27.227	-0.002	0.998	-53.498 53.367
dcoll	0.2974	52.411	0.006	0.995	-102.560 103.155
durban	-0.0420	11.294	-0.004	0.997	-22.207 22.123
dunemp	0.0870	43.738	0.002	0.998	-85.749 85.923
dincome	1.1e-05	0.002	0.005	0.996	-0.004 0.004
dpoverly	-0.0727	31.945	-0.002	0.998	-62.765 62.620
downer	0.0447	18.119	0.002	0.998	-35.515 35.604
dplumb	-0.0849	35.666	-0.002	0.998	-70.080 69.910
drevenue	1.403e-05	0.005	0.003	0.998	-0.009 0.009
dtaxprop	-7.075e-05	0.011	-0.007	0.995	-0.021 0.021
depend	-1.398e-05	0.005	-0.003	0.998	-0.010 0.010
deduc	-0.0111	9.178	-0.001	0.999	-18.023 18.000
dhighwy	-0.0213	22.102	-0.001	0.999	-43.397 43.355
dwelfr	-0.0597	20.062	-0.003	0.998	-39.432 39.313
dhlth	-0.0403	13.284	-0.003	0.998	-26.111 26.030
vacant70	0.7679	138.468	0.006	0.996	-270.977 272.513
vacant80	0.0695	27.414	0.003	0.998	-53.732 53.871
vacrnt70	0.0705	28.015	0.003	0.998	-54.910 55.051
blt1080	0.0915	17.399	0.005	0.996	-34.055 34.238
blt2080	-0.0586	24.527	-0.002	0.998	-48.193 48.076
bltold80	0.0327	13.327	0.002	0.998	-26.121 26.187
mtspgm74	-0.0011	0.170	-0.006	0.995	-0.336 0.333
mtspgm75	0.0006	0.102	0.006	0.995	-0.201 0.202
intercept	-0.0503	12.671	-0.004	0.997	-24.918 24.817
dgtsp_hat	0.9953	0.581	1.714	0.087	-0.145 2.135
tsp75	-0.0378	3.916	-0.010	0.992	-7.722 7.647

```
=====
Omnibus:                514.115      Durbin-Watson:           1.916
Prob(Omnibus):          0.000      Jarque-Bera (JB):        15770.348
Skew:                   -1.848      Prob(JB):                0.00
Kurtosis:               22.488      Cond. No.:               3.07e+05
=====
```

Warnings:

[1] The condition number is large, 3.07e+05. This might indicate that there are strong multicollinearity or other numerical problems.

X_2: first stage tsp75 coefficient:
-0.0378290867166

OLS Regression Results

```

=====
Dep. Variable:          dlhouse      R-squared:                0.570
Model:                  OLS          Adj. R-squared:           0.556
Method:                 Least Squares  F-statistic:              41.06
Date:                   Thu, 28 Apr 2016  Prob (F-statistic):      4.99e-148
Time:                   19:09:56      Log-Likelihood:           735.89
No. Observations:      962           AIC:                     -1410.
Df Residuals:          931           BIC:                     -1259.
Df Model:               30
=====

```

	coef	std err	t	P> t	[95.0% Conf. Int.]
ddens	-2.364e-06	1.76e-05	-0.134	0.893	-3.69e-05 3.22e-05
dmnfcg	0.2218	0.193	1.148	0.251	-0.157 0.601
dwhite	-0.5962	0.099	-6.044	0.000	-0.790 -0.403
dfeml	-0.2507	0.578	-0.433	0.665	-1.386 0.884
dage65	-1.3685	0.429	-3.190	0.001	-2.210 -0.527
dhs	0.3340	0.148	2.256	0.024	0.043 0.625
dcoll	0.5742	0.285	2.014	0.044	0.015 1.134
durban	-0.1761	0.061	-2.867	0.004	-0.297 -0.056
dunemp	-0.8280	0.238	-3.481	0.001	-1.295 -0.361
dincome	8.005e-05	1.11e-05	7.232	0.000	5.83e-05 0.000
dpoverly	-0.6994	0.174	-4.025	0.000	-1.040 -0.358
downer	-0.0819	0.099	-0.831	0.406	-0.275 0.111
dplumb	-0.2614	0.194	-1.348	0.178	-0.642 0.119
drevenue	3.586e-05	2.54e-05	1.411	0.159	-1.4e-05 8.57e-05
dtaxprop	-0.0002	5.74e-05	-2.754	0.006	-0.000 -4.54e-05
depend	-4.765e-05	2.67e-05	-1.786	0.074	-0.000 4.72e-06
deduc	0.1041	0.050	2.086	0.037	0.006 0.202
dhghwy	-0.1958	0.120	-1.629	0.104	-0.432 0.040
dwelfr	-0.3896	0.109	-3.570	0.000	-0.604 -0.175
dhlth	-0.0981	0.072	-1.357	0.175	-0.240 0.044
vacant70	-0.0464	0.753	-0.062	0.951	-1.524 1.432
vacant80	0.6243	0.149	4.187	0.000	0.332 0.917
vacrnt70	-0.0408	0.152	-0.268	0.789	-0.340 0.258
blt1080	0.4366	0.095	4.614	0.000	0.251 0.622
blt2080	-1.0170	0.133	-7.624	0.000	-1.279 -0.755
bltold80	-0.1850	0.072	-2.552	0.011	-0.327 -0.043
mtspgm74	0.0002	0.001	0.236	0.813	-0.002 0.002
mtspgm75	-0.0009	0.001	-1.571	0.117	-0.002 0.000
intercept	0.2269	0.069	3.292	0.001	0.092 0.362
dgtsp_hat	-0.0054	0.003	-1.719	0.086	-0.012 0.001
tsp75	-0.0221	0.021	-1.037	0.300	-0.064 0.020

```

=====
Omnibus:                74.453      Durbin-Watson:           1.412
Prob(Omnibus):          0.000      Jarque-Bera (JB):        141.674
Skew:                   0.511      Prob(JB):                1.72e-31
Kurtosis:               4.578      Cond. No.:               3.07e+05
=====

```

Warnings:

[1] The condition number is large, 3.07e+05. This might indicate that there are strong multicollinearity or other numerical problems.

X_2: reduced form tsp75 coefficient:
-0.0220829309408

X_2: IV estimate: -0.00270346245856

OLS Regression Results

```

=====
Dep. Variable:          dlhouse      R-squared:                0.569
Model:                  OLS          Adj. R-squared:           0.556
Method:                 Least Squares  F-statistic:              42.43
Date:                   Thu, 28 Apr 2016  Prob (F-statistic):      1.29e-148
Time:                   19:09:56      Log-Likelihood:           735.33
No. Observations:      962           AIC:                     -1411.
Df Residuals:          932           BIC:                     -1265.
Df Model:               29
=====

```

	coef	std err	t	P> t	[95.0% Conf. Int.]
ddens	-4.495e-06	1.75e-05	-0.257	0.797	-3.88e-05 2.98e-05
dmnfcg	0.0861	0.142	0.605	0.545	-0.193 0.366
dwhite	-0.5618	0.093	-6.046	0.000	-0.744 -0.379
dfeml	-0.5014	0.526	-0.954	0.340	-1.533 0.530
dage65	-1.5545	0.390	-3.988	0.000	-2.320 -0.789
dhs	0.3723	0.143	2.596	0.010	0.091 0.654
dcoll	0.4002	0.231	1.735	0.083	-0.053 0.853
durban	-0.1515	0.057	-2.673	0.008	-0.263 -0.040
dunemp	-0.8789	0.233	-3.775	0.000	-1.336 -0.422
dincome	7.362e-05	9.18e-06	8.022	0.000	5.56e-05 9.16e-05

```

dincome 1.302e-05 9.10e-00 8.023 0.000 3.30e-05 9.10e-05
dpoverty -0.6568 0.169 -3.889 0.000 -0.988 -0.325
downer -0.1081 0.095 -1.134 0.257 -0.295 0.079
dplumb -0.2117 0.188 -1.126 0.260 -0.581 0.157
drevenue 2.765e-05 2.42e-05 1.145 0.253 -1.98e-05 7.51e-05
dtaxprop -0.0001 4.13e-05 -2.824 0.005 -0.000 -3.56e-05
depend -3.947e-05 2.55e-05 -1.548 0.122 -8.95e-05 1.06e-05
deduc 0.1106 0.050 2.233 0.026 0.013 0.208
dhghwy -0.1833 0.120 -1.533 0.126 -0.418 0.051
dwelfr -0.3547 0.104 -3.416 0.001 -0.558 -0.151
dhlth -0.0745 0.069 -1.086 0.278 -0.209 0.060
vacant70 -0.4958 0.617 -0.804 0.422 -1.706 0.715
vacant80 0.5837 0.144 4.057 0.000 0.301 0.866
vacant70 -0.0820 0.147 -0.557 0.577 -0.371 0.207
blt1080 0.3831 0.079 4.826 0.000 0.227 0.539
blt2080 -0.9827 0.129 -7.603 0.000 -1.236 -0.729
bltold80 -0.2041 0.070 -2.911 0.004 -0.342 -0.066
mtspgm74 0.0008 0.001 1.204 0.229 -0.001 0.002
mtspgm75 -0.0012 0.000 -2.846 0.005 -0.002 -0.000
intercept 0.2563 0.063 4.079 0.000 0.133 0.380
dgtsp_hat -0.0027 0.002 -1.537 0.125 -0.006 0.001
=====
Omnibus: 73.161 Durbin-Watson: 1.414
Prob(Omnibus): 0.000 Jarque-Bera (JB): 137.826
Skew: 0.507 Prob(JB): 1.18e-30
Kurtosis: 4.553 Cond. No. 2.31e+05
=====

```

Warnings:

[1] The condition number is large, 2.31e+05. This might indicate that there are strong multicollinearity or other numerical problems.

X_3

OLS Regression Results

```

=====
Dep. Variable: dgtsp R-squared: 0.852
Model: OLS Adj. R-squared: 0.788
Method: Least Squares F-statistic: 13.39
Date: Thu, 28 Apr 2016 Prob (F-statistic): 1.09e-57
Time: 19:09:57 Log-Likelihood: -1195.0
No. Observations: 331 AIC: 2590.
Df Residuals: 231 BIC: 2970.
Df Model: 99
=====

```

	coef	std err	t	P> t	[95.0% Conf. Int.]
region	-2.1525	1.556	-1.384	0.168	-5.218 0.913
inchs	0.7265	0.489	1.486	0.139	-0.237 1.690
dlincome	-1116.3105	755.743	-1.477	0.141	-2605.340 372.719
lhouse70	66.5294	47.867	1.390	0.166	-27.782 160.840
incage	1.0830	0.740	1.464	0.145	-0.375 2.541
age6570	793.2809	541.339	1.465	0.144	-273.312 1859.874
hs3	-2.129e+04	1.48e+04	-1.440	0.151	-5.04e+04 7839.157
owner70	405.1673	274.088	1.478	0.141	-134.864 945.199
welfr70	-191.3388	134.368	-1.424	0.156	-456.082 73.404
TOTOB570	0.2106	0.142	1.485	0.139	-0.069 0.490
MAX1V80	0.0316	0.022	1.454	0.147	-0.011 0.075
built202	1.108e+04	7620.384	1.454	0.147	-3934.419 2.61e+04
XAROB574	-0.2802	0.205	-1.363	0.174	-0.685 0.125
revnue70	-0.0202	0.017	-1.191	0.235	-0.054 0.013
MTSPGM83	0.5125	0.377	1.358	0.176	-0.231 1.256
vacant70	1727.7465	1170.860	1.476	0.141	-579.184 4034.677
built102	-1030.7030	688.349	-1.497	0.136	-2386.947 325.541
dage65	-1552.3025	1063.753	-1.459	0.146	-3648.200 543.595
urban80	28.0186	20.330	1.378	0.169	-12.037 68.075
age3	-6.249e+04	6.57e+04	-0.951	0.342	-1.92e+05 6.69e+04
XAROB572	0.6816	0.459	1.487	0.138	-0.222 1.585
MAX1V78	-0.0515	0.034	-1.493	0.137	-0.119 0.016
dpoverty	-657.0775	443.095	-1.483	0.139	-1530.102 215.947
pctghw2	11.8179	323.992	0.036	0.971	-626.539 650.175
pctwelf3	-1.221e+04	8266.405	-1.478	0.141	-2.85e+04 4072.603
whtage	-9656.6937	6729.932	-1.435	0.153	-2.29e+04 3603.202
dwelfr	199.7880	134.193	1.489	0.138	-64.610 464.186
hospbed2	-5.584e-05	3.75e-05	-1.488	0.138	-0.000 1.81e-05
dunemp	-357.4530	252.912	-1.413	0.159	-855.762 140.856
built203	-1.228e+04	8492.303	-1.446	0.150	-2.9e+04 4452.764
white70	4.5702	34.237	0.133	0.894	-62.887 72.028
pop7080	-0.0001	9.5e-05	-1.468	0.143	-0.000 4.77e-05
coll2	4117.5690	2911.679	1.414	0.159	-1619.273 9854.411
vacant70	158.4176	115.103	1.376	0.170	-68.368 385.204
pcteduc2	788.0918	531.554	1.483	0.140	-259.222 1835.406
vacant80	913.0097	620.491	1.471	0.143	-309.536 2135.555
XGMOBS82	-0.2615	0.179	-1.464	0.145	-0.613 0.090
feml80	-780.4326	534.395	-1.460	0.146	-1833.345 272.480
epend2	-4.837e-05	3.33e-05	-1.453	0.148	-0.000 1.72e-05
house70	0.0016	0.001	1.426	0.155	-0.001 0.004
dfeml	-134.6756	214.578	-0.628	0.531	-557.455 288.104

XAR0BS83	-0.3453	0.234	-1.477	0.141	-0.806	0.115
XAR0BS77	0.1965	0.144	1.367	0.173	-0.087	0.480
pophs	0.4399	0.341	1.291	0.198	-0.231	1.111
MTSPAR73	1.5772	1.089	1.448	0.149	-0.569	3.723
educ80	56.1113	40.778	1.376	0.170	-24.233	136.456
unemp70	-438.4895	305.221	-1.437	0.152	-1039.863	162.884
TOT0BS74	-0.1387	0.093	-1.487	0.138	-0.323	0.045
XGM0BS77	-0.1936	0.138	-1.402	0.162	-0.466	0.078
XTSPAR74	-0.1917	0.128	-1.498	0.135	-0.444	0.060
MAX1V76	-0.0761	0.051	-1.489	0.138	-0.177	0.025
hlth80	-320.4276	216.625	-1.479	0.140	-747.241	106.385
hs70	266.9284	180.300	1.480	0.140	-88.313	622.170
MTSPGM84	-0.5278	0.387	-1.365	0.174	-1.290	0.234
gtsp7780	12.7637	8.613	1.482	0.140	-4.207	29.734
TOT0BS72	0.0465	0.032	1.468	0.143	-0.016	0.109
XGM0BS73	0.5766	0.387	1.489	0.138	-0.186	1.339
police80	277.9258	211.756	1.312	0.191	-139.295	695.146
linc70	-529.6397	366.527	-1.445	0.150	-1251.803	192.524
femal3	340.6824	472.618	0.721	0.472	-590.511	1271.876
age6580	-748.9738	518.081	-1.446	0.150	-1769.741	271.794
MAX2V70	-1.1231	0.756	-1.486	0.139	-2.612	0.366
plumb80	1569.1813	1056.072	1.486	0.139	-511.583	3649.945
femal2	2.387e+04	1.82e+04	1.310	0.191	-1.2e+04	5.98e+04
poverty3	-9918.2708	7517.393	-1.319	0.188	-2.47e+04	4893.149
povrty80	-1044.0167	703.127	-1.485	0.139	-2429.378	341.345
MTSPGM74	-2.8376	1.891	-1.500	0.135	-6.564	0.889
fstate	1.2371	0.840	1.473	0.142	-0.418	2.892
dhghwy	265.4162	187.130	1.418	0.157	-103.283	634.115
dincome	-0.1045	0.073	-1.440	0.151	-0.247	0.038
XAR0BS71	0.8010	0.538	1.487	0.138	-0.260	1.862
epend70	0.1600	0.108	1.485	0.139	-0.052	0.372
inccoll	0.5744	0.396	1.451	0.148	-0.206	1.354
XGM0BS72	-0.7169	0.482	-1.486	0.139	-1.668	0.234
revenue2	7.878e-06	6.26e-06	1.259	0.209	-4.45e-06	2.02e-05
TOT0BS76	0.0265	0.018	1.482	0.140	-0.009	0.062
blt1080	-92.4368	90.926	-1.017	0.310	-271.587	86.714
TOT0BS75	0.0055	0.008	0.679	0.498	-0.010	0.021
lrent80	-200.6693	135.616	-1.480	0.140	-467.872	66.533
mnfcg80	53.4429	39.147	1.365	0.174	-23.687	130.573
income80	0.0063	0.009	0.707	0.480	-0.011	0.024
MTSPAR78	0.5485	0.397	1.382	0.168	-0.233	1.330
TOT0BS71	-0.0203	0.014	-1.462	0.145	-0.048	0.007
hs2	3581.8037	2581.712	1.387	0.167	-1504.908	8668.516
MTSPGM73	-6.3676	4.298	-1.482	0.140	-14.835	2.100
manwhite	7731.7286	5249.317	1.473	0.142	-2610.931	1.81e+04
MAX1V73	0.1886	0.127	1.483	0.139	-0.062	0.439
MAX2V71	-0.2323	0.157	-1.484	0.139	-0.541	0.076
downer	-63.3971	53.625	-1.182	0.238	-169.053	42.259
dmnfcg	1240.2234	834.918	1.485	0.139	-404.804	2885.250
MTSPAR69	-1.0437	0.702	-1.487	0.138	-2.426	0.339
hospbed3	1.578e-08	1.06e-08	1.486	0.139	-5.15e-09	3.67e-08
blt2080	-3417.9713	2335.609	-1.463	0.145	-8019.791	1183.848
bltold80	-815.4448	549.679	-1.483	0.139	-1898.471	267.581
XGM0BS75	0.0583	0.050	1.172	0.243	-0.040	0.156
txprop80	0.0765	0.052	1.463	0.145	-0.027	0.180
rent70	-0.4819	0.327	-1.475	0.142	-1.126	0.162
drevenue	0.0346	0.025	1.373	0.171	-0.015	0.084
mnfcg2	8543.0261	5737.389	1.489	0.138	-2761.275	1.98e+04
hghwy70	-415.7583	282.565	-1.471	0.143	-972.492	140.976
pctpol3	-6293.4589	6297.597	-0.999	0.319	-1.87e+04	6114.612
MTSPGM77	-1.0680	0.749	-1.426	0.155	-2.544	0.408
educ70	-93.0503	63.824	-1.458	0.146	-218.801	32.701
MAX1V77	0.0222	0.015	1.466	0.144	-0.008	0.052
poptot80	0.0003	0.000	1.465	0.144	-8.8e-05	0.001
crime82	6.649e-07	4.46e-07	1.492	0.137	-2.13e-07	1.54e-06
XAR0BS84	0.9109	0.615	1.482	0.140	-0.300	2.122
MAX1V75	0.0909	0.061	1.480	0.140	-0.030	0.212
ddens	-0.0960	0.069	-1.400	0.163	-0.231	0.039
XTSPGM75	0.2831	0.194	1.458	0.146	-0.100	0.666
white80	-45.3676	45.486	-0.997	0.320	-134.987	44.252
XGM0BS74	0.3762	0.269	1.397	0.164	-0.154	0.907
povrty70	-389.6375	266.662	-1.461	0.145	-915.039	135.764
XAR0BS76	-0.4887	0.330	-1.482	0.140	-1.138	0.161
intercept	5643.9753	3860.652	1.462	0.145	-1962.617	1.33e+04
dgtspl_hat	-11.4559	8.380	-1.367	0.173	-27.967	5.055
tsp75	6.8139	3.683	1.850	0.066	-0.442	14.070

Omnibus:	40.407	Durbin-Watson:	2.031
Prob(Omnibus):	0.000	Jarque-Bera (JB):	194.174
Skew:	0.330	Prob(JB):	6.85e-43
Kurtosis:	6.694	Cond. No.	nan

Warnings:

[1] The smallest eigenvalue is -0.0114. This might indicate that there are strong multicollinearity problems or that the design matrix is singular.

X_3: first stage tsp75 coefficient:
6.81392673115

OLS Regression Results

```

=====
Dep. Variable:          dlhouse      R-squared:                0.869
Model:                  OLS          Adj. R-squared:           0.813
Method:                 Least Squares   F-statistic:             15.45
Date:                  Thu, 28 Apr 2016   Prob (F-statistic):      1.82e-63
Time:                  19:09:59         Log-Likelihood:          436.24
No. Observations:      331             AIC:                    -672.5
Df Residuals:          231             BIC:                    -292.3
Df Model:              99
=====

```

```

=====
              coef      std err          t      P>|t|      [95.0% Conf. Int.]
-----
region          0.0405      0.011      3.592      0.000      0.018      0.063
inchs          -0.0046      0.004     -1.301      0.195     -0.012      0.002
dlincome       7.3481      5.471      1.343      0.181     -3.432     18.128
lhouse70       -0.9943      0.347     -2.869      0.004     -1.677     -0.311
incage        -0.0069      0.005     -1.287      0.199     -0.017      0.004
age6570       -4.5364      3.919     -1.157      0.248     -12.258      3.185
hs3          124.1738     107.022      1.160      0.247     -86.690     335.037
owner70       -3.1828      1.984     -1.604      0.110     -7.093      0.727
welfr70        1.6499      0.973      1.696      0.091     -0.267      3.567
TOTOB570      -0.0013      0.001     -1.252      0.212     -0.003      0.001
MAX1V80       -0.0002      0.000     -1.051      0.294     -0.000      0.000
built202      -81.2062      55.170     -1.472      0.142    -189.906     27.494
XAROB574        0.0021      0.001      1.427      0.155     -0.001      0.005
revnuce70       0.0001      0.000      0.998      0.319     -0.000      0.000
MTSPGM83      -0.0039      0.003     -1.424      0.156     -0.009      0.001
vacant70      -13.6662      8.477     -1.612      0.108     -30.368      3.035
built102        4.8710      4.983      0.977      0.329     -4.948     14.690
dage65        10.2123      7.701      1.326      0.186     -4.961     25.386
urban80       -0.2438      0.147     -1.656      0.099     -0.534      0.046
age3          642.8365     475.514      1.352      0.178    -294.062    1579.735
XAROB572      -0.0043      0.003     -1.286      0.200     -0.011      0.002
MAX1V78        0.0003      0.000      1.186      0.237     -0.000      0.001
dpoverity      3.9723      3.208      1.238      0.217     -2.348     10.293
pctghw2        0.8937      2.346      0.381      0.704     -3.728      5.515
pctwelf3       95.8605     59.847      1.602      0.111     -22.054     213.775
whtage        55.6654     48.723      1.142      0.254     -40.333     151.664
dwelfr        -1.3275      0.972     -1.366      0.173     -3.242      0.587
hospbed2       3.094e-07     2.72e-07     1.139      0.256     -2.26e-07     8.45e-07
dunemp         1.6718      1.831      0.913      0.362     -1.936      5.279
built203       93.3681     61.482      1.519      0.130     -27.769     214.505
white70        0.5619      0.248      2.267      0.024      0.073      1.050
pop7080        7.183e-07     6.88e-07     1.045      0.297     -6.36e-07     2.07e-06
coll2         -26.7613     21.080     -1.270      0.206     -68.295     14.772
vacrnt70       -1.4588      0.833     -1.751      0.081     -3.101      0.183
pcteduc2       -5.0040      3.848     -1.300      0.195     -12.586      2.578
vacant80       -6.1272      4.492     -1.364      0.174     -14.978      2.724
XGMOBS82        0.0020      0.001      1.578      0.116     -0.001      0.005
feml80         4.3601      3.869      1.127      0.261     -3.263     11.983
epend2         2.552e-07     2.41e-07     1.059      0.291     -2.2e-07      7.3e-07
house70       -4.324e-06     8.36e-06     -0.517      0.605     -2.08e-05     1.21e-05
dfeml          0.2578      1.553      0.166      0.868     -2.803      3.319
XAROB583        0.0018      0.002      1.074      0.284     -0.002      0.005
XAROB577       -0.0014      0.001     -1.351      0.178     -0.003      0.001
pophs          -0.0010      0.002     -0.417      0.677     -0.006      0.004
MTSPAR73       -0.0104      0.008     -1.324      0.187     -0.026      0.005
educ80         -0.2966      0.295     -1.005      0.316     -0.878      0.285
unemp70        2.7298      2.210      1.235      0.218     -1.624      7.084
TOTOB574        0.0008      0.001      1.243      0.215     -0.000      0.002
XGMOBS77        0.0014      0.001      1.372      0.171     -0.001      0.003
XTSPAR74        0.0009      0.001      0.973      0.332     -0.001      0.003
MAX1V76        0.0005      0.000      1.307      0.192     -0.000      0.001
hlth80         2.0980      1.568      1.338      0.182     -0.992      5.188
hs70          -1.0269      1.305     -0.787      0.432     -3.599      1.545
MTSPGM84        0.0037      0.003      1.312      0.191     -0.002      0.009
gtsp7780       -0.0764      0.062     -1.225      0.222     -0.199      0.046
TOTOB572       -0.0003      0.000     -1.285      0.200     -0.001      0.000
XGMOBS73       -0.0037      0.003     -1.335      0.183     -0.009      0.002
polic80        -1.6027      1.533     -1.045      0.297     -4.623      1.418
linc70         3.3910      2.654      1.278      0.203     -1.837      8.619
femal3         -0.1081      3.422     -0.032      0.975     -6.850      6.634
age6580        5.5736      3.751      1.486      0.139     -1.816     12.964
MAX2V70        0.0069      0.005      1.268      0.206     -0.004      0.018
plumb80       -9.8682      7.646     -1.291      0.198     -24.932      5.196
femal2       -131.7801     131.863     -0.999      0.319    -391.587     128.027
poverty3       52.9107     54.424      0.972      0.332     -54.320     160.141
povrty80        6.5998      5.090      1.297      0.196     -3.430     16.629
MTSPGM74        0.0178      0.014      1.299      0.195     -0.009      0.045
fstate         -0.0083      0.006     -1.365      0.173     -0.020      0.004
dhghwy         -1.4221      1.355     -1.050      0.295     -4.091      1.247
dincome        0.0007      0.001      1.324      0.187     -0.000      0.002
XAROB571       -0.0052      0.004     -1.325      0.186     -0.013      0.003
=====

```

```

=====
pend70      -0.0011      0.001      -1.332      0.178      -0.003      0.000
inccoll     -0.0037      0.003      -1.277      0.203      -0.009      0.002
XGMOBS72    0.0046      0.003      1.318      0.189      -0.002      0.011
revenue2    2.104e-08    4.53e-08    0.464      0.643      -6.82e-08    1.1e-07
TOT0BS76    -0.0001      0.000      -0.892      0.373      -0.000      0.000
blt1080     1.8570      0.658      2.821      0.005      0.560      3.154
TOT0BS75    -3.833e-05    5.84e-05    -0.656      0.513      -0.000      7.68e-05
lrent80     1.7537      0.982      1.786      0.075      -0.181      3.688
mnfcg80     -0.1497      0.283      -0.528      0.598      -0.708      0.409
income80    -4.707e-05    6.46e-05    -0.728      0.467      -0.000      8.03e-05
MTSPAR78    -0.0037      0.003      -1.293      0.197      -0.009      0.002
TOT0BS71    0.0001      0.000      1.056      0.292      -9.17e-05    0.000
hs2         -16.4912     18.691     -0.882      0.379     -53.318     20.335
MTSPGM73    0.0388      0.031      1.249      0.213      -0.022      0.100
manwhite    -56.0418     38.004     -1.475      0.142     -130.920    18.836
MAX1V73     -0.0012      0.001     -1.313      0.191      -0.003      0.001
MAX2V71     0.0014      0.001      1.250      0.213      -0.001      0.004
downer      0.2765      0.388      0.712      0.477      -0.488      1.041
dmnfcg      -8.6638      6.045     -1.433      0.153     -20.573      3.246
MTSPAR69    0.0064      0.005      1.258      0.210      -0.004      0.016
hospbed3    -8.568e-11    7.69e-11    -1.114      0.266     -2.37e-10    6.58e-11
blt2080     23.8374     16.909     1.410      0.160     -9.479      57.153
bltold80     5.1929      3.980      1.305      0.193     -2.648      13.034
XGMOBS75    -0.0002      0.000     -0.473      0.637      -0.001      0.001
txprop80    -0.0004      0.000     -1.142      0.255      -0.001      0.000
rent70      0.0027      0.002      1.142      0.255      -0.002      0.007
drevenue    -0.0004      0.000     -1.959      0.051      -0.001      2.09e-06
mnfcg2      -53.4758     41.537     -1.287      0.199     -135.316    28.364
hghwy70     2.8833      2.046      1.409      0.160     -1.147      6.914
pctpol3     12.3874     45.593     0.272      0.786     -77.444     102.219
MTSPGM77    0.0063      0.005      1.158      0.248      -0.004      0.017
educ70      0.5962      0.462      1.290      0.198      -0.314      1.507
MAX1V77     -0.0001      0.000     -1.368      0.173      -0.000      6.59e-05
poptot80    -1.275e-06    1.26e-06    -1.012      0.313     -3.76e-06    1.21e-06
crime82     -4.33e-09    3.23e-09    -1.342      0.181     -1.07e-08    2.03e-09
XAR0BS84    -0.0059      0.004     -1.317      0.189      -0.015      0.003
MAX1V75     -0.0006      0.000     -1.313      0.190      -0.001      0.000
ddens       0.0003      0.000      0.649      0.517      -0.001      0.001
XTSPGM75    -0.0017      0.001     -1.198      0.232      -0.004      0.001
white80     -0.2058      0.329     -0.625      0.533      -0.855      0.443
XGMOBS74    -0.0026      0.002     -1.349      0.179      -0.006      0.001
povrty70    2.6547      1.931      1.375      0.170     -1.149      6.459
XAR0BS76    0.0029      0.002      1.225      0.222      -0.002      0.008
intercept   -33.0003     27.950     -1.181      0.239     -88.070     22.069
dgtsp_hat   0.0766      0.061      1.263      0.208      -0.043      0.196
tsp75       -0.0082      0.027     -0.306      0.760      -0.061      0.044
=====
Omnibus:                0.919    Durbin-Watson:                1.633
Prob(Omnibus):          0.632    Jarque-Bera (JB):             0.672
Skew:                   0.060    Prob(JB):                     0.715
Kurtosis:               3.185    Cond. No.:                    nan
=====

```

Warnings:

[1] The smallest eigenvalue is -0.0114. This might indicate that there are strong multicollinearity problems or that the design matrix is singular.

X_3: reduced form tsp75 coefficient:

-0.00816685798422

X_3: IV estimate: -0.000471408758903

OLS Regression Results

```

=====
Dep. Variable:          dlhouse      R-squared:                0.867
Model:                  OLS          Adj. R-squared:          0.811
Method:                 Least Squares  F-statistic:            15.45
Date:                   Thu, 28 Apr 2016  Prob (F-statistic):      1.86e-63
Time:                   19:10:01      Log-Likelihood:         434.11
No. Observations:      331          AIC:                   -670.2
Df Residuals:          232          BIC:                   -293.8
Df Model:              98
=====

```

```

=====
              coef      std err          t      P>|t|      [95.0% Conf. Int.]
-----
region         0.0280      0.005        5.804      0.000         0.018      0.037
inchs        -0.0002      0.000       -0.370      0.712        -0.001      0.001
dlincome      0.5104      0.873        0.584      0.560        -1.211      2.231
lhouse70     -0.5839      0.126       -4.623      0.000        -0.833     -0.335
incage       -0.0002      0.001       -0.204      0.839        -0.002      0.002
age6570       0.4554      0.599        0.761      0.448        -0.724      1.635
hs3          -6.5790     28.716       -0.229      0.819       -63.156     49.998
owner70      -0.6577      0.188       -3.493      0.001        -1.029     -0.287
welfr70       0.4121      0.216        1.911      0.057        -0.013      0.837
TOT0BS70     1.941e-05    7.08e-05      0.274      0.784        -0.000      0.000
MAX1V80      2.652e-05    3.95e-05      0.671      0.503       -5.13e-05    0.000
built202     -10.5772      8.138       -1.300      0.195       -26.610      5.456
XAR0BS74      0.0004      0.001        0.638      0.524        -0.001      0.002
revnue70     1.22e-05    8.01e-05      0.152      0.879        -0.000      0.000
=====

```


MTSPGM83	-0.0009	0.001	-0.705	0.481	-0.003	0.002
vacant70	-3.0895	1.418	-2.179	0.030	-5.883	-0.296
built102	-1.3076	0.643	-2.033	0.043	-2.575	-0.040
dage65	0.4402	1.164	0.378	0.706	-1.853	2.733
urban80	-0.0731	0.058	-1.254	0.211	-0.188	0.042
age3	306.4641	380.576	0.805	0.421	-443.364	1056.292
XAR0BS72	-9.858e-05	0.000	-0.256	0.799	-0.001	0.001
MAX1V78	-3.898e-06	5.33e-05	-0.073	0.942	-0.000	0.000
dpoverty	-0.0290	0.448	-0.065	0.949	-0.913	0.855
pctghw2	1.8562	2.290	0.811	0.418	-2.656	6.368
pctwelf3	21.8466	11.007	1.985	0.048	0.160	43.533
whtage	-3.2880	14.077	-0.234	0.816	-31.023	24.447
dwelfr	-0.2058	0.271	-0.759	0.448	-0.740	0.328
hospbed2	-3.197e-08	3.08e-08	-1.037	0.301	-9.27e-08	2.88e-08
dunemp	-0.6247	0.483	-1.294	0.197	-1.576	0.326
built203	14.9526	10.829	1.381	0.169	-6.383	36.288
white70	0.5644	0.248	2.273	0.024	0.075	1.054
pop7080	-1.426e-07	1.2e-07	-1.189	0.236	-3.79e-07	9.37e-08
coll2	-1.4174	6.788	-0.209	0.835	-14.792	11.957
vacrnt70	-0.4613	0.305	-1.512	0.132	-1.062	0.140
pcteduc2	-0.2327	0.643	-0.362	0.718	-1.500	1.035
vacant80	-0.3884	0.464	-0.837	0.403	-1.303	0.526
XGMOBS82	0.0004	0.000	1.806	0.072	-3.81e-05	0.001
feml80	-0.4469	0.802	-0.557	0.578	-2.027	1.133
epend2	-5.238e-08	3.8e-08	-1.377	0.170	-1.27e-07	2.26e-08
house70	5.737e-06	2.56e-06	2.243	0.026	6.99e-07	1.08e-05
dfeml	-0.1314	1.462	-0.090	0.928	-3.011	2.749
XAR0BS83	-0.0003	0.000	-1.144	0.254	-0.001	0.000
XAR0BS77	-0.0001	0.000	-0.330	0.741	-0.001	0.001
pophs	0.0017	0.001	1.354	0.177	-0.001	0.004
MTSPAR73	-0.0006	0.002	-0.345	0.731	-0.004	0.003
educ80	0.0173	0.137	0.126	0.900	-0.253	0.287
unemp70	-0.0358	0.515	-0.069	0.945	-1.051	0.980
TOT0BS74	-1.227e-05	6.87e-05	-0.179	0.858	-0.000	0.000
XGMOBS77	0.0001	0.000	0.461	0.646	-0.000	0.001
XTSPAR74	-0.0002	0.000	-0.603	0.547	-0.001	0.000
MAX1V76	1.802e-05	3.86e-05	0.466	0.641	-5.81e-05	9.41e-05
hlth80	0.1045	0.151	0.693	0.489	-0.193	0.402
hs70	0.6007	0.206	2.919	0.004	0.195	1.006
MTSPGM84	0.0004	0.001	0.367	0.714	-0.002	0.003
gtsp7780	0.0031	0.004	0.689	0.492	-0.006	0.012
TOT0BS72	-3.623e-06	3.16e-05	-0.115	0.909	-6.58e-05	5.86e-05
XGMOBS73	-0.0002	0.000	-0.811	0.418	-0.001	0.000
police80	0.0859	0.748	0.115	0.909	-1.387	1.559
linc70	0.0549	0.559	0.098	0.922	-1.046	1.156
femal3	-0.6102	2.112	-0.289	0.773	-4.771	3.551
age6580	0.7745	0.699	1.107	0.269	-0.603	2.152
MAX2V70	-1.786e-05	0.000	-0.050	0.960	-0.001	0.001
plumb80	-0.2165	0.772	-0.280	0.780	-1.738	1.305
femal2	11.3232	65.818	0.172	0.864	-118.354	141.000
poverty3	-5.3077	27.305	-0.194	0.846	-59.104	48.489
povrty80	0.1454	0.489	0.298	0.766	-0.817	1.108
MTSPGM74	0.0007	0.001	0.579	0.563	-0.002	0.003
fstate	-0.0005	0.001	-0.884	0.378	-0.002	0.001
dhghwy	0.2882	0.333	0.867	0.387	-0.367	0.943
dincome	3.658e-05	0.000	0.311	0.756	-0.000	0.000
XAR0BS71	-0.0002	0.000	-0.743	0.458	-0.001	0.000
epend70	-7.162e-05	8.66e-05	-0.827	0.409	-0.000	9.9e-05
inccoll	-6.99e-05	0.001	-0.117	0.907	-0.001	0.001
XGMOBS72	0.0002	0.000	0.517	0.605	-0.001	0.001
revenue2	7.456e-08	2.14e-08	3.483	0.001	3.24e-08	1.17e-07
TOT0BS76	3.436e-05	3.69e-05	0.931	0.353	-3.84e-05	0.000
blt1080	1.1425	0.427	2.676	0.008	0.301	1.984
TOT0BS75	-6.49e-06	5.26e-05	-0.123	0.902	-0.000	9.71e-05
lrent80	0.5125	0.115	4.464	0.000	0.286	0.739
mnfcg80	0.1932	0.103	1.867	0.063	-0.011	0.397
income80	-7.594e-08	5.54e-05	-0.001	0.999	-0.000	0.000
MTSPAR78	-0.0005	0.001	-0.416	0.678	-0.003	0.002
TOT0BS71	-1.559e-05	2.51e-05	-0.622	0.535	-6.5e-05	3.38e-05
hs2	5.6035	6.892	0.813	0.417	-7.976	19.183
MTSPGM73	-0.0007	0.003	-0.254	0.800	-0.006	0.005
manwhite	-7.9209	5.013	-1.580	0.115	-17.797	1.955
MAX1V73	-3.819e-05	7.22e-05	-0.529	0.597	-0.000	0.000
MAX2V71	-2.543e-05	8.1e-05	-0.314	0.754	-0.000	0.000
downer	-0.1104	0.240	-0.461	0.645	-0.582	0.362
dmnfcg	-1.0127	0.547	-1.851	0.065	-2.091	0.065
MTSPAR69	-5.541e-05	0.000	-0.160	0.873	-0.001	0.001
hospbed3	9.924e-12	1.17e-11	0.846	0.398	-1.32e-11	3.3e-11
blt2080	2.1828	2.033	1.074	0.284	-1.823	6.189
bltold80	0.1314	0.294	0.447	0.655	-0.448	0.710
XGMOBS75	0.0002	0.000	0.841	0.401	-0.000	0.001
txprop80	4.209e-05	6.91e-05	0.609	0.543	-9.41e-05	0.000
rent70	-0.0003	0.000	-0.914	0.362	-0.001	0.000
drevenue	-0.0001	6.19e-05	-2.150	0.033	-0.000	-1.11e-05
mnfcg2	-1.4140	4.903	-0.288	0.773	-11.074	8.246
hghwy70	0.2998	0.295	1.016	0.311	-0.282	0.881
pctpol3	-30.3408	32.680	-0.928	0.354	-94.729	34.047

```

MTSPGM77      -0.0007      0.001      -0.616      0.539      -0.003      0.001
educ70         0.0416      0.125      0.334      0.739      -0.204      0.287
MAX1V77      -1.111e-05      1.64e-05      -0.676      0.500      -4.35e-05      2.13e-05
poptot80      3.016e-07      2.32e-07      1.302      0.194      -1.55e-07      7.58e-07
crime82      -2.896e-10      3.65e-10      -0.793      0.429      -1.01e-09      4.3e-10
XAR0BS84      -0.0002      0.000      -0.535      0.593      -0.001      0.001
MAX1V75      -2.214e-05      5.21e-05      -0.425      0.671      -0.000      8.05e-05
ddens         -0.0003      0.000      -1.495      0.136      -0.001      8.42e-05
XTSPGM75      3.452e-05      0.000      0.102      0.919      -0.001      0.001
white80       -0.4528      0.255      -1.775      0.077      -0.955      0.050
XGM0BS74      -0.0002      0.001      -0.373      0.709      -0.001      0.001
povrty70      0.2315      0.326      0.709      0.479      -0.412      0.875
XAR0BS76      -0.0001      0.000      -0.448      0.654      -0.001      0.000
intercept     2.4405      4.365      0.559      0.577      -6.160      11.041
dgtsp_hat     -0.0005      0.004      -0.121      0.904      -0.008      0.007
=====
Omnibus:              0.603      Durbin-Watson:              1.625
Prob(Omnibus):        0.740      Jarque-Bera (JB):           0.375
Skew:                 -0.015      Prob(JB):                   0.829
Kurtosis:             3.162      Cond. No.:                  nan
=====

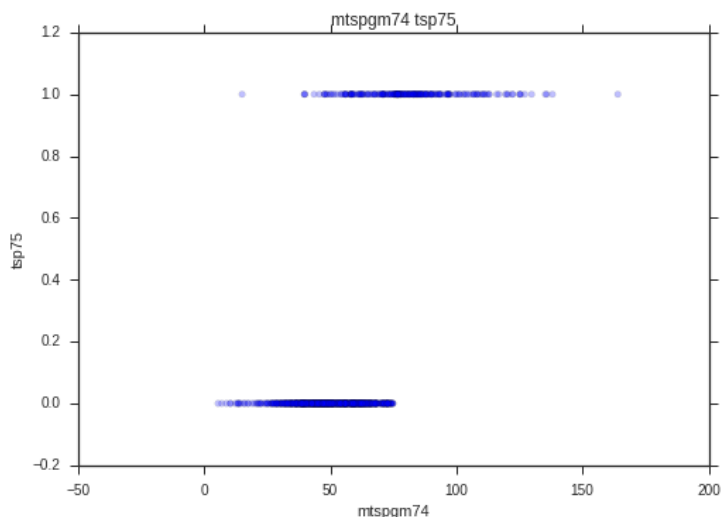
```

Warnings:

[1] The smallest eigenvalue is -0.0106. This might indicate that there are strong multicollinearity problems or that the design matrix is singular.

d. In principle, the 1975 regulation indicator variable, `tsp75`, should be a discrete function of pollution levels in 1974. Specifically, the EPA is supposed to regulate those counties in 1975 who had either an annual geometric mean of TSPs above 75 units ($\mu\text{g}/\text{m}^3$) or a 2nd highest daily concentration above 260 units in 1974. Describe how one could use this discontinuity in treatment assignment to derive alternative estimates of the capitalization of pollution changes. Under what conditions will these estimates be valid? Describe the graphical analysis you would use to examine the validity of these conditions.

Answer: We could take only the section of the dataframe + and - a certain delta around the threshold value of pollution in 1974. Then we could construct a Wald Estimator with it, i.e. find the difference in price changes and pollution changes for a group just under the threshold, as well as for a group just over the threshold, then divide the differences to find change in `dlhouse` per change in TSPs. I'd want to see that the discontinuity wasn't fuzzy, so a graph like that below would be helpful. I'd want to verify that group means were similar in below-threshold and above-threshold groups.



e. Describe (in words) the theoretical reasons why the effects of pollution changes on housing price changes may be heterogeneous. Under what assumptions will two-stage least squares identify the average treatment effect (ATE)? What is the economic interpretation of ATE in the context of hedonic theory? If ATE is not identified, describe what may be identifiable with two-stage least squares estimation. The ATE in the context of the hedonic theory represents the amount people have revealed themselves willing to pay for clean air.

Answer: Small, unnoticeable changes in pollution might have no effect on changes in price, while larger changes in pollution may have large effects on price changes, perhaps increasing at an increasing rate as pollution changes become noticeable, then at a diminishing rate when jumps in pollution are extreme. 2SLS will identify the ATE if effects of pollution changes on price changes are homogenous. The ATE in the context of the hedonic theory represents the amount people have revealed themselves willing to pay for clean air. In this case, however, we've only identified the LATE, as our results are only applicable around the pollution threshold. The LATE is the effect of pollution changes on house price changes in the small window around the regulatory threshold for those cities which were induced into cleaning up as a result of regulations, but wouldn't have done so otherwise. We should also be aware of selection effects: People in the highly-polluted areas eligible for treatment may be less sensitive to changes in pollution.

e to pollution, so we're measuring the effect amongst a demographic that may not be representative of the greater population.

f. Now provide a concise synthesis/summary of your results. Discuss the "credibility" of the research designs underlying the results.

Answer: In our simple OLS models, we measured a slightly positive effect of changes in pollution on changes in house price. On the face of it, this runs counter to what we expect the relationship to be. When we consider the omitted variable of economic shocks, however, we see how this paradoxical result came about--negative economic shocks decrease both pollution and house prices. Controlling for a few manifestations of economic shocks (unemployment, changes in income, etc) helped ameliorate OVB to some extent.

To more thoroughly purge our model of OVB, we used an IV approach, (hopefully) capturing only the variation in `dgts` uncorrelated with our confounding omitted variable. Using this approach, we captured a more expected result: A 1% increase in pollution is associated with an approximate .3% decrease in price. This result was robust to our selection of control variables, probably because our IV was uncorrelated with the OV. This strikes me as a credible approach.

In []:

