

## **The effect of incarceration on unemployment in the United States**

### **Abstract:**

This paper examines the relationship between prisoner incarceration in the United States and the rate of unemployment. Using state panel data we construct a fixed effects model of unemployment that incorporates a comprehensive range of macroeconomic variables with a focus on state unemployment rates, prison populations, and crime rates. First, we find that growth in prison incarceration rates drastically reduces unemployment. Next, concerned with potential endogeneity between unemployment and prison population we construct vector auto regression models for a representative selection of states and find significant causation both directions between prison population and unemployment. We then attempt to correct for endogeneity with a fixed effect 2SLS regression but cannot find strong instruments.

### **Introduction:**

The prison as it exists in modern times is a relatively novel invention that traces its history back to the mid nineteen hundreds and the utilitarian social philosophy of Jeremy Bentham. The ideal prison in Bentham's mind was exemplary of the panopticon, institutions where the observers are unobservable and the observed police themselves due to the constant threat of observation. In Bentham's mind panoptic institutions maximized the effectiveness of the reformation process by forcing introspection and conformation while minimizing and offsetting expenditures by using a skeleton staff and prison labor.

Since the early 1980's no country has more readily embraced mass incarceration than the United States. More than one in every one hundred American males eighteen years or older reside in prison. The combined male and female imprisonment rate in the US is 500 per 100,000 inhabitants as of 2011. In contrast in the UK 152 people in every 100,000 inhabitants are imprisoned in any given year. In China as of 2007 119 people out of every 100,000 inhabitants were imprisoned. The average rate of imprisonment by EU members stands at 129 per 100,000 inhabitants.

Further, historically the US has experienced consistently lower unemployment rates than those experienced by European economies. However, structurally the explanation for the unemployment gap is far from clear. The EU and US similar economic and policy institutions along with similar

industry compositions and similar levels of output, 47,000 international dollars per capita in the US and 31,000 international dollars per capita in the EU.

One potential explanation for this difference is that prisoners are not counted by official unemployment statistics and higher imprisonment in the US masks unemployment. Evidence for this claim has been produced by converting the difference between the US and EU prison populations into unemployed. This yield the following equation  $500 - 129 = 371$  prisoners per 100,000 in the US greater than the EU, then  $371/500 = 0.742$  the percent difference,  $0.742 * 1,612,395 = 1,196,397$  difference in total prison populations. Next we add this to the current number of unemployed  $14,726,400 + 1,196,397 = 15,922,797$ . Then  $15,922,797/153,400,000$  gives the adjusted unemployment rate of 10.4% or an increase of 0.8%. This indicates that the US may be concealing unemployment through increased prison populations.

This project addresses the concern that unemployment in the US may be artificially low due to an interaction effect with prison populations. Due to gendered nature of the US corrections system, male inmate outnumber female inmates more than ten to one, we chose to look at only male corrections. We use panel data analysis across the 48 continental United States between the years 1967 and 2010 to model the unemployment rate with various correction and crime variables included. After correcting for non-stationary variables we find a statistically significant effect of -1.735 on the unemployment rate for every percent the growth of incarceration increases. This finding supports the idea that the US could pursue a policy of mass incarceration to reduce unemployment.

However, if the US were to pursue mass incarceration to reduce unemployment it would imply endogeneity between unemployment and prison population. Imprisonment directly lowers the number of individuals in the labor force and thus the unemployment rate as either the prisoners were unemployed or leave a job opening to be filled. Policies that broaden or harshen sentencing in such a way to increase prison growth rates will also lower unemployment rates. Further, policy setters are incentivized to lower unemployment rates to signal positive economic policy and increase their odds of reelection. Hence, if one were to find endogeneity between prison population and unemployment it would suggest that the US does artificially lower unemployment using mass incarceration.

We proceed to use a simple vector autoregressive model to determine potential endogeneity between the unemployment rate and the growth of prison population rate. We choose to use a standard VAR model to look at representative states. For each state we find statistically significant granger causation in both directions between prison population growth rate and the unemployment rate. However, we are unable to definitely determine an effect.

After the VAR models suggested endogeneity we attempted to use an IV 2SLS model to correct for endogeneity. However, our instrumental variables were not strong.

## **Data and Collection Methodology**

This paper utilized a balanced panel data set that contains a diverse range of variables for the 48 continental States across a varying number of years from a variety of different sources.

Expenditure data was compiled from the Annual Survey of State and Local Government Finances conducted by the United States Census Bureau. The expenditure dataset is in nominal US dollars as reported by state and local agencies to the US Census Bureau from 1967 to 2010 for the 48 continental United States.

For state-by-state crime statistics we used the Uniform Crime Reporting Statistics dataset compiled annually by the Federal Bureau of Investigation using self-reported crime statistics from state and local agencies which are representative of 94.6% of the US population.

We used the Annual Parole Survey conducted by the Bureau of Justice Statistics (BJS) contains state-by-state data on number of parolees as reported by parole agencies from 1977 to 2010. We omitted female parolees from the dataset due to the small sample size.

The total number of prisoners by state was compiled by the BJS in the National Prisoner Statistics Survey, which surveys local, state and federal corrections facilities. The sample runs from 1978 to 2010.

Data on unionization was collected for the Current Population Survey conducted jointly by the Census Bureau and the U.S. Bureau of Labor Statistics (BLS). The dataset contains state-by-state observations from 1984 to 2010.

State-by-state CPI rates were collected from the economic report of the president from 1977 to 2010.

Minimum wage data by state was compiled by the BLS from 1968 to 1999 using data from the Book of the States, 1968-1999 edition, and from 2000 to 2010 using data provided by the U.S. Department of Labor.

A dataset on unemployment benefits, average weekly wage, and average duration of unemployment was procured from the Department of Labor's *Unemployment Insurance Financial Data Handbook* (ET Financial Data Handbook 397), which contains observations by state from 1968 to 2010.

Further data on population demographics was acquired from Reed College economics professor Jon Rork.

## **Dataset Definitions and Summaries**

Stfips – State id code that runs from 1 to 48 alphabetically by continental State

Year – year of sample collection from 1967 to 2010

Crime Rates – all crime rates are reported in incidents per 100,000 inhabitants, denoted by the suffix *rate*

Violent crime - murder and nonnegligent manslaughter, forcible rape, robbery, and aggravated assault.

Murder and nonnegligent manslaughter - The willful (non-negligent) killing of one human being by another.

Forcible rape - The carnal knowledge of a female forcibly and against her will. Rapes by force and attempts or assaults to rape, regardless of the age of the victim, are included. Statutory offenses (no force used—victim under age of consent) are excluded.

Robbery - The taking or attempting to take anything of value from the care, custody, or control of a person or persons by force or threat of force or violence and/or by putting the victim in fear.

Aggravated Assault - An unlawful attack by one person upon another for the purpose of inflicting severe or aggravated bodily injury. This type of assault usually is accompanied by the use of a weapon or by means likely to produce death or great bodily harm. Simple assaults are excluded.

Property Crime Total - Burglary, larceny-theft, motor vehicle theft, and arson. The object of the theft-type offenses is the taking of money or property, but there is no force or threat of force against the victims. The property crime category includes arson because the offense involves the destruction of property; however, arson victims may be subjected to force.

Burglary - The unlawful entry of a structure to commit a felony or a theft. Attempted forcible entry is included.

Larceny-theft - The unlawful taking, carrying, leading, or riding away of property from the possession or constructive possession of another. Examples are thefts of bicycles, motor vehicle parts and accessories, shoplifting, pocketpicking, or the stealing of any property or article that is not taken by force and violence or by fraud. Attempted larcenies are included. Embezzlement, confidence games, forgery, check fraud, etc., are excluded.

Motor Vehicle Theft - The theft or attempted theft of a motor vehicle. A motor vehicle is self-propelled and runs on land surface and not on rails. Motorboats, construction equipment, airplanes, and farming equipment are specifically excluded from this category.

Adults on probation – Total number of male adults on probation

Prisoner Population – Male's incarcerated in local jails and state or federal prisons.

Education – Expenditure on schools, colleges, and other educational institutions (e.g., for blind, deaf, and other handicapped individuals), and educational programs for adults, veterans, and other special classes. State institutions of higher education includes activities of institutions operated by the state, except that agricultural extension services and experiment stations are classified under Natural resources and hospitals serving the public are classified under Hospitals. Revenue and expenditure for dormitories, cafeterias, athletic events, bookstores, and other auxiliary enterprises financed mainly through charges for services are reported on a gross basis. Reported in nominal US dollars.

**Publicwelfare** - Expenditure on support of and assistance to needy persons contingent upon their need. Excludes pensions to former employees and other benefits not contingent on need. Expenditures under this heading include: Cash assistance paid directly to needy persons under the categorical programs (Old Age Assistance, Temporary Assistance for Needy Families (TANF) and under any other welfare programs; Vendor payments made directly to private purveyors for medical care, burials, and other commodities and services provided under welfare programs; and provision and operation by the government of welfare institutions. Other public welfare includes payments to other governments for welfare purposes, amounts for administration, support of private welfare agencies, and other public welfare services. Health and hospital services provided directly by the government through its own hospitals and health agencies, and any payments to other governments for such purposes are classed under those functional headings rather than here. Reported in nominal US dollars.

**Hospitals** - Expenditure on financing, construction acquisition, maintenance or operation of hospital facilities, provision of hospital care, and support of public or private hospitals. Own hospitals are facilities administered directly by the government concerned; Other hospitals refers to support for hospital services in private hospitals or other governments. However, see welfare concerning vendor payments under welfare programs. Nursing homes are included under Public welfare unless they are directly associated with a government hospital. Reported in nominal US dollars.

**Health** - Expenditure on outpatient health services, other than hospital care, including: public health administration; research and education; categorical health programs; treatment and immunization clinics; nursing; environmental health activities such as air and water pollution control; ambulance service if provided separately from fire protection services, and other general public health activities such as mosquito abatement. School health services provided by health agencies (rather than school agencies) are included here. Sewage treatment operations are classified separately. Reported in nominal US dollars.

**Police** - Expenditure on police departments. Reported in nominal US dollars.

**Correction** - Expenditure on local and state jails and prisons. Reported in nominal US dollars.

**Just** - Expenditure on courts and activities associated with courts including law libraries, prosecutorial and defendant programs, probate functions, and juries. Reported in nominal US dollars.

**Fedtrans** - Amounts received from other governments as fiscal aid in the form of shared revenues and grants-in -aid, as reimbursements for performance of general government functions and specific services for the paying government (e.g., care of prisoners or contractual research), or in lieu of taxes, Excludes amounts received from other governments for sale of property, commodities, and utility services. All intergovernmental revenue is classified as General revenue. Reported in nominal US dollars.

**Unionmem** - percent of non-agricultural labor force unionized

Medhhinc – Median household income

Pct85 – Percent of population over 85 years of age.

Pctold – Percent of population over 65 years of age.

Pctkid – Percent of population between 5 and 17

Urate – State unemployment rate

StateGSP – Gross state product

Pcthighschool - percent of population holding a GED

Pctcollege – percent of population holding an associates degree or higher

Pop – population by state

Cpi – Consumer Price Index controlled by state

Avgactdurunemp - The average duration of compensable unemployment is the number of weeks compensated during the year divided by the number of first payments. It may include more than one period of continuous unemployment. It excludes all unemployment for which no benefits were paid, such as waiting periods, disqualifications, and any time after exhaustion of benefits.

Avgweeklywage - The average weekly wage in total reimbursable covered employment is the total wages paid in covered reimbursable employment divided by the quantity of 52 times the average monthly covered employment.

Avgweeklybenefit - The average weekly benefit amount is the benefits paid for total unemployment during the year divided by the number of weeks for which benefits were paid (weeks compensated for total unemployment). Payments for partial unemployment are excluded from both numerator and denominator.

A summary of the transformed data is reproduced below:

Variable	Obs	Mean	Std. Dev.	Min	Max
-----+-----					
stfips	2112	24.5	13.85668	1	48
year	2112	1988.5	12.70143	1967	2010
pct85	2064	.0125926	.0046166	.0027	.0284459
urate	2064	5.681347	2.034393	1.4	18
pcthighsch~1	1920	72.17151	12.59988	35.2	93
pctcollege	1920	18.41156	6.505847	2.5	40.4

-----+-----					
avgactduru~p	2112	13.64801	2.660646	5.4	27.1
cpi	1584	1.700422	.6483181	.9964422	3.540215
violentcrime	2112	414.6416	227.7138	20.6	1244.3
mnmsr	2112	6.361979	3.686524	.2	20.3
forciblera~e	2112	30.10966	13.30476	2.7	88.1
-----+-----					
robberyrate	2112	127.0042	96.96543	1.9	684
propertycrime	2112	3910.009	1235.544	786.4	7996
larcenythe~e	2112	2546.325	782.8021	471.9	5106.1
unionmem	1344	13.03981	5.933564	2.3	32.5
ln_police	2112	10.79515	1.386358	4.729421	14.33658
-----+-----					
ln_fedtrans	1728	6.962477	1.282614	3.526361	10.72663
ln_medhhinc	1296	10.4652	.2967468	9.644069	11.12813
dln_overal~e	2064	.0816738	.2502961	-6.616005	6.729381
dln_stateexp	2064	.0830343	.1804791	-3.588841	6.981441
dln_educat~n	2064	.0774265	.0661517	-.2876825	.6093216
-----+-----					
dln_hospit~s	2062	.0628626	.1686332	-2.863505	1.853703
dln_health	2064	.1033844	.1615146	-1.237097	1.146395
dln_correc~n	2064	.0981009	.1337395	-.5736666	2.272883
dln_pop	2016	.0108022	.0182215	-.31178	.3406944
dln_stategsp	2015	.0697292	.0419947	-.216671	.4214654
-----+-----					
dln_just	1532	.0527838	.6354785	-4.158883	3.245544
dln_adults~n	1568	.0336822	.2016994	-2.601924	2.222885
dln_prison~p	1584	.0497774	.0839935	-.621757	.607132
d_pctold	2016	.0008779	.0031934	-.039079	.038858
-----+-----					

```

      d_pctkid |      2016   -.0006302   .0118485   -.0534   .105
d_pcthighs~l |      1824   .9463268   .9730982  -3.199997  4.700005
d_avgweekl~e |      2064   16.46375   10.82907  -75.91003  93.53992
d_avgweekl~t |      2064    5.908973    7.395509   -35.81   76.63998
d_aggravat~e |      2064    3.07093   25.93498   -113.7   172.1
-----+-----
d_burglary~e |      2064   -.3502423   94.87356  -401.2999   575.7
d_motorveh~e |      2064  -1.518023   44.96524   -263     256
dln_minwage |      2016   .0435726   .1038004  -.3184538  1.168993

```

### ***Dickey Fuller Tests for Nonstationarity***

We performed Dickey Fuller tests for nonstationarity on each of the variables. To do this we used the Dickey Fuller version of Stata's panel data unit-root test. The syntax of the command is as follows:

```
xtunitroot fisher [var], dfuller lags() [options]
```

The theory behind the test is the same as the Dickey Fuller test for nonstationarity that we discussed in class in relation to non-panel data. Stata outputs of these tests can be found in Appendix A.1 The results are summarized in Table 1 below.

Table 1. Dickey Fuller Tests for Nonstationarity - Results

Stationary	Nonstationary (Stationary I(1) )
ln_publicwelfare	ln_prisonpop
ln_police	ln_education
ln_fedtrans	ln_hospitals
urate	ln_health
pctcollege	ln_correction
avgactdurunemp	ln_pop
cpi	ln_stategsp



unionmem	ln_debt
larcenytheft	ln_just
propertycrimrate	ln_minwage
robberyrate	ln_adultsonprobation
forcibleraprate	pct85
mnnmsr	pctold
violentcrimrate	pctkid
	pcthighshool
	avgweeklywage
	avgweeklybenefit
	motorvehicletheft
	burglaryrate
	aggravatedassault

We found all of the nonstationary variables to be integrated of order one. Thus, we used first differenced versions of each of these variables in our regressions.

### ***Fixed Effects vs. Random Effects***

In panel data regressions, we use intercept terms to account for individual heterogeneity in states. We want to control for state-specific time-invariant characteristics because we are more interested in looking at the effects of the explanatory variables on the unemployment rate, not so much the effects of the varying state characteristics. There are two ways to account for individual heterogeneity: fixed effects and random effects. Since the “individuals” in our data are states, and all states are included (except for HI, AK, DC), it makes sense that the intercepts that capture individual heterogeneity are “fixed”.

However, there are advantages to treating these state-specific time-invariant characteristics as random. The random effects model saves us more degrees of freedom, which would result in more accurate estimates of the coefficients. It is also capable of estimating the effects of explanatory variables that only vary across states, not time. The only catch is that if there exists correlation between the unobserved difference between states and the existing explanatory variables, then the random effects regression becomes inconsistent. We are going to regress our panel data twice, one with random effects and one with fixed effects. Then, we will use the Hausman test to see if such correlation exists. If so, then we move on to the fixed effects model.

In terms of the nature of the unobserved state-specific time-invariant characteristics, it is highly plausible that the omitted time-invariant variables that explain the unemployment rate are correlated with the existing explanatory variables we are using. For example, any related state policies that we didn't account for would contribute to that correlation. Therefore, we wouldn't be surprised if we have to use a fixed effects model instead of a random effects model.

Note that when we use the Hausman test, Stata does not allow the standard errors in the regression to be robust to heteroskedasticity. However, once we have decided on either random or fixed, we need to use clustering robust standard errors so that we do not need to assume that errors are uncorrelated over time for each state. Below are the Stata commands we used to perform the Hausman test.

```
. quietly xtreg urate dln_education dln_hospitals dln_health dln_correction ln_police
dln_pop dln_statategsp dln_just dln_adultsonprobation dln_prisonpop d_pctold d_pctkid
d_pct85 d_pcthighschool pctcollege avgactdurunemp d_avgweeklywage d_avgweeklybenefit
d_motorvehicletheftrate dln_minwage ln_fedtrans unionmem larcenytheftrate
propertycrimrate robberyrate forcibleraperate mnnmsr violentcrimrate
d_aggravatedassaultrate d_burglaryrate cpi, fe
```

```
. estimates store fe
```

```
. quietly xtreg urate dln_education dln_hospitals dln_health dln_correction ln_police
dln_pop dln_statategsp dln_just dln_adultsonprobation dln_prisonpop d_pctold d_pctkid
d_pct85 d_pcthighschool pctcollege avgactdurunemp d_avgweeklywage d_avgweeklybenefit
d_motorvehicletheftrate dln_minwage ln_fedtrans unionmem larcenytheftrate
propertycrimrate robberyrate forcibleraperate mnnmsr violentcrimrate
d_aggravatedassaultrate d_burglaryrate cpi, re
```

```
. estimates store re
```

```
. hausman fe re
```

Note: the rank of the differenced variance matrix (20) does not equal the number of

coefficients being tested (31); be sure this is what you expect, or there may be problems computing the test. Examine the output of your estimators for anything unexpected and possibly consider scaling your variables so that the coefficients are on a similar scale.

b = consistent under  $H_0$  and  $H_a$ ; obtained from xtreg

B = inconsistent under  $H_a$ , efficient under  $H_0$ ; obtained from xtreg

Test:  $H_0$ : difference in coefficients not systematic

```
chi2(20) = (b-B)'[(V_b-V_B)^(-1)](b-B)
          =          77.27
Prob>chi2 =          0.0000
(V_b-V_B is not positive definite)
```

Since the Hausman test gives a  $\chi^2$  statistic of 77.27, which is bigger than the critical value (20, 0.95) of 31.41, we reject the null hypothesis “ $\text{corr}(u_i, X) = 0$ ” that there exists no correlation between the unobserved difference across states and the existing explanatory variables. Thus, we conclude that we need to use the fixed effects model because the random effects model would create inconsistent estimates. Below is a summary table of the regression results of the two models.

	(1)	(2)
	Fixed Effects	Random Effects
VARIABLES	urate	urate
dln_education	-0.662 (0.484)	-0.554 (0.506)
dln_hospitals	-0.548** (0.239)	-0.446* (0.250)
dln_health	-0.0131 (0.239)	-0.175 (0.250)
dln_correction	-0.417	-0.398

	(0.254)	(0.267)
ln_police	-0.278*	-0.211
	(0.153)	(0.133)
dln_pop	-2.697	-2.789
	(2.161)	(2.228)
dln_statategsp	-5.924***	-6.004***
	(1.187)	(1.220)
dln_just	-0.0464	-0.0821*
	(0.0473)	(0.0495)
dln_adultsonprobation	-0.0372	0.0144
	(0.234)	(0.245)
dln_prisonpop	-1.735***	-1.583***
	(0.423)	(0.442)
d_pctold	10.39	15.28
	(10.74)	(11.22)
d_pctkid	5.185	5.108
	(8.294)	(8.610)
d_pct85	-24.90	-33.31
	(45.13)	(47.10)
d_pcthighschool	0.00912	0.0186
	(0.0459)	(0.0475)
pctcollege	0.0202	-0.0463**
	(0.0221)	(0.0183)
avgactdurunemp	0.483***	0.473***
	(0.0240)	(0.0228)
d_avgweeklywage	-0.0122***	-0.0143***
	(0.00418)	(0.00432)
d_avgweeklybenefit	-0.0205***	-0.0223***
	(0.00406)	(0.00424)

d_motorvehicletheft	-0.00314***	-0.00340***
	(0.000749)	(0.000781)
dlm_minwage	0.345	0.345
	(0.290)	(0.303)
ln_fedtrans	0.0382	0.273*
	(0.237)	(0.158)
unionmem	0.143***	0.0329**
	(0.0254)	(0.0168)
larcenytheft	-0.000974***	-0.000958***
	(0.000348)	(0.000315)
propertycrimrate	0.000446*	0.000479**
	(0.000252)	(0.000229)
robberyrate	-0.000611	-0.00430***
	(0.00164)	(0.00144)
forciblerape	0.0120**	0.0140***
	(0.00548)	(0.00518)
mnmmsr	0.0109	0.107***
	(0.0301)	(0.0273)
violentcrimrate	0.000207	0.000263
	(0.000667)	(0.000602)
d_aggravatedassault	0.00175	0.00138
	(0.00111)	(0.00113)
d_burglaryrate	0.000218	0.000193
	(0.000444)	(0.000464)
cpi	2.408***	2.765***
	(0.459)	(0.311)
Constant	-3.012	-3.399**
	(2.922)	(1.437)

Observations	908	908
R-squared (within)	0.748	0.7338
R-squared (between)	0.1229	0.4380
R-squared (overall)	0.3664	0.6073
Number of stfips	48	48

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Standard errors in parentheses

\*\*\* p<0.01, \*\* p<0.05, \* p<0.1

### *Analysis of the Preferred Model: the Fixed Effects Model*

```
. xtreg urate dln_education dln_hospitals dln_health dln_correction ln_police dln_pop
dln_statessp dln_just dln_adultsonprobation dln_prisonpop d_pctold d_pctkid d_pct85
d_pcthighschool pctcollege avgactdurunemp d_avgweeklywage d_avgweeklybenefit
d_motorvehicletheft rate dln_minwage ln_fedtrans unionmem larcenytheft rate propertycrim rate
robberyrate forcibleraperate mnmmsr violentcrim rate d_aggravatedassault rate d_burglaryrate cpi,
fe vce(cluster stfips)
```

Fixed-effects (within) regression	Number of obs	=	908
Group variable: stfips	Number of groups	=	48
R-sq: within = 0.7477	Obs per group: min =		17
between = 0.1229	avg =		18.9
overall = 0.3664	max =		19
	F(31,47)	=	66.71
corr(u_i, Xb) = -0.5562	Prob > F	=	0.0000

(Std. Err. adjusted for 48 clusters in stfips)

---

	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
dln_education	-.6615825	.4521723	-1.46	0.150	-1.571236 .2480709

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dln_hospitals		-.5483006	.2446897	-2.24	0.030	-1.040553	-.0560484
dln_health		-.0130769	.1913305	-0.07	0.946	-.3979842	.3718304
dln_correction		-.4170741	.209997	-1.99	0.053	-.8395335	.0053853
ln_police		-.277609	.2656034	-1.05	0.301	-.811934	.256716
dln_pop		-2.696942	1.528233	-1.76	0.084	-5.77135	.3774663
dln_statensp		-5.924324	1.514444	-3.91	0.000	-8.970992	-2.877657
dln_just		-.0464058	.0415328	-1.12	0.270	-.1299589	.0371474
dln_adultsonprobation		-.0372263	.2855898	-0.13	0.897	-.6117588	.5373062
dln_prisonpop		-1.7345	.488286	-3.55	0.001	-2.716805	-.7521955
d_pctold		10.38621	7.607436	1.37	0.179	-4.917973	25.6904
d_pctkid		5.18526	7.198255	0.72	0.475	-9.295762	19.66628
d_pct85		-24.89758	29.72356	-0.84	0.406	-84.69366	34.8985
d_pcthighschool		.0091218	.039362	0.23	0.818	-.0700644	.088308
pctcollege		.0201529	.0264906	0.76	0.451	-.0331392	.073445
avgactdurunemp		.4826801	.0473876	10.19	0.000	.3873484	.5780117
d_avgweeklywage		-.0122453	.0043056	-2.84	0.007	-.0209071	-.0035835
d_avgweeklybenefit		-.0205006	.0046496	-4.41	0.000	-.0298544	-.0111468
d_motorvehiclethefttrate		-.0031433	.0009222	-3.41	0.001	-.0049986	-.001288
dln_minwage		.3446052	.3241691	1.06	0.293	-.3075389	.9967493
ln_fedtrans		.0382169	.25483	0.15	0.881	-.4744349	.5508687
unionmem		.1427206	.04343	3.29	0.002	.0553508	.2300904
larcenythefttrate		-.0009745	.0004257	-2.29	0.027	-.0018308	-.0001181
propertycrimerate		.000446	.0003164	1.41	0.165	-.0001904	.0010824
robberyrate		-.0006113	.002563	-0.24	0.813	-.0057673	.0045447
forcibleraperate		.0119852	.0066091	1.81	0.076	-.0013106	.0252811
mnmsr		.0109469	.0379144	0.29	0.774	-.0653271	.087221
violentcrimerate		.0002067	.0010015	0.21	0.837	-.0018082	.0022215
d_aggravatedassaulttrate		.0017531	.0011854	1.48	0.146	-.0006315	.0041377
d_burglaryrate		.0002177	.0004433	0.49	0.626	-.0006741	.0011095
cpi		2.408425	.5654813	4.26	0.000	1.270823	3.546026
_cons		-3.011854	4.352629	-0.69	0.492	-11.76821	5.744506

-----+

```

sigma_u | 1.6304231
sigma_e | .81457717
rho | .80024899 (fraction of variance due to u_i)

```

---

The variables with statistically significant coefficients at a significance level of 0.05 are highlighted in the regression results table. Note that the constant term, which is the average of the states' intercepts that measure individual heterogeneity, is insignificant. This tells us that individual heterogeneity is not significantly evident when we are looking at the estimation of unemployment rate. The variable we are most interested in is `dln_prisonpop`, which is interpreted as the growth rate of the state's prison population. According to this fixed effects model, a 1% increase in this growth rate would result in an approximately 1.73% decrease in the unemployment rate. This is consistent with our hypothesis in that an explanation for a lower than expected unemployment rate in the US may be attributed to the positive growth rate of prison population. Another statistically significant variable is the gross state product (`dln_stategsp`). Results show that a \$1000 increase in GSP corresponds to a 5.9% decrease in the unemployment rate. This is consistent with macroeconomic theory that higher output leads to more jobs. Furthermore for the variable the average duration of compensable unemployment (`avgactdurunemp`), if the number of weeks each person received unemployment benefits increased by one week, the unemployment rate would be predicted to increase by 0.48%. This makes sense because there exists a higher incentive to remain unemployed. Another important finding is that if a change in average weekly wage increases by \$1, the unemployment rate is expected to decrease by 0.01%. In terms the change in average weekly benefits per person for unemployment, our results show that a \$1 increase in benefits is likely to produce a 0.02% decrease in the unemployment rate. This may imply that a higher benefits package leads to more success in finding a job. In addition, the coefficients of the two statistically significant crime-rate variables (motor vehicle theft and larceny) imply a negative effect on the unemployment rate. Though the coefficients are small, they are consistent with our hypothesis. CPI was included as an indicator of inflation, without it, it is likely that omitted variable would have been a serious issue. Lastly, union membership percentage was found to have a positive effect on the unemployment rate (a 0.14% increase in the unemployment rate). This is likely due to the incentive for unions to attempt to exclude non-unionized workers from the labor force to maximize wages.

### ***Endogeneity, Granger Causality, and Impulse Response***

Up until this point, we have assumed that the unemployment rate is the dependent variable. However, we believe that variables like prison population and the unemployment rate might be dynamically interdependent. We want to explore this bivariate system and examine the unique relationship between `urate` and `dln.prisonpop` (both stationary) with the vector autoregressive (VAR) model. We decided to pick a few states that "roughly" represent the United States: Texas, Oregon,



Minnesota, New York, California, and Wisconsin. Then, we examine how these two variables behave interdependently in these states with 6 separate VAR models.

For each state, we first use a long lag length (11), which we believed was sufficient to eliminate autocorrelation in the error term. Then, we used the `varsoc` command in Stata to output several selection-order criteria including AIC and SBIC. In the `varsoc` tables, we chose the optimal lag length by examining the lag that produces the most desired selection-order criteria values (denoted by \*). However, for most of the states we didn't have enough degrees of freedom to employ the optimal lag length to perform Granger causality tests and IR functions. As a result, we used the lag length that is as close to the optimal lag length as possible while accounted for degrees of freedom.

Since it is difficult to interpret the coefficients of the VAR models directly, we turn to Granger Causality tests and Impulse Response functions to interpret the dynamics of `urate` and `dln.prisonpop`. For the Granger Causality test, we use the Stata command "`vargranger`" to perform several Wald tests. For instance, if we reject the hypothesis that the coefficients on all the lags of the growth rate of prison population are jointly zero, then we conclude that the growth rate of prison population Granger causes the unemployment rate. The Impulse Response functions (IRF) model the contemporaneous effect of a shock in one variable on the other variable. In Stata, we make sure to use the "orthogonalized" IRF plots for the "contemporaneous" effects. Below are the regression and test results for each state followed by analysis.

## TEXAS

```
. varbasic dln_prisonpop urate if stfips == 41, lags(1/9) step(8)
```

```
. vargranger
```

### Granger causality Wald tests

+-----+					
Equation	Excluded	chi2	df	Prob >	chi2
+-----+					
dln_prisonpop	urate	48.687	9	0.000	
dln_prisonpop	ALL	48.687	9	0.000	
+-----+					
urate	dln_prisonpop	35.669	9	0.000	

urate	ALL	35.669	9	0.000
-------	-----	--------	---	-------

+-----+

Test results (3<sup>rd</sup> row) show that the growth rate of prison population Granger-causes the unemployment rate: given past values of the unemployment rate, past values of the growth rate of prison population are helping for predicting the unemployment rate. Similarly, we can conclude that the unemployment rate Granger-causes the growth rate of prison population (1<sup>st</sup> row). As a result, there exists Granger-causality between the growth rate of prison population in Texas and the unemployment rate in Texas in both directions.

```
. irf graph oirf, irf(varbasic) impulse(dln_prisonpop) response(urate)
```

```
. irf graph oirf, irf(varbasic) impulse(urate) response(dln_prisonpop)
```

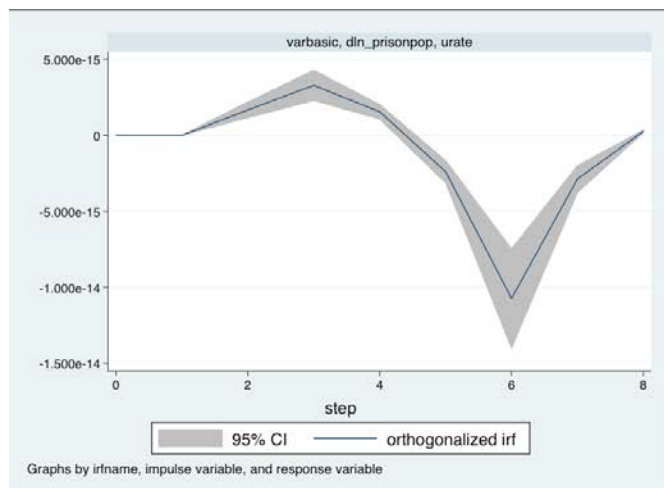


Figure 1. dln\_prisonpop, urate

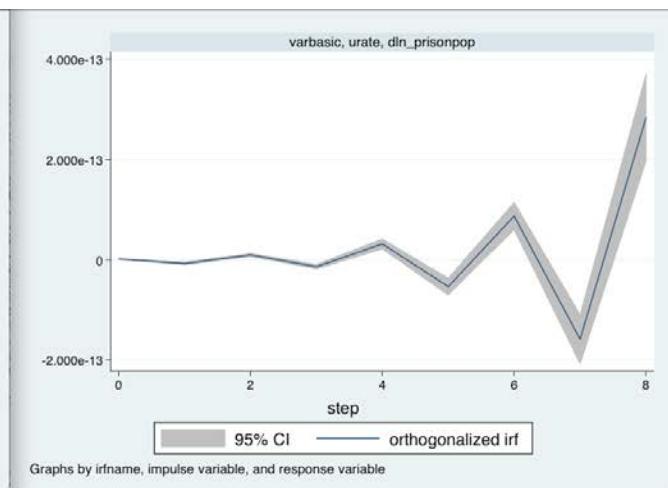


Figure 2. Urate, dln\_prisonpop

Figure 1 shows the response of the unemployment rate to a 1% increase in the growth rate of Texas' prison population. It indicates a slight increase in the unemployment rate between years 2 and 4, after which it decreases and remains below its previous level until year 8. Figure 2, which shows the response of the prison population growth rate to a 1% increase in the unemployment rate, implies a significant increase in the long run.

While the confidence intervals in each graph are encouragingly slim, it is important to note the small unit size on the y-axis. This indicates that the interpretation is certainly statistically significant, but its economic significance is questionable.

The OIRF results for most of the remaining states were generally inconclusive. That is, their confidence intervals tended to include zero at most points. It is possible that this is because we had to use sub-optimal lag lengths as a result of degrees of freedom restrictions.

OREGON

```
. varbasic dln_prisonpop urate if stfips == 35, lags(1/10) step(8)
. vargranger
```

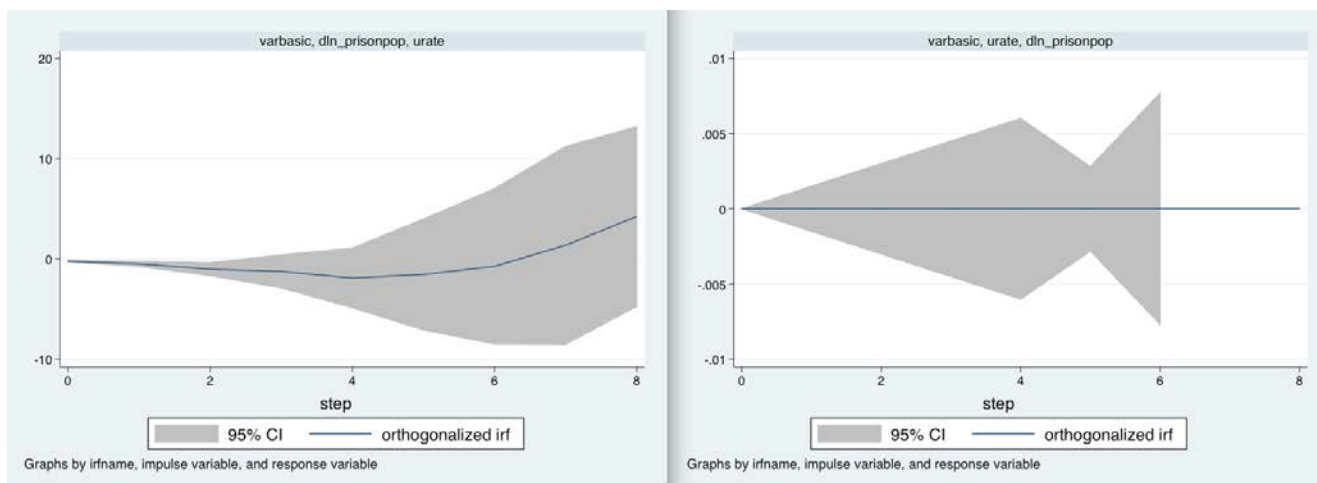
Granger causality Wald tests

+-----+						
Equation	Excluded	chi2	df	Prob >	chi2	
+-----+						
dln_prisonpop	urate	280.09	10	0.000		
dln_prisonpop	ALL	280.09	10	0.000		
+-----+						
urate	dln_prisonpop	334.9	10	0.000		
urate	ALL	334.9	10	0.000		
+-----+						

Test results (3<sup>rd</sup> row) show that the growth rate of prison population Granger-causes the unemployment rate. Similarly, we can conclude that the unemployment rate Granger-causes the growth rate of prison population (1<sup>st</sup> row). As a result, there exists Granger-causality between the growth rate of prison population and the unemployment rate in both directions for Oregon.

```
. irf graph oirf, irf(varbasic) impulse(dln_prisonpop) response(urate)

. irf graph oirf, irf(varbasic) impulse(urate) response(dln_prisonpop)
```



## MINNESOTA

```
. varbasic urate dln_prisonpop if stfips == 21, lags(1/10) step(8)
. vargranger
```

### Granger causality Wald tests

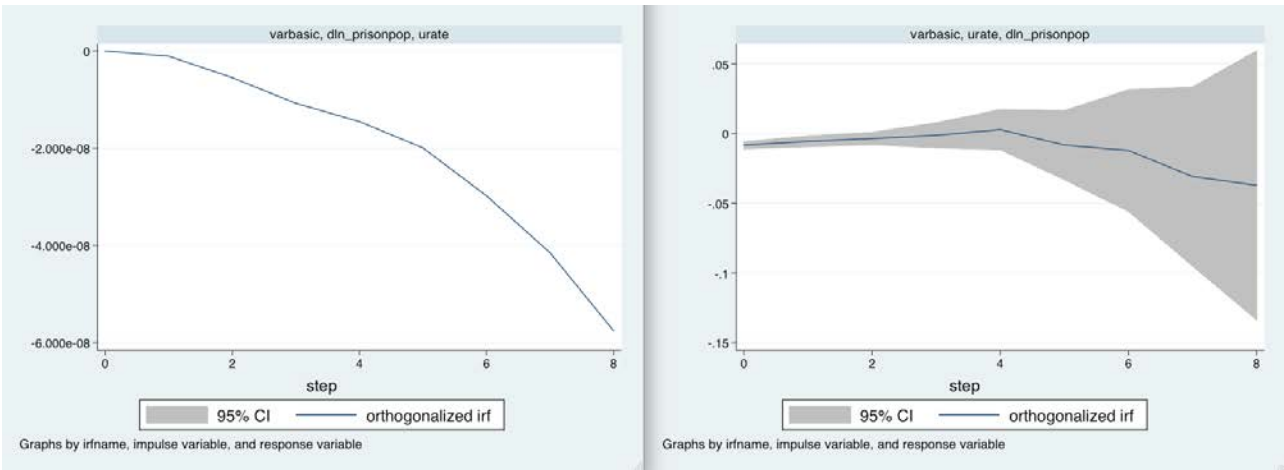
+-----+						
Equation	Excluded	chi2	df	Prob >	chi2	
+-----+						
urate	dln_prisonpop	2813.8	10	0.000		
urate	ALL	2813.8	10	0.000		
+-----+						
dln_prisonpop	urate	105.57	10	0.000		
dln_prisonpop	ALL	105.57	10	0.000		
+-----+						

Test results (3<sup>rd</sup> row) show that the growth rate of prison population Granger-causes the unemployment rate. Similarly, we can conclude that the unemployment rate Granger-causes the growth

rate of prison population (1<sup>st</sup> row). As a result, there exists Granger-causality between the growth rate of prison population and the unemployment rate in both directions for Minnesota.

```
. irf graph oirf, irf(varbasic) impulse(dln_prisonpop) response(urate)

. irf graph oirf, irf(varbasic) impulse(urate) response(dln_prisonpop)
```



NEW YORK

```
. varbasic dln_prisonpop urate if stfips == 30, lags(1/9) step(8)

. vargranger
```

Granger causality Wald tests

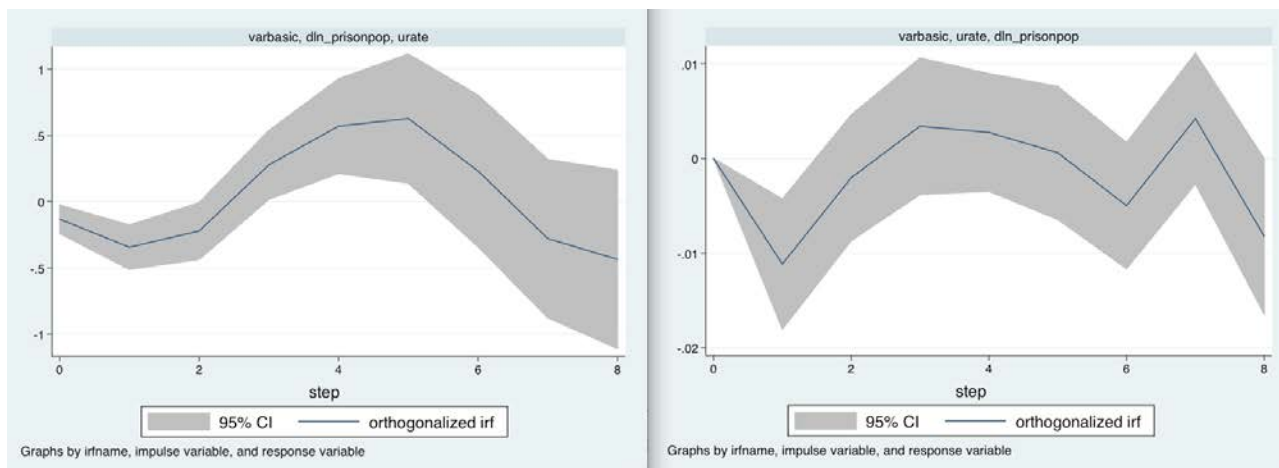
+-----+					
	Equation	Excluded		chi2	df Prob > chi2
	-----+				
	dln_prisonpop	urate		39.165	9 0.000
	dln_prisonpop	ALL		39.165	9 0.000
	-----+				

	urate	dln_prisonpop		97.83	9	0.000	
	urate	ALL		97.83	9	0.000	
+-----+							

Test results (3<sup>rd</sup> row) show that the growth rate of prison population Granger-causes the unemployment rate. Similarly, we can conclude that the unemployment rate Granger-causes the growth rate of prison population (1<sup>st</sup> row). As a result, there exists Granger-causality between the growth rate of prison population and the unemployment rate in both directions for New York.

```
. irf graph oirf, irf(varbasic) impulse(dln_prisonpop) response(urate)
```

```
. irf graph oirf, irf(varbasic) impulse(urate) response(dln_prisonpop)
```



## CALIFORNIA

```
. varbasic dln_prisonpop urate if stfips == 4, lags(1/9) step(8)
```

```
. vargranger
```

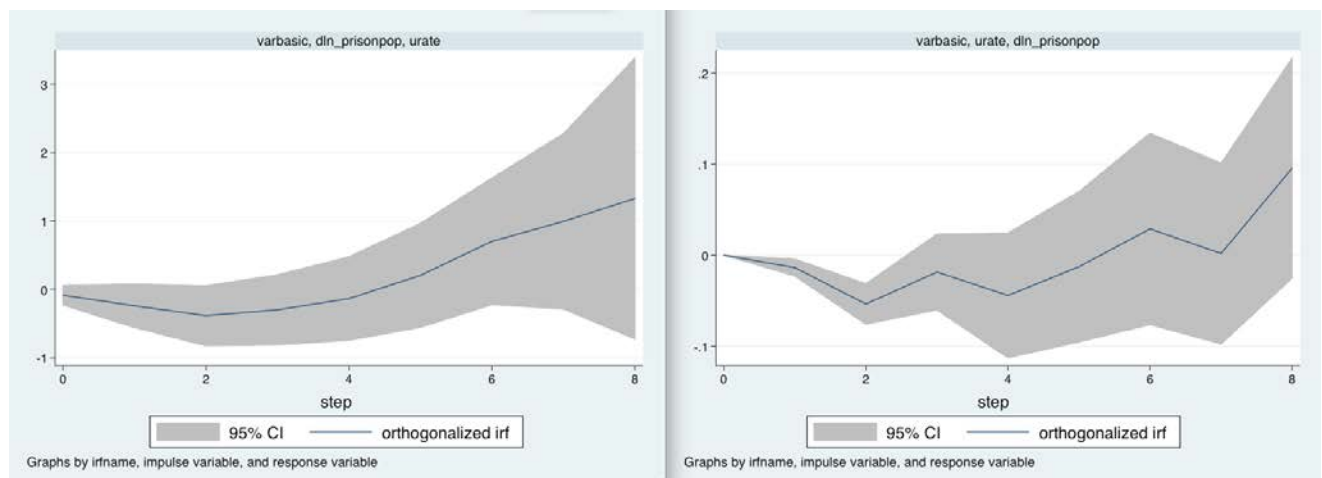
Granger causality Wald tests

+-----+					
Equation	Excluded	chi2	df	Prob > chi2	
+-----+					
dln_prisonpop	urate	100.39	9	0.000	
dln_prisonpop	ALL	100.39	9	0.000	
+-----+					
urate	dln_prisonpop	45.57	9	0.000	
urate	ALL	45.57	9	0.000	
+-----+					

Test results (3<sup>rd</sup> row) show that the growth rate of prison population Granger-causes the unemployment rate. Similarly, we can conclude that the unemployment rate Granger-causes the growth rate of prison population (1<sup>st</sup> row). As a result, there exists Granger-causality between the growth rate of prison population and the unemployment rate in both directions for California.

```
. irf graph oirf, irf(varbasic) impulse(dln_prisonpop) response(urate)
```

```
. irf graph oirf, irf(varbasic) impulse(urate) response(dln_prisonpop)
```



WISCONSIN

```
. varbasic dln_prisonpop urate if stfips == 47, lags(1/9) step(8)
```

```
. vargranger
```

Granger causality Wald tests

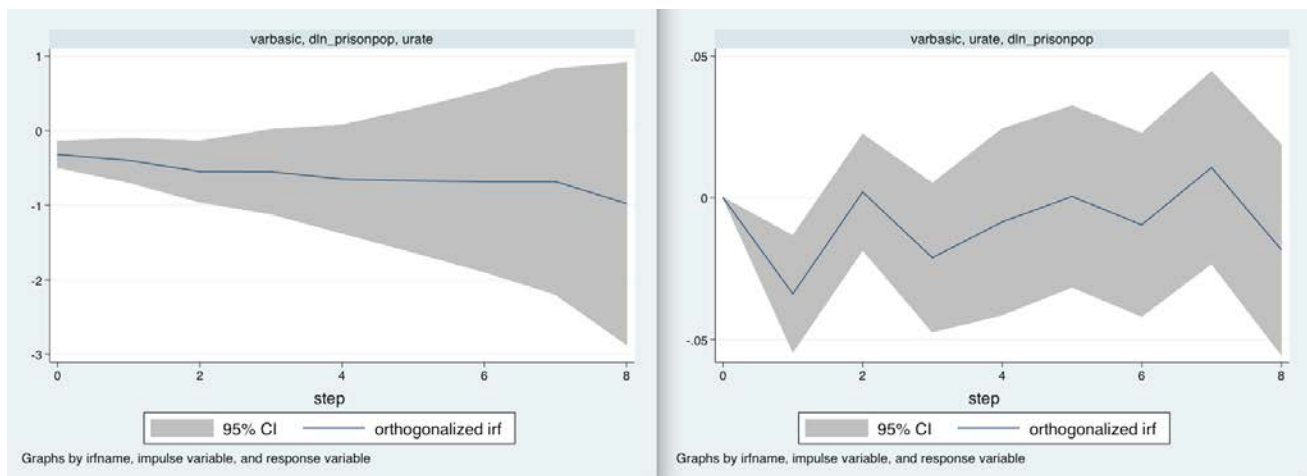
+-----+					
Equation	Excluded	chi2	df	Prob > chi2	
+-----+					
dln_prisonpop	urate	26.351	9	0.002	
dln_prisonpop	ALL	26.351	9	0.002	
+-----+					
urate	dln_prisonpop	55.133	9	0.000	
urate	ALL	55.133	9	0.000	
+-----+					

Test results (3<sup>rd</sup> row) show that the growth rate of prison population Granger-causes the unemployment rate. Similarly, we can conclude that the unemployment rate Granger-causes the growth rate of prison population (1<sup>st</sup> row). As a result, there exists Granger-causality between the growth rate of prison population and the unemployment rate in both directions for Wisconsin.

```
. irf graph oirf, irf(varbasic) impulse(dln_prisonpop) response(urate)
```

```
. irf graph oirf, irf(varbasic) impulse(urate) response(dln_prisonpop)
```





## IV Regression

Since we believe that the variable `dln_prisonpop` might be endogenous, we want to use instrumental variables to account for simultaneity bias. This is so that we can just examine the effect of prison population on the unemployment rate without worrying about the effect of the unemployment rate on prison population.

We picked our instrumental variables by looking at the insignificant explanatory variables in our fixed effects model and picking out the ones that seemed theoretically correlated with `dln_prisonpop`. The potential instrumental variables are shown below in the correlation matrix. These variables are valid instruments since they do not directly affect the unemployment rate but are correlated with the prison population. Note that even if the correlation between each of these potential instruments with `dln_prisonpop` is small, we are hoping that the instruments will be valid when they are regressed together in a 2SLS IV regression.

CORRELATION MATRIX: PRISONPOP AND POTENTIAL INSTRUMENTS

```
. corr dln_prisonpop dln_adultsonprobation violentcrimerate mnmmsr forcibleraperate robberyrate
propertycrimerate d_aggravatedassault rate d_burglaryrate

(obs=1568)
```

	dl_n_pr~p	dl_n_ad~n	violence	mnnmsr	forci~te	robber~e	proper~e	d_aggr~e	d_burg~e
dl_n_prison~p	1.0000								
dl_n_adults~n	0.0873	1.0000							
violentcri~e	0.0563	0.0389	1.0000						
mnnmsr	0.1160	0.0999	0.7358	1.0000					
forcibler~te	0.0494	0.0396	0.5394	0.3812	1.0000				
robberyrate	0.0773	0.0634	0.8553	0.6705	0.3556	1.0000			
propertycr~e	0.2000	0.1647	0.6366	0.5431	0.5010	0.5573	1.0000		
d_aggravat~e	0.0529	0.0338	0.0889	0.1039	0.0821	0.0553	0.1116	1.0000	
d_burglary~e	-0.1353	-0.0074	-0.0698	0.0349	-0.0475	-0.0705	-0.0235	0.2338	1.0000

Note that with panel data IV regressions, Stata does not allow the option of robust standard errors, thus our coefficients might not be as efficient because of heteroskedasticity. Also, we are still using a fixed effects model based on our previous analysis.

#### 2SLS IV REGRESSION:

```
. xtivreg urate dl_n_education dl_n_hospitals dl_n_health dl_n_correction ln_police dl_n_pop
dl_n_statgsp dl_n_just d_pctold d_pctkid d_pct85 d_pcthighschool pctcollege avgactdurunemp
d_avgweeklywage d_avgweeklybenefit d_motorvehicletheft rate dl_n_minwage ln_fedtrans unionmem
larcenytheft rate (dl_n_prisonpop = dl_n_adultsonprobation violentcrimerate mnnmsr forcibleraperate
robberyrate propertycrimerate d_aggravatedassault rate d_burglaryrate), fe
```

Fixed-effects (within) IV regression	Number of obs	=	908
Group variable: stfips	Number of groups	=	48
R-sq: within = 0.7329	Obs per group: min	=	17
between = 0.0123	avg	=	18.9
overall = 0.2078	max	=	19
	Wald chi2(22)	=	47390.06
corr(u_i, Xb) = -0.6633	Prob > chi2	=	0.0000

urate	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
dln_prisonpop	-2.57937	1.923535	-1.34	0.180	-6.349429	1.190688
dln_education	-.5887862	.4972933	-1.18	0.236	-1.563463	.3858907
dln_hospitals	-.4535484	.2450076	-1.85	0.064	-.9337546	.0266577
dln_health	.1160472	.2451559	0.47	0.636	-.3644495	.596544
dln_correction	-.2910745	.2955427	-0.98	0.325	-.8703275	.2881784
ln_police	-.4491624	.1526808	-2.94	0.003	-.7484113	-.1499134
dln_pop	-2.714675	2.201235	-1.23	0.217	-7.029016	1.599666
dln_statategsp	-5.458705	1.173828	-4.65	0.000	-7.759365	-3.158045
dln_just	-.0340231	.0508028	-0.67	0.503	-.1335948	.0655486
d_pctold	8.095799	10.93426	0.74	0.459	-13.33496	29.52655
d_pctkid	-4.776816	8.314392	-0.57	0.566	-21.07273	11.51909
d_pct85	-33.86556	46.09389	-0.73	0.463	-124.2079	56.47681
d_pcthighschool	.0042987	.046862	0.09	0.927	-.0875492	.0961465
pctcollege	-.015103	.0213902	-0.71	0.480	-.057027	.026821
avgactdurunemp	.5184034	.0236917	21.88	0.000	.4719686	.5648383
d_avgweeklywage	-.0169876	.0042194	-4.03	0.000	-.0252574	-.0087178
d_avgweeklybenefit	-.0207814	.0043822	-4.74	0.000	-.0293704	-.0121923
d_motorvehicletheftrate	-.0019587	.000694	-2.82	0.005	-.0033188	-.0005986
dln_minwage	.2054964	.2992126	0.69	0.492	-.3809494	.7919423
ln_fedtrans	-1.00838	.1560527	-6.46	0.000	-1.314238	-.7025224
unionmem	.1714825	.0249955	6.86	0.000	.1224922	.2204727
larcenythefttrate	-.0003643	.0001071	-3.40	0.001	-.0005741	-.0001544
_cons	11.29029	1.576554	7.16	0.000	8.200304	14.38028
sigma_u	2.0817598					
sigma_e	.83359312					
rho	.86181496	(fraction of variance due to u_i)				

```
F test that all u_i=0:      F(47,838) =      27.16          Prob > F      = 0.0000
```

```
-----
Instrumented:  dln_prisonpop

Instruments:   dln_education dln_hospitals dln_health dln_correction ln_police dln_pop
               dln_statategsp dln_just d_pctold d_pctkid d_pct85 d_pcthighschool
               pctcollege avgactdurunemp d_avgweeklywage d_avgweeklybenefit
               d_motorvehicletheft rate dln_minwage ln_fedtrans unionmem larcenytheft rate
               dln_adultsonprobation violentcrim rate mnnmsr forcibleraperate
               robberyrate propertycrim rate d_aggravatedassault rate d_burglaryrate
-----
```

Now, let us test the **validity of our instruments**. We can test for instrument validity since we have over-identifying restrictions (8 instruments but only one endogenous variable). When we look at the residuals from the IV 2SLS regression, they tell us the part of the unemployment rate that is unexplained by both the 1st-stage and 2nd-stage regressions. If we regress these residuals on the exogenous variables as well as the instrumental variables and find that the coefficients on the instruments are significant, then we conclude that the instruments directly affect the unemployment rate. If that is the case, the instruments are invalid and the IV estimator is not consistent. Below are the Stata commands and regression results for testing instrument validity.

```
. predict ehat, e

. quietly xtreg ehat dln_education dln_hospitals dln_health dln_correction ln_police
dln_pop dln_statategsp dln_just d_pctold d_pctkid d_pct85 d_pcthighschool pctcollege
avgactdurunemp d_avgweeklywage d_avgweeklybenefit d_motorvehicletheft rate dln_minwage
ln_fedtrans unionmem larcenytheft rate dln_adultsonprobation violentcrim rate mnnmsr
forcibleraperate robberyrate propertycrim rate d_aggravatedassault rate d_burglaryrate

. di 908*0.01

9.08
```

Our null hypothesis is that the coefficients on all exogenous variables and the instruments are zero. But we are mostly focused on the coefficients of the instruments. We use the value  $N \cdot R^2$  from the regression as our test-statistic. If the value  $N \cdot R^2$  follows the chi2 distribution of L-B degrees of freedom (the number of instruments minus the number of endogenous variables), then we conclude that the instruments are valid. Looking at the results above, we see that our  $N \cdot R^2$  value is 9.08, which is

smaller than the  $\chi^2(7, 0.95)$  critical value of 14.067. Thus, we fail to reject the null hypothesis and conclude that it is plausible that the instruments employed are valid. Specifically, the instruments employed are not directly correlated with the unemployment rate.

Since it is safe to assume that our instruments are valid, let us test the **instrument strength**. We perform the 1st-stage regression with the endogenous variable `dl_n_prisonpop` as the dependent variable and all exogenous and instrumental variables as the regressors. Then, we use a joint F-test to test the null hypothesis that the coefficients of all the instrument regressors are zero. In this test, if we reject the null, we conclude that at least one of the instruments are strong. Thus, we need our F-statistic to be larger than 10 as a rule of thumb.

#### TEST FOR INSTRUMENT STRENGTH

```
. quietly xtreg dl_n_prisonpop dl_n_education dl_n_hospitals dl_n_health dl_n_correction ln_police  
dl_n_pop dl_n_statensp dl_n_just d_pctold d_pctkid d_pct85 d_pcthighschool pctcollege avgactdurunemp  
d_avgweeklywage d_avgweeklybenefit d_motorvehicthefttrate dl_n_minwage ln_fedtrans unionmem  
larcenythefttrate dl_n_adultsonprobation violentcrimrate mnnmsr forcibleraperate robberyrate  
propertycrimrate d_aggravatedassaulttrate d_burglaryrate, fe
```

```
. test dl_n_adultsonprobation violentcrimrate mnnmsr forcibleraperate robberyrate propertycrimera  
> te d_aggravatedassaulttrate d_burglaryrate
```

```
( 1) dl_n_adultsonprobation = 0  
( 2) violentcrimrate = 0  
( 3) mnnmsr = 0  
( 4) forcibleraperate = 0  
( 5) robberyrate = 0  
( 6) propertycrimrate = 0  
( 7) d_aggravatedassaulttrate = 0  
( 8) d_burglaryrate = 0
```

```
F( 8, 831) = 5.26
```

```
Prob > F = 0.0000
```

Our F-statistic is not greater than 10, our rule of thumb value. Therefore, even though our p-value is 0.000, our F-statistic is not big enough for us to conclude that at least one of the instruments is strong. This is worrisome since we have assumed endogeneity, but our instruments are not strong enough. The result of weak instruments is the possibility of badly biased instrumental variables estimation.

We continued to see if `dl_n_prisonpop` is actually endogenous using the **Hausman test for endogeneity**. The idea of the test is that we estimate `dl_n_prisonpop` with the exogenous variables and the instruments (1<sup>st</sup>-stage), and then use the residuals from this regression as an explanatory variable in the original regression (where we regress `urate` on all the exogenous variables and `dl_n_prisonpop`). If the coefficient on the 1<sup>st</sup>-stage residuals is significant, then there exists endogeneity in `dl_n_prisonpop`.

```
. quietly xtreg dl_n_prisonpop dl_n_education dl_n_hospitals dl_n_health dl_n_correction ln_police
dl_n_pop dl_n_statgsp dl_n_just d_pctold d_pctkid d_pct85 d_pcthighschool pctcollege avgactdurunemp
d_avgweeklywage d_avgweeklybenefit d_motorvehicletheft rate dl_n_minwage ln_fedtrans unionmem
larcenytheft rate dl_n_adultsonprobation violentcrim rate mnmmsr forcibleraperate robberyrate
propertycrim rate d_aggravatedassault rate d_burglaryrate, fe
```

```
. predict ehat6, e
```

```
(1204 missing values generated)
```

```
. xtreg urate dl_n_education dl_n_hospitals dl_n_health dl_n_correction ln_police dl_n_pop
dl_n_statgsp dl_n_just d_pctold d_pctkid d_pct85 d_pcthighschool pctcollege avgactdurunemp
d_avgweeklywage d_avgweeklybenefit d_motorvehicletheft rate dl_n_minwage ln_fedtrans unionmem
larcenytheft rate ehat6 dl_n_prisonpop, fe
```

Fixed-effects (within) regression	Number of obs	=	908
Group variable: stfips	Number of groups	=	48
R-sq: within = 0.7339	Obs per group: min	=	17
between = 0.0123	avg	=	18.9
overall = 0.2072	max	=	19
	F(23,837)	=	100.36
corr(u_i, Xb) = -0.6642	Prob > F	=	0.0000

urate	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
dln_education	-.5887862	.4966898	-1.19	0.236	-1.56369	.3861176
dln_hospitals	-.4535484	.2447103	-1.85	0.064	-.9338664	.0267695
dln_health	.1160472	.2448584	0.47	0.636	-.3645614	.5966559
dln_correction	-.2910745	.295184	-0.99	0.324	-.8704623	.2883133
ln_police	-.4491624	.1524956	-2.95	0.003	-.748481	-.1498438
dln_pop	-2.714675	2.198564	-1.23	0.217	-7.030021	1.60067
dln_statategsp	-5.458705	1.172403	-4.66	0.000	-7.7599	-3.157509
dln_just	-.0340231	.0507412	-0.67	0.503	-.133618	.0655718
d_pctold	8.095799	10.92099	0.74	0.459	-13.33995	29.53154
d_pctkid	-4.776816	8.304302	-0.58	0.565	-21.07652	11.52289
d_pct85	-33.86556	46.03796	-0.74	0.462	-124.229	56.49785
d_pcthighschool	.0042987	.0468051	0.09	0.927	-.0875705	.0961679
pctcollege	-.015103	.0213642	-0.71	0.480	-.0570368	.0268308
avgactdurunemp	.5184034	.0236629	21.91	0.000	.4719578	.5648491
d_avgweeklywage	-.0169876	.0042142	-4.03	0.000	-.0252593	-.0087159
d_avgweeklybenefit	-.0207814	.0043769	-4.75	0.000	-.0293724	-.0121903
d_motorvehicthetrate	-.0019587	.0006931	-2.83	0.005	-.0033191	-.0005982
dln_minwage	.2054964	.2988495	0.69	0.492	-.381086	.7920788
ln_fedtrans	-1.00838	.1558634	-6.47	0.000	-1.314309	-.7024512
unionmem	.1714825	.0249651	6.87	0.000	.1224808	.2204841
larcenythetrate	-.0003643	.0001069	-3.41	0.001	-.0005741	-.0001544
ehat6	.7537365	1.969273	0.38	0.702	-3.111557	4.61903
dln_prisonpop	-2.579371	1.9212	-1.34	0.180	-6.350307	1.191566
_cons	11.29029	1.574641	7.17	0.000	8.199585	14.381
sigma_u	2.0817598					
sigma_e	.8325815					
rho	.86210393	(fraction of variance due to u_i)				

F test that all  $u_i=0$ :  $F(47, 837) = 27.22$  Prob > F = 0.0000

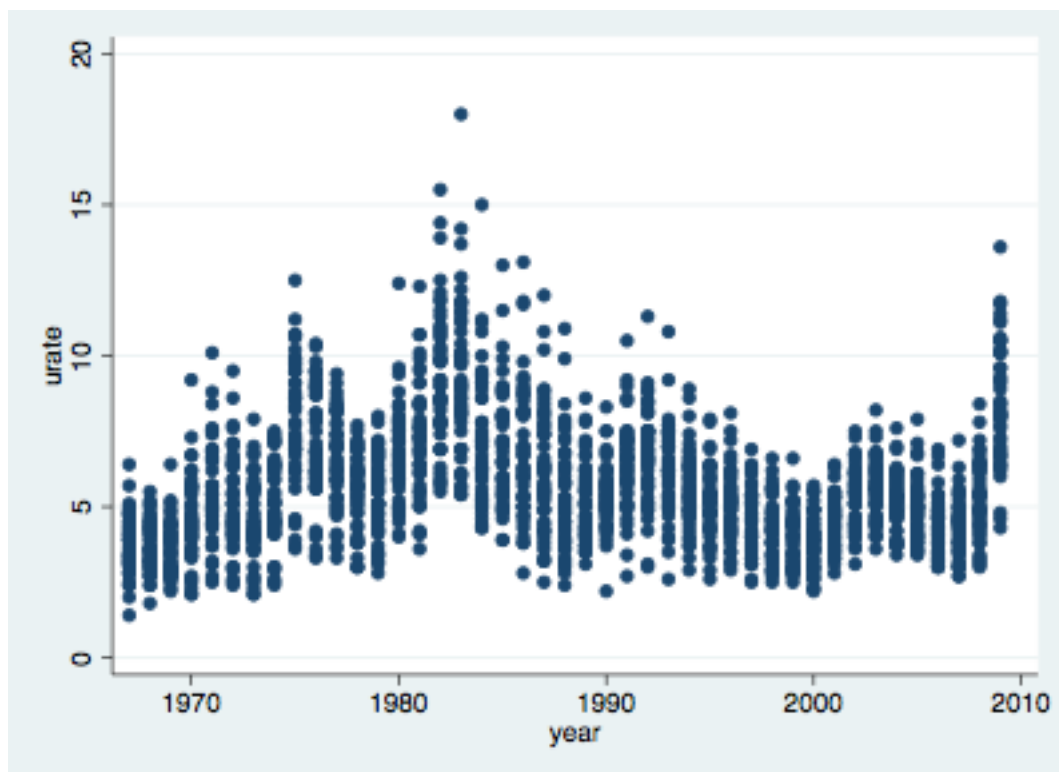
Based on our regression results, we find that the coefficient on the residuals ( $\hat{e}_6$ ) is actually insignificant with a p-value of 0.702, thus it is possible that the variable  $\ln\_prisonpop$  is not endogenous in the first place. Therefore, we should be able to interpret the effect of the growth rate of prison population on the unemployment rate in the fixed effects model both statistically and economically without worrying too much about endogeneity bias. Note that since we found our instruments to be valid but weak, the Hausman test for endogeneity might still produce questionable results. Therefore, we don't have enough information to prove or disprove endogeneity of the  $\ln\_prisonpop$  variable.

## APPENDIX A.1

Dickey Fuller Tests for Nonstationarity (`xtunitroot fisher [var], dfuller lags() [options]`)

## UNEMPLOYMENT RATE





```
. xtunitroot fisher urate, dfuller lags(0)
(48 missing values generated)
```

Fisher-type unit-root test for urate  
Based on augmented Dickey-Fuller tests

```
-----
Ho: All panels contain unit roots          Number of panels =    48
Ha: At least one panel is stationary       Number of periods =   43
```

```
AR parameter: Panel-specific              Asymptotics: T -> Infinity
Panel means:   Included
Time trend:    Not included
Drift term:    Not included                ADF regressions: 0 lags
```

		Statistic	p-value
Inverse chi-squared(96)	P	146.2396	0.0007
Inverse normal	Z	-5.0082	0.0000
Inverse logit t(244)	L*	-4.6531	0.0000
Modified inv. chi-squared	Pm	3.6257	0.0001

```
-----
P statistic requires number of panels to be finite.
Other statistics are suitable for finite or infinite number of panels.
-----
```

**Reject the null hypothesis that all the panels contain a unit root.**  
**=> stationary**

STATE GOVERNMENT EXPENDITURES



Fisher-type unit-root test for ln\_publicwelfare  
Based on augmented Dickey-Fuller tests

```
-----
Ho: All panels contain unit roots      Number of panels =    48
Ha: At least one panel is stationary   Number of periods =    44
```

```
AR parameter: Panel-specific          Asymptotics: T -> Infinity
Panel means:   Included
Time trend:    Included
Drift term:    Not included            ADF regressions: 0 lags
-----
```

		Statistic	p-value
Inverse chi-squared(96)	P	143.3923	0.0012
Inverse normal	Z	-0.6985	0.2424
Inverse logit t(244)	L*	-1.2383	0.1084
Modified inv. chi-squared	Pm	3.4202	0.0003

P statistic requires number of panels to be finite.  
Other statistics are suitable for finite or infinite number of panels.

**Reject the null hypothesis that all the panels contain a unit root.**  
**=> stationary**

### ~Hospitals

```
. xtunitroot fisher ln_hospitals, dfuller lags(0) trend
(1 missing value generated)
```

Fisher-type unit-root test for ln\_hospitals  
Based on augmented Dickey-Fuller tests

```
-----
Ho: All panels contain unit roots      Number of panels      =    48
Ha: At least one panel is stationary   Avg. number of periods =  43.98
```

```
AR parameter: Panel-specific          Asymptotics: T -> Infinity
Panel means:   Included
Time trend:    Included
Drift term:    Not included            ADF regressions: 0 lags
-----
```

		Statistic	p-value
Inverse chi-squared(96)	P	91.2490	0.6180
Inverse normal	Z	0.5814	0.7195
Inverse logit t(244)	L*	0.4943	0.6892
Modified inv. chi-squared	Pm	-0.3429	0.6342

P statistic requires number of panels to be finite.  
Other statistics are suitable for finite or infinite number of panels.

**Fail to reject the null hypothesis that all the panels contain a unit root.**  
**=> nonstationary**

### ~Health

```
. xtunitroot fisher ln_health, dfuller lags(0) trend
```

Fisher-type unit-root test for ln\_health  
Based on augmented Dickey-Fuller tests

```
-----
Ho: All panels contain unit roots      Number of panels =    48
Ha: At least one panel is stationary   Number of periods =    44
```

```
AR parameter: Panel-specific          Asymptotics: T -> Infinity
Panel means:   Included
Time trend:    Included
```

Drift term: Not included

ADF regressions: 0 lags

		Statistic	p-value
Inverse chi-squared(96)	P	42.3491	1.0000
Inverse normal	Z	6.7919	1.0000
Inverse logit t(244)	L*	6.8868	1.0000
Modified inv. chi-squared Pm		-3.8719	0.9999
P statistic requires number of panels to be finite. Other statistics are suitable for finite or infinite number of panels.			

**Fail to reject the null hypothesis that all the panels contain a unit root.  
=> nonstationary**

### ~Corrections

. xtunitroot fisher ln\_correction, dfuller lags(0) trend

Fisher-type unit-root test for ln\_correction  
Based on augmented Dickey-Fuller tests

Ho: All panels contain unit roots                      Number of panels =        48  
Ha: At least one panel is stationary                  Number of periods =      44

AR parameter: Panel-specific                              Asymptotics: T -> Infinity  
Panel means: Included  
Time trend: Included  
Drift term: Not included                                      ADF regressions: 0 lags

		Statistic	p-value
Inverse chi-squared(96)	P	78.4685	0.9037
Inverse normal	Z	9.2428	1.0000
Inverse logit t(234)	L*	8.7687	1.0000
Modified inv. chi-squared Pm		-1.2652	0.8971
P statistic requires number of panels to be finite. Other statistics are suitable for finite or infinite number of panels.			

**Fail to reject the null hypothesis that all the panels contain a unit root.  
=> nonstationary**

### ~Police

. xtunitroot fisher ln\_police, dfuller lags(0) trend

Fisher-type unit-root test for ln\_police  
Based on augmented Dickey-Fuller tests

Ho: All panels contain unit roots                      Number of panels =        48  
Ha: At least one panel is stationary                  Number of periods =      44

AR parameter: Panel-specific                              Asymptotics: T -> Infinity  
Panel means: Included  
Time trend: Included  
Drift term: Not included                                      ADF regressions: 0 lags

		Statistic	p-value
Inverse chi-squared(96)	P	214.6505	0.0000
Inverse normal	Z	-3.3690	0.0004
Inverse logit t(244)	L*	-5.1939	0.0000
Modified inv. chi-squared Pm		8.5629	0.0000

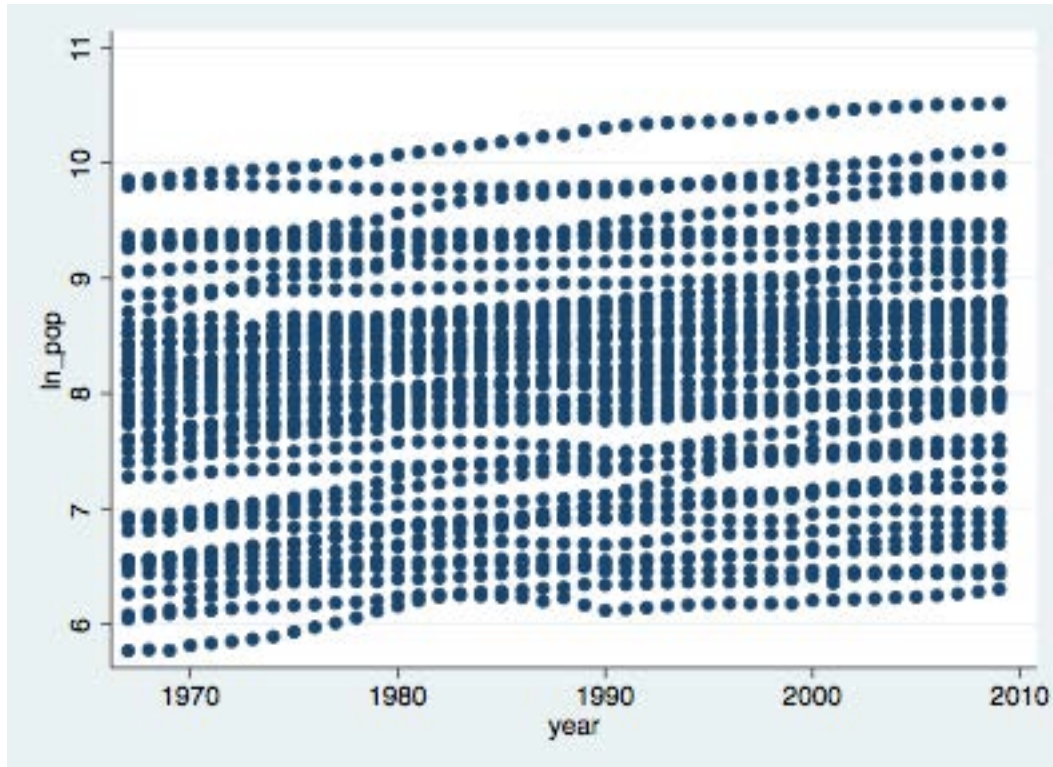
P statistic requires number of panels to be finite.

Other statistics are suitable for finite or infinite number of panels.

-----

Reject the null hypothesis that all the panels contain a unit root.  
=> stationary

## State Population



```
. xtunitroot fisher ln_pop, dfuller lags(0) trend
(48 missing values generated)
```

Fisher-type unit-root test for ln\_pop  
Based on augmented Dickey-Fuller tests

-----  
Ho: All panels contain unit roots                      Number of panels =        48  
Ha: At least one panel is stationary                Number of periods =      43

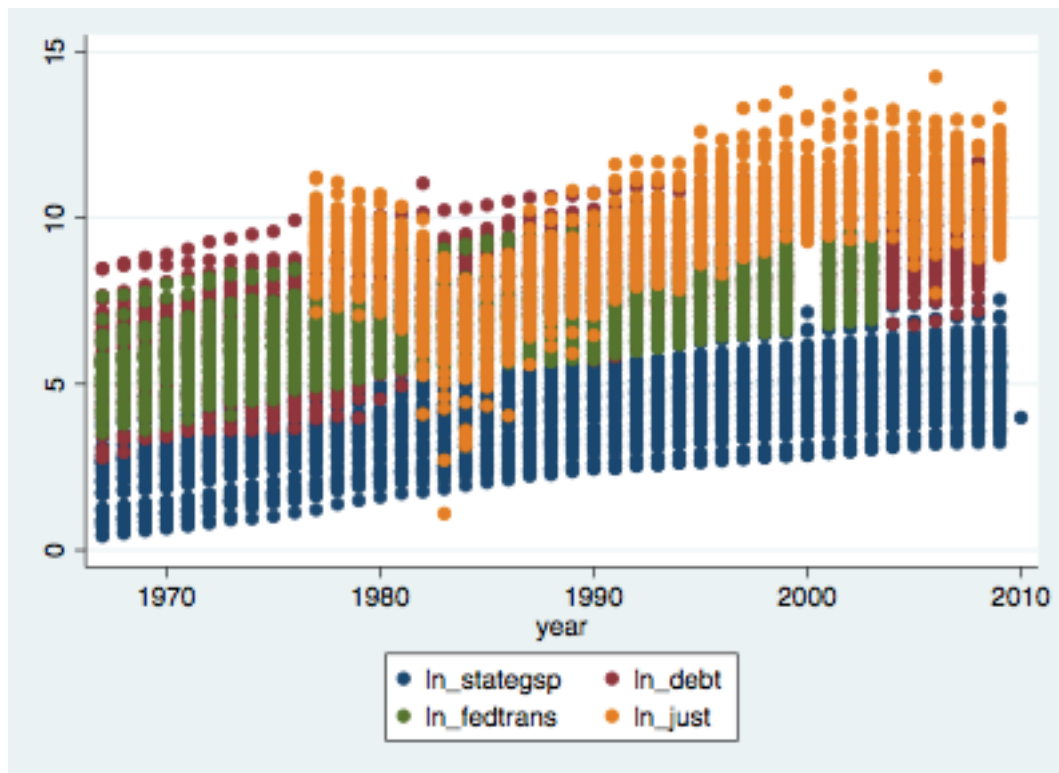
AR parameter: Panel-specific                      Asymptotics: T -> Infinity  
Panel means:    Included  
Time trend:     Included  
Drift term:     Not included                      ADF regressions: 0 lags

		Statistic	p-value
Inverse chi-squared(96)	P	96.5086	0.4662
Inverse normal	Z	3.9383	1.0000
Inverse logit t(239)	L*	2.8717	0.9978
Modified inv. chi-squared	Pm	0.0367	0.4854

-----  
P statistic requires number of panels to be finite.  
Other statistics are suitable for finite or infinite number of panels.  
-----

Fail to reject the null hypothesis that all the panels contain a unit root.  
=> nonstationary

## STATE FINANCES AND OUTPUT



### ~Gross State Product (GSP)

```
. xtunitroot fisher ln_statgsp, dfuller lags(0) trend
(48 missing values generated)
```

Fisher-type unit-root test for ln\_statgsp  
Based on augmented Dickey-Fuller tests

```
-----
Ho: All panels contain unit roots      Number of panels      =      48
Ha: At least one panel is stationary   Avg. number of periods =  43.00
```

```
AR parameter: Panel-specific           Asymptotics: T -> Infinity
Panel means:   Included
Time trend:    Included
Drift term:    Not included             ADF regressions: 0 lags
```

		Statistic	p-value
Inverse chi-squared(96)	P	6.7767	1.0000
Inverse normal	Z	12.7304	1.0000
Inverse logit t(214)	L*	13.9424	1.0000
Modified inv. chi-squared	Pm	-6.4391	1.0000

P statistic requires number of panels to be finite.  
Other statistics are suitable for finite or infinite number of panels.

Fail to reject the null hypothesis that all the panels contain a unit root.  
=> nonstationary

### ~Debt

```
. xtunitroot fisher ln_debt, dfuller lags(0) trend
(144 missing values generated)
```

Fisher-type unit-root test for ln\_debt  
Based on augmented Dickey-Fuller tests

```
-----
Ho: All panels contain unit roots          Number of panels =    48
Ha: At least one panel is stationary       Number of periods =   41
```

```
AR parameter: Panel-specific              Asymptotics: T -> Infinity
Panel means:   Included
Time trend:    Included
Drift term:    Not included                ADF regressions: 0 lags
```

		Statistic	p-value
Inverse chi-squared(96)	P	114.2241	0.0990
Inverse normal	Z	4.0875	1.0000
Inverse logit t(244)	L*	3.1070	0.9989
Modified inv. chi-squared Pm		1.3152	0.0942

P statistic requires number of panels to be finite.  
Other statistics are suitable for finite or infinite number of panels.

**Fail to reject the null hypothesis that all the panels contain a unit root.**  
**=> nonstationary**

### ~Federal Transfer of Funding

```
. xtunitroot fisher ln_fedtrans, dfuller lags(0) trend
(384 missing values generated)
```

Fisher-type unit-root test for ln\_fedtrans  
Based on augmented Dickey-Fuller tests

```
-----
Ho: All panels contain unit roots          Number of panels =    48
Ha: At least one panel is stationary       Number of periods =   36
```

```
AR parameter: Panel-specific              Asymptotics: T -> Infinity
Panel means:   Included
Time trend:    Included
Drift term:    Not included                ADF regressions: 0 lags
```

		Statistic	p-value
Inverse chi-squared(96)	P	201.8959	0.0000
Inverse normal	Z	-4.1439	0.0000
Inverse logit t(244)	L*	-5.5848	0.0000
Modified inv. chi-squared Pm		7.6424	0.0000

P statistic requires number of panels to be finite.  
Other statistics are suitable for finite or infinite number of panels.

**Reject the null hypothesis that all the panels contain a unit root.**  
**=> stationary**

### ~Department of Justice Spending in the State

```
. xtunitroot fisher ln_just, dfuller lags(0)
(530 missing values generated)
```

Fisher-type unit-root test for ln\_just  
Based on augmented Dickey-Fuller tests

Ho: All panels contain unit roots                      Number of panels                      =        48  
Ha: At least one panel is stationary                      Avg. number of periods =    32.96

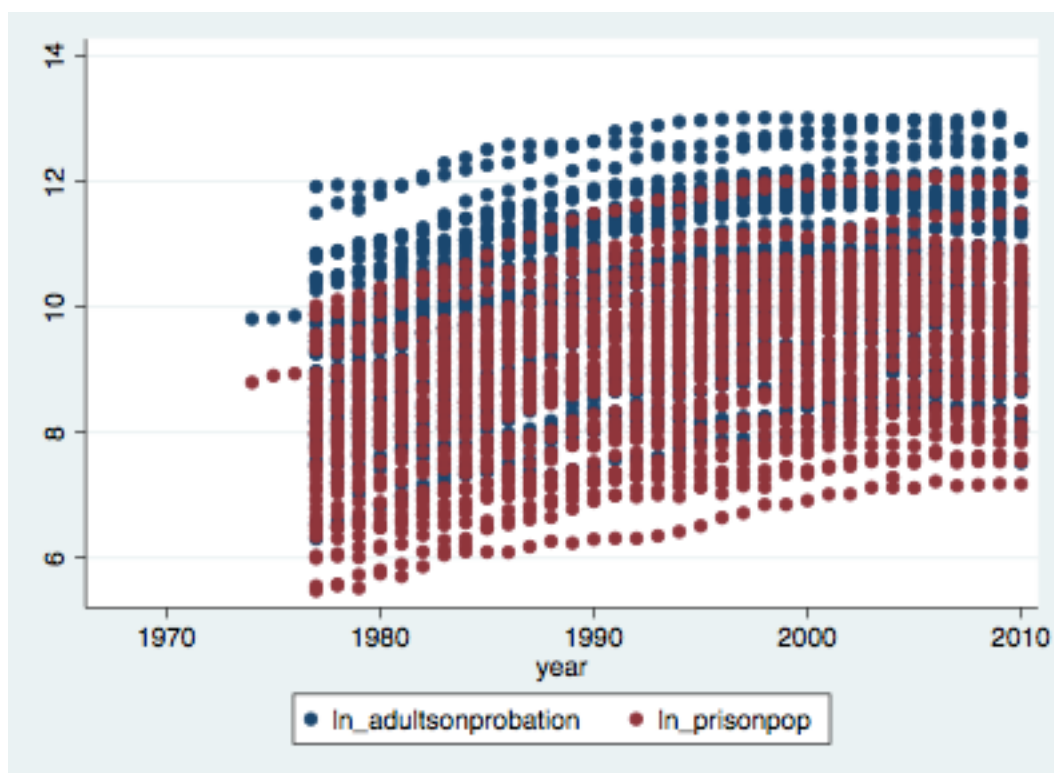
AR parameter: Panel-specific                      Asymptotics: T -> Infinity  
Panel means:    Included  
Time trend:     Not included  
Drift term:      Not included                      ADF regressions: 0 lags

		Statistic	p-value
Inverse chi-squared(96)	P	34.5351	1.0000
Inverse normal	Z	4.7089	1.0000
Inverse logit t(244)	L*	4.2758	1.0000
Modified inv. chi-squared	Pm	-4.4359	1.0000

P statistic requires number of panels to be finite.  
Other statistics are suitable for finite or infinite number of panels.

**Fail to reject the null hypothesis that all the panels contain a unit root.**  
**=> nonstationary**

## PRISON RELATED STATISTICS



### ~Adults on Probation in the State

. xtunitroot fisher ln\_adultsonprobation, dfuller lags(0) trend  
(495 missing values generated)

Fisher-type unit-root test for ln\_adultsonprobation  
Based on augmented Dickey-Fuller tests

Ho: All panels contain unit roots                      Number of panels                      =        48  
Ha: At least one panel is stationary                      Avg. number of periods =    33.69



AR parameter: Panel-specific                      Asymptotics: T -> Infinity  
Panel means: Included  
Time trend: Included  
Drift term: Not included                      ADF regressions: 0 lags

		Statistic	p-value
Inverse chi-squared(96)	P	64.0805	0.9950
Inverse normal	Z	7.4227	1.0000
Inverse logit t(194)	L*	7.2999	1.0000
Modified inv. chi-squared Pm		-2.3036	0.9894

P statistic requires number of panels to be finite.  
Other statistics are suitable for finite or infinite number of panels.

**Fail to reject the null hypothesis that all the panels contain a unit root.**  
=> nonstationary

### ~State Prison Population

. xtunitroot fisher ln\_prisonpop, dfuller lags(0) trend  
(480 missing values generated)

Fisher-type unit-root test for ln\_prisonpop  
Based on augmented Dickey-Fuller tests

Ho: All panels contain unit roots                      Number of panels = 48  
Ha: At least one panel is stationary                      Avg. number of periods = 34.00

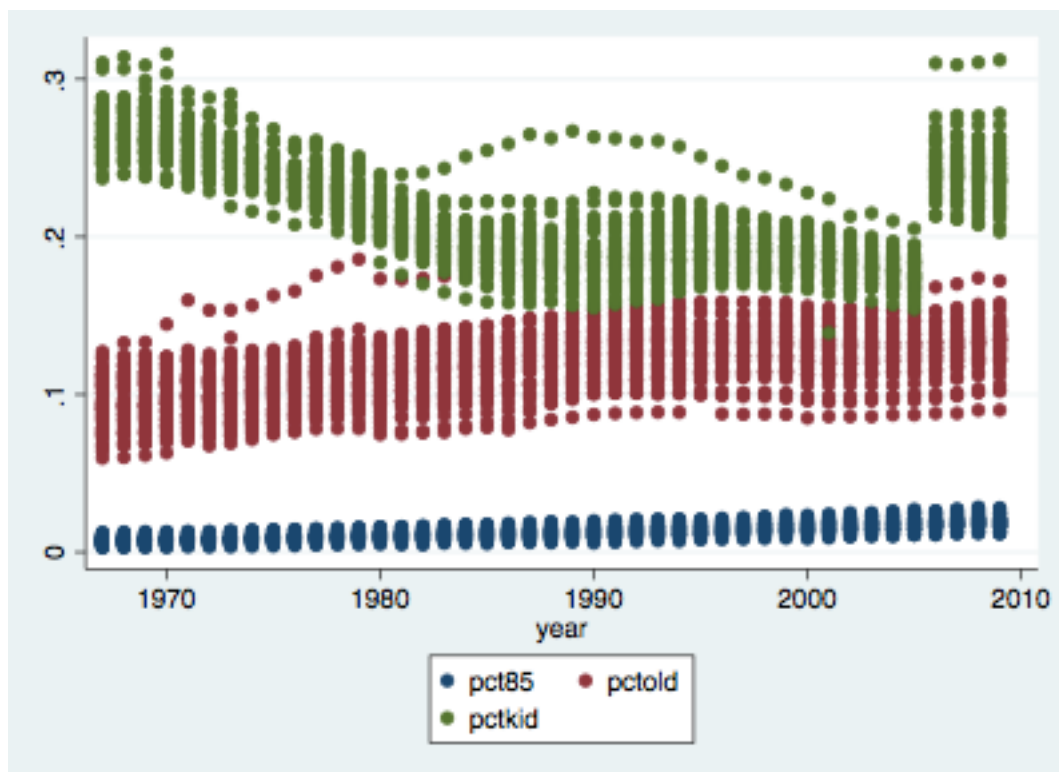
AR parameter: Panel-specific                      Asymptotics: T -> Infinity  
Panel means: Included  
Time trend: Included  
Drift term: Not included                      ADF regressions: 0 lags

		Statistic	p-value
Inverse chi-squared(96)	P	22.0076	1.0000
Inverse normal	Z	9.4937	1.0000
Inverse logit t(239)	L*	10.0475	1.0000
Modified inv. chi-squared Pm		-5.3399	1.0000

P statistic requires number of panels to be finite.  
Other statistics are suitable for finite or infinite number of panels.

**Fail to reject the null hypothesis that all the panels contain a unit root.**  
=> nonstationary

### AGE DEMOGRAPHICS



### ~Percentage of the Population over 85

```
. xtunitroot fisher pct85, dfuller lags(0)
(48 missing values generated)
```

Fisher-type unit-root test for pct85  
Based on augmented Dickey-Fuller tests

```
-----
Ho: All panels contain unit roots          Number of panels =      48
Ha: At least one panel is stationary       Number of periods =     43
```

```
AR parameter: Panel-specific              Asymptotics: T -> Infinity
Panel means:   Included
Time trend:    Not included
Drift term:    Not included                ADF regressions: 0 lags
```

		Statistic	p-value
Inverse chi-squared(96)	P	13.2140	1.0000
Inverse normal	Z	10.9140	1.0000
Inverse logit t(244)	L*	11.3070	1.0000
Modified inv. chi-squared	Pm	-5.9746	1.0000

P statistic requires number of panels to be finite.  
Other statistics are suitable for finite or infinite number of panels.

**Fail to reject the null hypothesis that all the panels contain a unit root.**  
**=> nonstationary**

### ~Percentage of the Population over 65

```
. xtunitroot fisher pctold, dfuller lags(0) trend
(48 missing values generated)
```

Fisher-type unit-root test for pctold  
Based on augmented Dickey-Fuller tests

```
-----
Ho: All panels contain unit roots      Number of panels =      48
Ha: At least one panel is stationary   Number of periods =     43
```

```
AR parameter: Panel-specific           Asymptotics: T -> Infinity
Panel means:   Included
Time trend:    Included
Drift term:    Not included             ADF regressions: 0 lags
-----
```

		Statistic	p-value
Inverse chi-squared(96)	P	77.3286	0.9188
Inverse normal	Z	4.0906	1.0000
Inverse logit t(239)	L*	3.8782	0.9999
Modified inv. chi-squared	Pm	-1.3475	0.9111

P statistic requires number of panels to be finite.  
Other statistics are suitable for finite or infinite number of panels.

**Fail to reject the null hypothesis that all the panels contain a unit root.**  
**=> nonstationary**

#### ~Percentage of the Population between 5-17

```
. xtunitroot fisher pctkid, dfuller lags(0) trend
(48 missing values generated)
```

Fisher-type unit-root test for pctkid  
Based on augmented Dickey-Fuller tests

```
-----
Ho: All panels contain unit roots      Number of panels =      48
Ha: At least one panel is stationary   Number of periods =     43
```

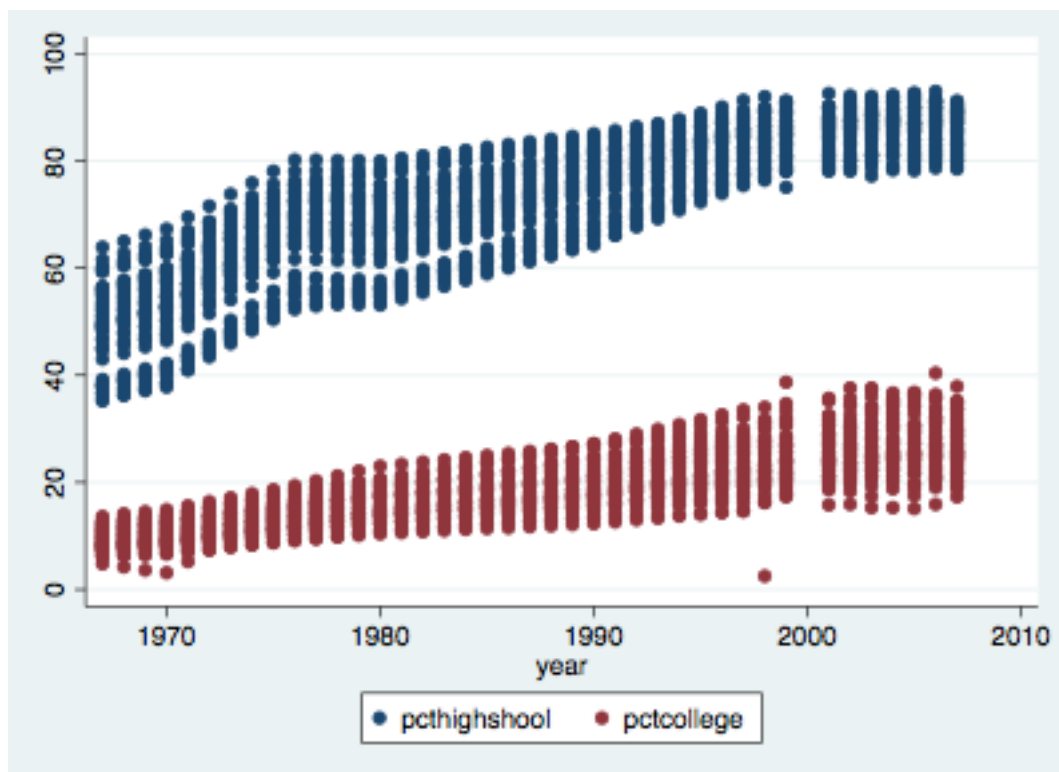
```
AR parameter: Panel-specific           Asymptotics: T -> Infinity
Panel means:   Included
Time trend:    Included
Drift term:    Not included             ADF regressions: 0 lags
-----
```

		Statistic	p-value
Inverse chi-squared(96)	P	3.6677	1.0000
Inverse normal	Z	13.2208	1.0000
Inverse logit t(244)	L*	13.7289	1.0000
Modified inv. chi-squared	Pm	-6.6635	1.0000

P statistic requires number of panels to be finite.  
Other statistics are suitable for finite or infinite number of panels.

**Fail to reject the null hypothesis that all the panels contain a unit root.**  
**=> nonstationary**

#### EDUCATION DEMOGRAPHICS



### ~Percentage of the Population with a High School Diploma

```
. xtunitroot fisher pcthighshool, dfuller lags(0) trend
(192 missing values generated)
```

Fisher-type unit-root test for pcthighshool  
Based on augmented Dickey-Fuller tests

```
-----
Ho: All panels contain unit roots           Number of panels =      48
Ha: At least one panel is stationary        Number of periods =     40
```

```
AR parameter: Panel-specific                Asymptotics: T -> Infinity
Panel means:   Included
Time trend:    Included
Drift term:    Not included                 ADF regressions: 0 lags
```

		Statistic	p-value
Inverse chi-squared(96)	P	11.0299	1.0000
Inverse normal	Z	10.3747	1.0000
Inverse logit t(244)	L*	10.4831	1.0000
Modified inv. chi-squared	Pm	-6.1322	1.0000

P statistic requires number of panels to be finite.  
Other statistics are suitable for finite or infinite number of panels.

**Fail to reject the null hypothesis that all the panels contain a unit root.  
=> nonstationary**

### ~Percentage of the Population with a College Degree

```
. xtunitroot fisher pctcollege, dfuller lags(0) trend
(192 missing values generated)
```

Fisher-type unit-root test for pctcollege  
Based on augmented Dickey-Fuller tests

```
-----
Ho: All panels contain unit roots      Number of panels =    48
Ha: At least one panel is stationary   Number of periods =   40
```

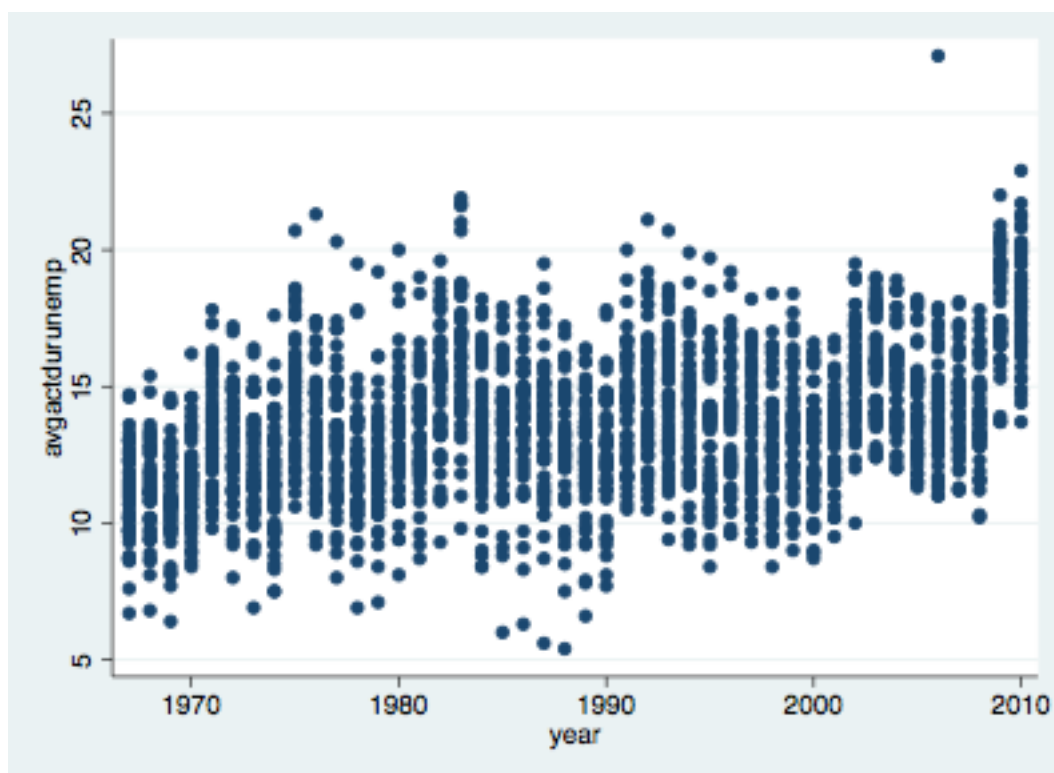
```
AR parameter: Panel-specific           Asymptotics: T -> Infinity
Panel means:   Included
Time trend:    Included
Drift term:    Not included             ADF regressions: 0 lags
-----
```

		Statistic	p-value
Inverse chi-squared(96)	P	217.1277	0.0000
Inverse normal	Z	-3.9651	0.0000
Inverse logit t(239)	L*	-5.3444	0.0000
Modified inv. chi-squared	Pm	8.7416	0.0000

```
-----
P statistic requires number of panels to be finite.
Other statistics are suitable for finite or infinite number of panels.
-----
```

**Reject the null hypothesis that all the panels contain a unit root.**  
**=> stationary**

AVERAGE ACTUAL DURATION OF UNEMPLOYMENT BENEFITS in weeks



```
. xtunitroot fisher avgactdurunemp, dfuller lags(0) trend
```

Fisher-type unit-root test for avgactdurunemp

Based on augmented Dickey-Fuller tests

```
-----
Ho: All panels contain unit roots      Number of panels =    48
Ha: At least one panel is stationary   Number of periods =    44

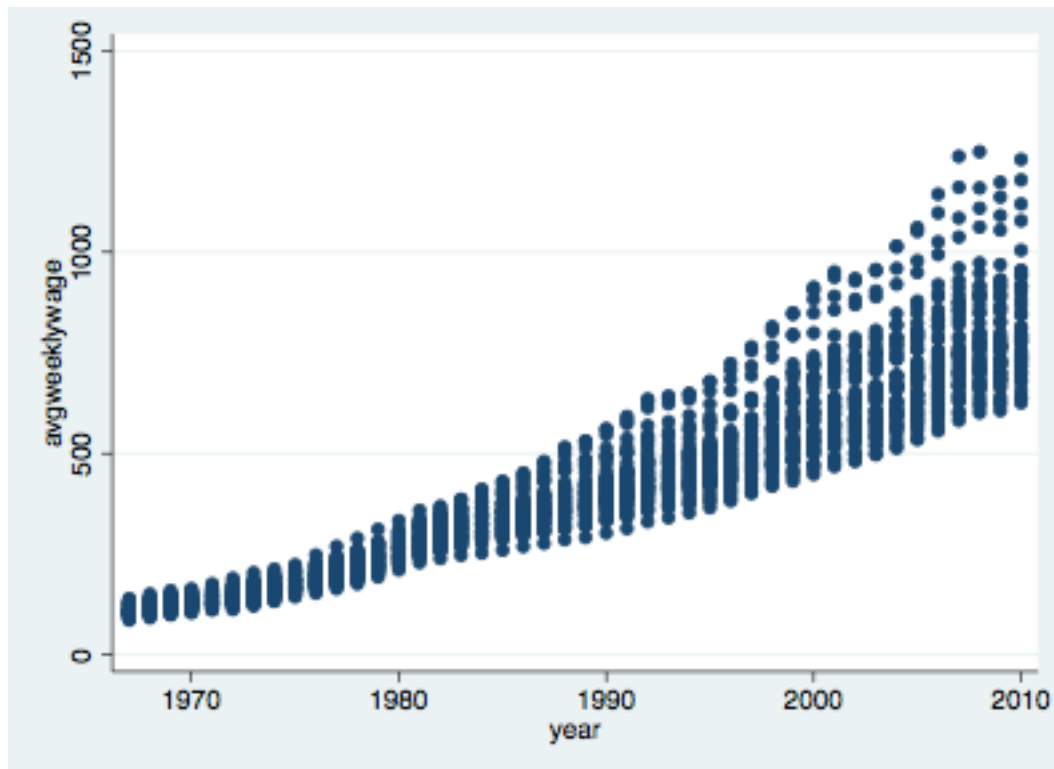
AR parameter: Panel-specific           Asymptotics: T -> Infinity
Panel means:   Included
Time trend:    Included
Drift term:    Not included              ADF regressions: 0 lags
-----
```

		Statistic	p-value
Inverse chi-squared(96)	P	306.3697	0.0000
Inverse normal	Z	-10.4649	0.0000
Inverse logit t(244)	L*	-11.5001	0.0000
Modified inv. chi-squared Pm		15.1821	0.0000

P statistic requires number of panels to be finite.  
Other statistics are suitable for finite or infinite number of panels.

**Reject the null hypothesis that all the panels contain a unit root.**  
**=> stationary**

## AVERAGE WEEKLY WAGE



```
. xtunitroot fisher avgweeklywage, dfuller lags(0) trend
```

Fisher-type unit-root test for avgweeklywage  
Based on augmented Dickey-Fuller tests

```
-----
Ho: All panels contain unit roots      Number of panels =    48
Ha: At least one panel is stationary   Number of periods =    44
```

```

AR parameter: Panel-specific
Panel means:   Included
Time trend:    Included
Drift term:    Not included
Asymptotics: T -> Infinity
ADF regressions: 0 lags

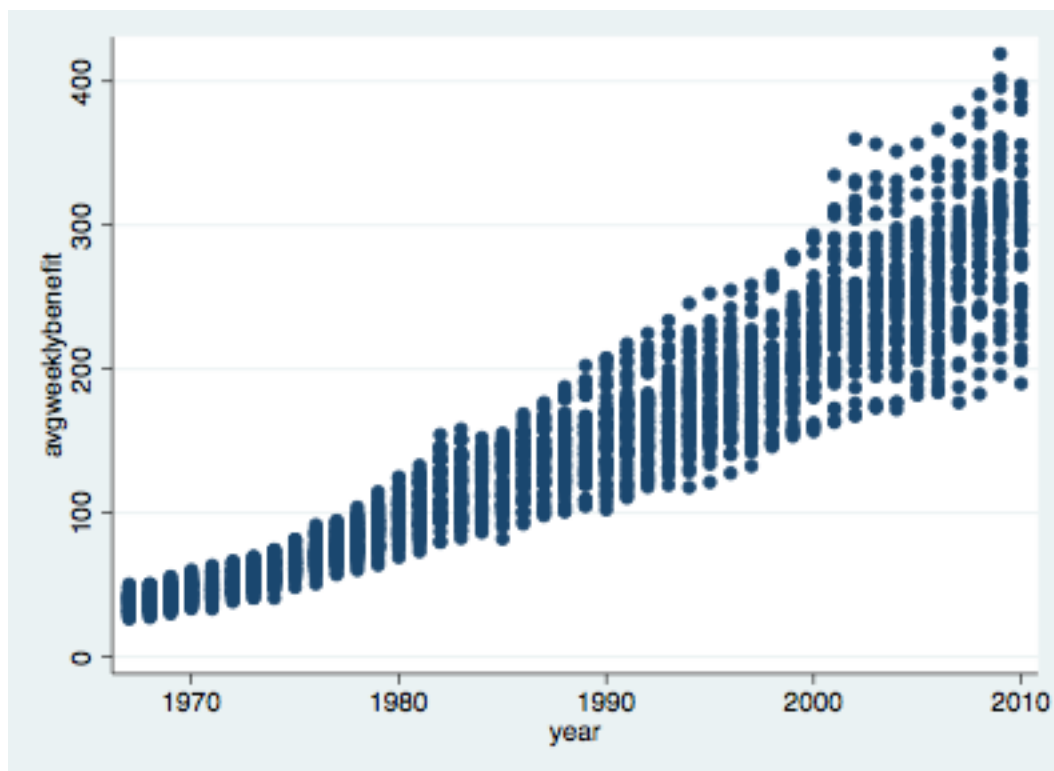
```

		Statistic	p-value
Inverse chi-squared(96)	P	61.0690	0.9979
Inverse normal	Z	2.8931	0.9981
Inverse logit t(239)	L*	3.0378	0.9987
Modified inv. chi-squared Pm		-2.5209	0.9941

P statistic requires number of panels to be finite.  
Other statistics are suitable for finite or infinite number of panels.

Fail to reject the null hypothesis that all the panels contain a unit root.  
=> nonstationary

## AVERAGE WEEKLY UNEMPLOYMENT BENEFITS



```
. xtunitroot fisher avgweeklybenefit, dfuller lags(0) trend
```

Fisher-type unit-root test for avgweeklybenefit  
Based on augmented Dickey-Fuller tests

```

-----
Ho: All panels contain unit roots      Number of panels =      48
Ha: At least one panel is stationary   Number of periods =     44

```

```

AR parameter: Panel-specific
Panel means:   Included
Time trend:    Included
Drift term:    Not included
Asymptotics: T -> Infinity
ADF regressions: 0 lags

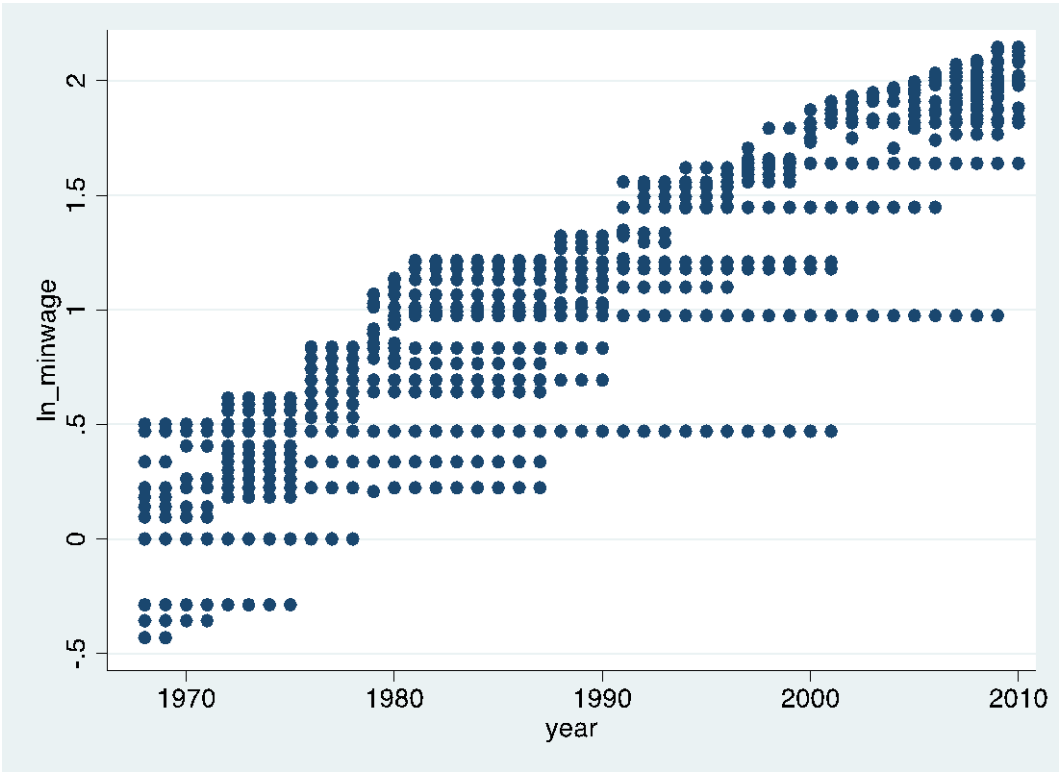
```

		Statistic	p-value
Inverse chi-squared(96)	P	100.4050	0.3590
Inverse normal	Z	0.1059	0.5421
Inverse logit t(239)	L*	0.1105	0.5439
Modified inv. chi-squared Pm		0.3179	0.3753

P statistic requires number of panels to be finite.  
Other statistics are suitable for finite or infinite number of panels.

Fail to reject the null hypothesis that all the panels contain a unit root.  
=> nonstationary

MINIMUM WAGE



```
. xtunitroot fisher ln_minwage, dfuller lags(0) trend
(48 missing values generated)

Fisher-type unit-root test for ln_minwage
Based on augmented Dickey-Fuller tests
-----
Ho: All panels contain unit roots          Number of panels =      48
Ha: At least one panel is stationary        Number of periods =     43

AR parameter: Panel-specific                Asymptotics: T -> Infinity
Panel means:   Included
Time trend:    Included
Drift term:    Not included                  ADF regressions: 0 lags
-----
Statistic      p-value
Inverse chi-squared(96)  P      99.3280      0.3876
```



Inverse normal	Z	-1.7858	0.0371
Inverse logit t(244)	L*	-1.6870	0.0464
Modified inv. chi-squared Pm		0.2402	0.4051

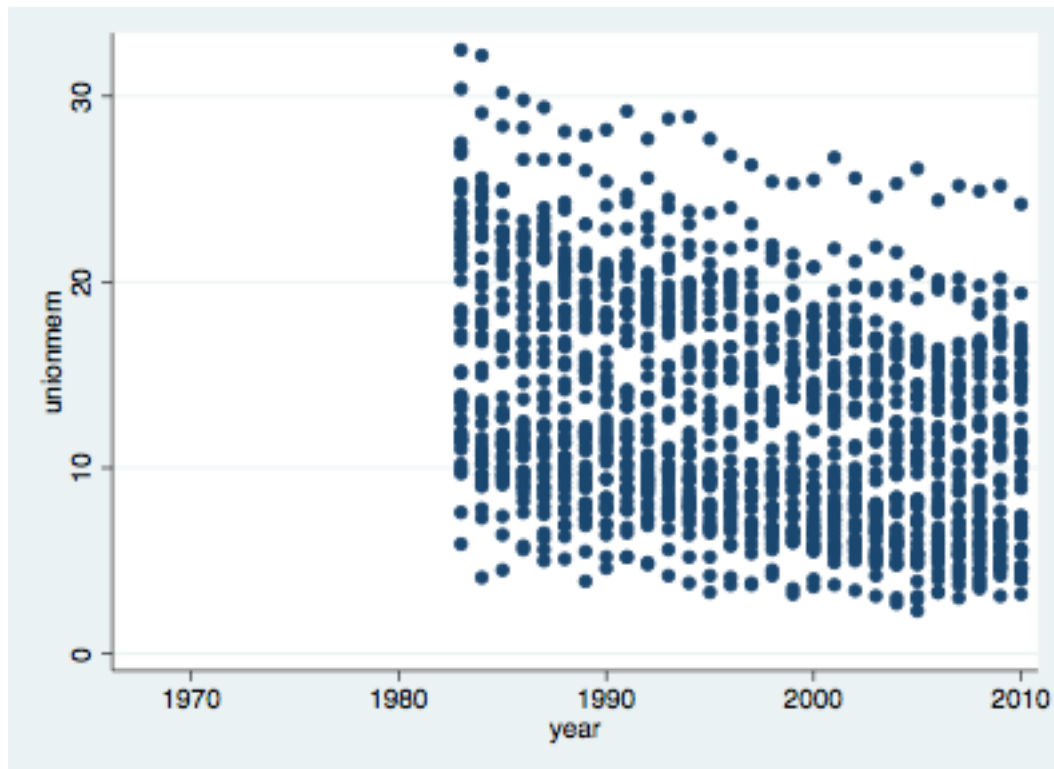
-----

P statistic requires number of panels to be finite.  
 Other statistics are suitable for finite or infinite number of panels.

-----

#### Nonstationary

#### PERCENTAGE OF WORKFORCE WITH UNION MEMBERSHIP



```
. xtunitroot fisher unionmem, dfuller lags(0) trend
(768 missing values generated)
```

Fisher-type unit-root test for unionmem  
 Based on augmented Dickey-Fuller tests

-----

Ho: All panels contain unit roots	Number of panels =	48
Ha: At least one panel is stationary	Number of periods =	28

AR parameter: Panel-specific	Asymptotics: T -> Infinity
Panel means: Included	
Time trend: Included	
Drift term: Not included	ADF regressions: 0 lags

-----

		Statistic	p-value
Inverse chi-squared(96)	P	394.9616	0.0000
Inverse normal	Z	-12.9744	0.0000
Inverse logit t(244)	L*	-15.1089	0.0000
Modified inv. chi-squared Pm		21.5757	0.0000

-----

P statistic requires number of panels to be finite.  
 Other statistics are suitable for finite or infinite number of panels.

-----  
**Reject the null hypothesis that all the panels contain a unit root.**  
**=>Stationary**

## CONSUMER PRICE INDEX (CPI)

. xtunitroot fisher cpi, dfuller lags(0) trend  
 (528 missing values generated)

Fisher-type unit-root test for cpi  
 Based on augmented Dickey-Fuller tests

-----  
 Ho: All panels contain unit roots                      Number of panels =        48  
 Ha: At least one panel is stationary                  Number of periods =      33

AR parameter: Panel-specific                              Asymptotics: T -> Infinity  
 Panel means:    Included  
 Time trend:     Included  
 Drift term:      Not included                              ADF regressions: 0 lags

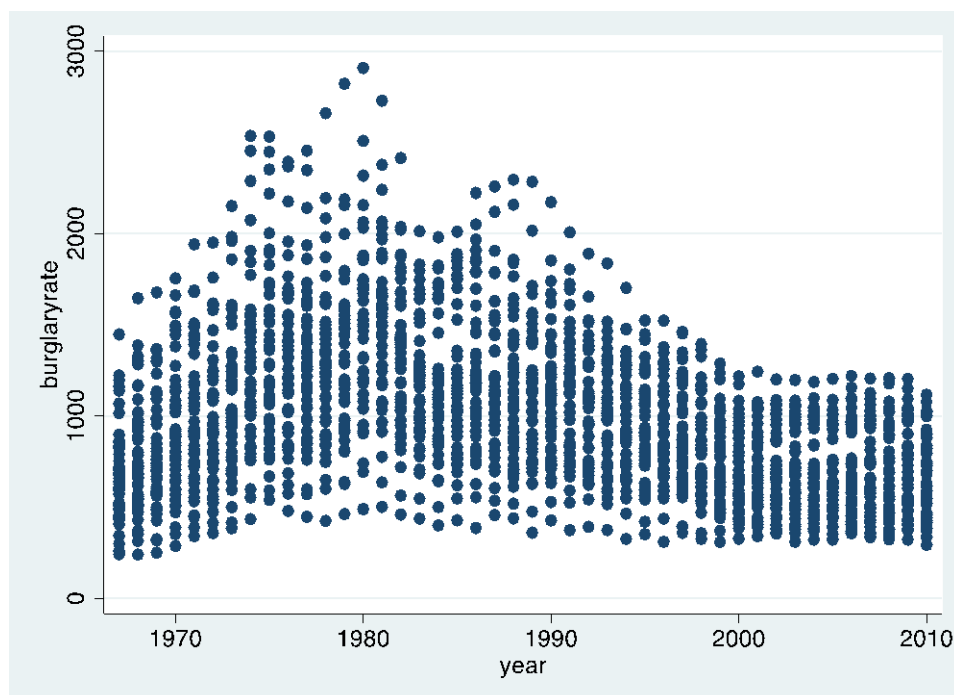
		Statistic	p-value
Inverse chi-squared(96)	P	2265.0036	0.0000
Inverse normal	Z	-44.6730	0.0000
Inverse logit t(244)	L*	-90.3076	0.0000
Modified inv. chi-squared	Pm	156.5343	0.0000

-----  
 P statistic requires number of panels to be finite.  
 Other statistics are suitable for finite or infinite number of panels.

-----  
**Reject the null hypothesis that all the panels contain a unit root.**  
**=> stationary**

## CRIME RATE STATISTICS

~Burglary Rate



```
. xtunitroot fisher burglaryrate, dfuller lags(0)
```

Fisher-type unit-root test for burglaryrate  
Based on augmented Dickey-Fuller tests

```
-----
Ho: All panels contain unit roots      Number of panels =      48
Ha: At least one panel is stationary   Number of periods =     44
```

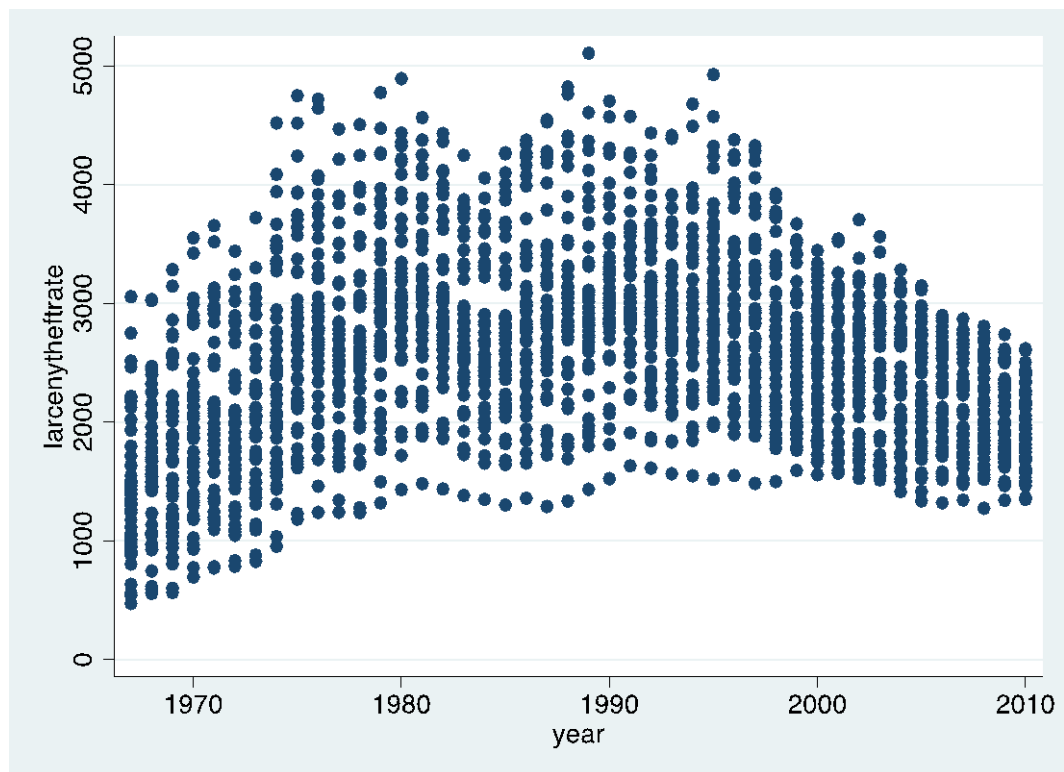
```
AR parameter: Panel-specific          Asymptotics: T -> Infinity
Panel means:   Included
Time trend:    Not included
Drift term:    Not included            ADF regressions: 0 lags
```

```
-----
                        Statistic      p-value
-----
Inverse chi-squared(96)  P           75.2696      0.9419
Inverse normal           Z           2.1857      0.9856
Inverse logit t(244)     L*          2.0315      0.9784
Modified inv. chi-squared Pm -1.4961      0.9327
-----
```

```
P statistic requires number of panels to be finite.
Other statistics are suitable for finite or infinite number of panels.
-----
```

**Nonstationary**

~Larceny Theft Rate



```
. xtunitroot fisher larcenytheft rate, dfuller lags(0)
```

Fisher-type unit-root test for **larcenytheft rate**

Based on augmented Dickey-Fuller tests

```
-----
Ho: All panels contain unit roots           Number of panels =      48
Ha: At least one panel is stationary        Number of periods =     44
```

```
AR parameter: Panel-specific                Asymptotics: T -> Infinity
Panel means:   Included
Time trend:    Not included
Drift term:    Not included                 ADF regressions: 0 lags
```

```
-----
                        Statistic      p-value
-----
Inverse chi-squared(96)  P           142.0195    0.0016
Inverse normal           Z            -3.5075    0.0002
Inverse logit t(244)     L*          -3.3315    0.0005
Modified inv. chi-squared Pm      3.3212    0.0004
-----
```

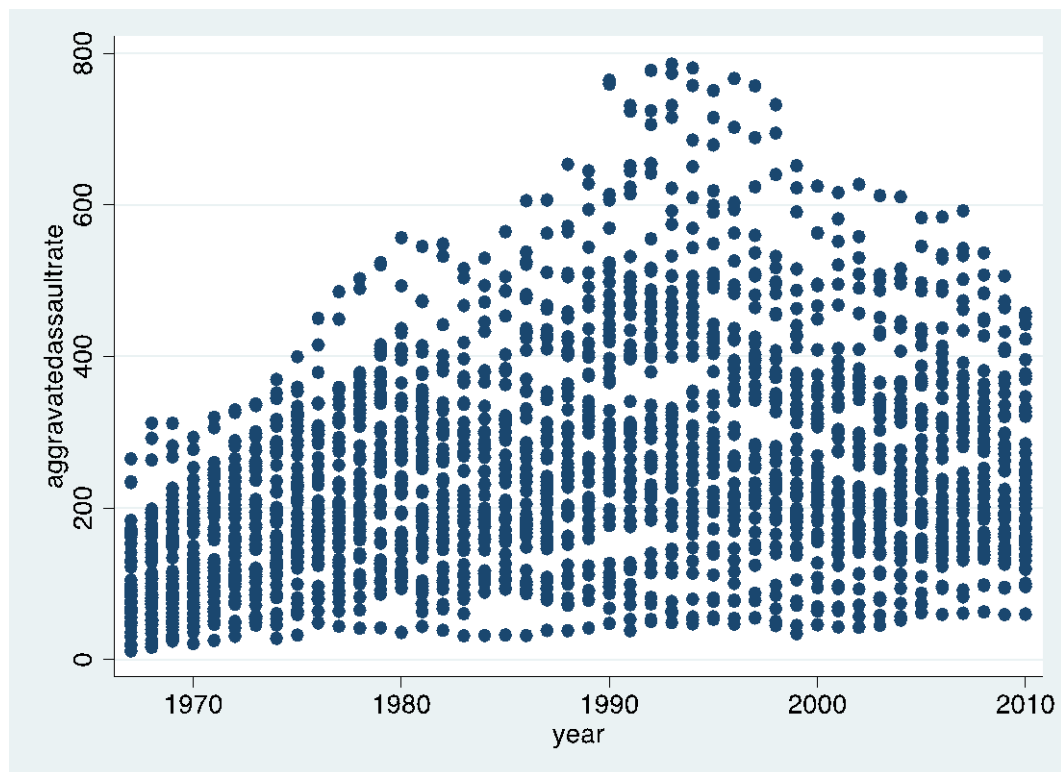
P statistic requires number of panels to be finite.

Other statistics are suitable for finite or infinite number of panels.

```
-----
Reject the null hypothesis that all the panels contain a unit root.
```

```
=> stationary
```

```
~Aggravated Assault Rate
```



```
. xtunitroot fisher aggravatedassaultrate, dfuller lags(0)
```

Fisher-type unit-root test for aggravatedassaultrate  
Based on augmented Dickey-Fuller tests

```
-----
Ho: All panels contain unit roots      Number of panels =    48
Ha: At least one panel is stationary   Number of periods =   44
```

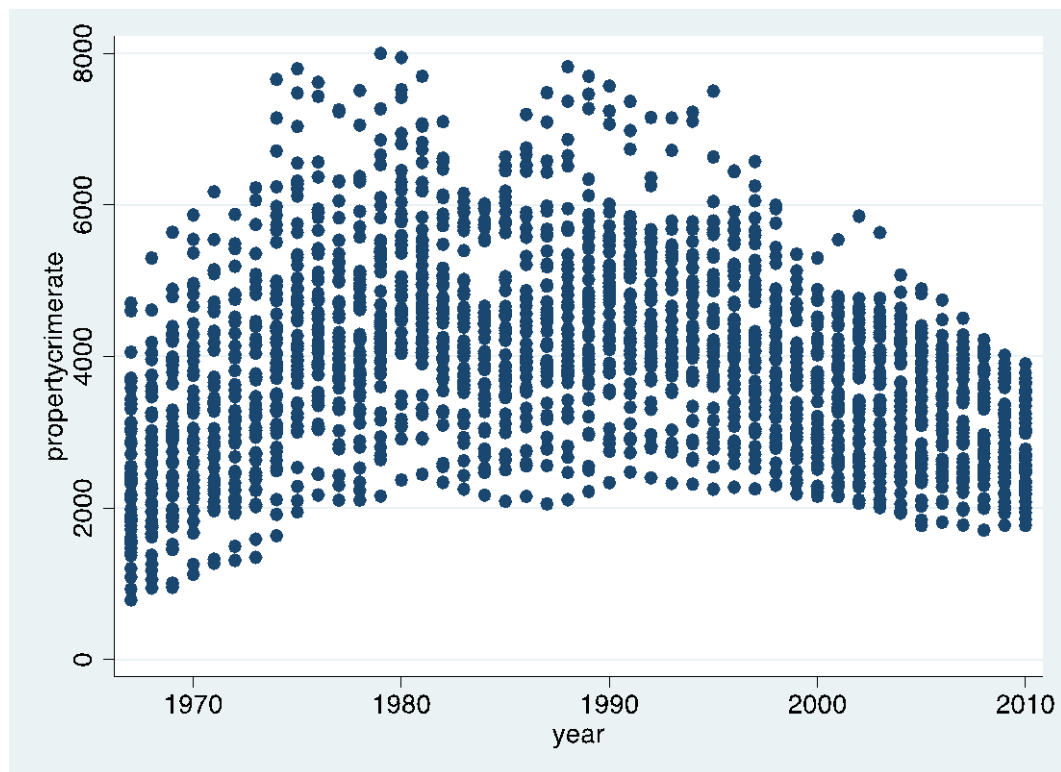
```
AR parameter: Panel-specific           Asymptotics: T -> Infinity
Panel means:   Included
Time trend:    Not included
Drift term:    Not included             ADF regressions: 0 lags
-----
```

		Statistic	p-value
Inverse chi-squared(96)	P	116.2495	0.0782
Inverse normal	Z	-2.6642	0.0039
Inverse logit t(244)	L*	-2.4391	0.0077
Modified inv. chi-squared	Pm	1.4614	0.0720

```
-----
P statistic requires number of panels to be finite.
Other statistics are suitable for finite or infinite number of panels.
-----
```

Fail to reject the null hypothesis that all the panels contain a unit root.  
=> nonstationary

~Property Crime Rate



```
. xtunitroot fisher propertycrimerate, dfuller lags(0)
```

Fisher-type unit-root test for propertycrimerate  
Based on augmented Dickey-Fuller tests

```
-----
Ho: All panels contain unit roots      Number of panels =    48
Ha: At least one panel is stationary   Number of periods =   44
```

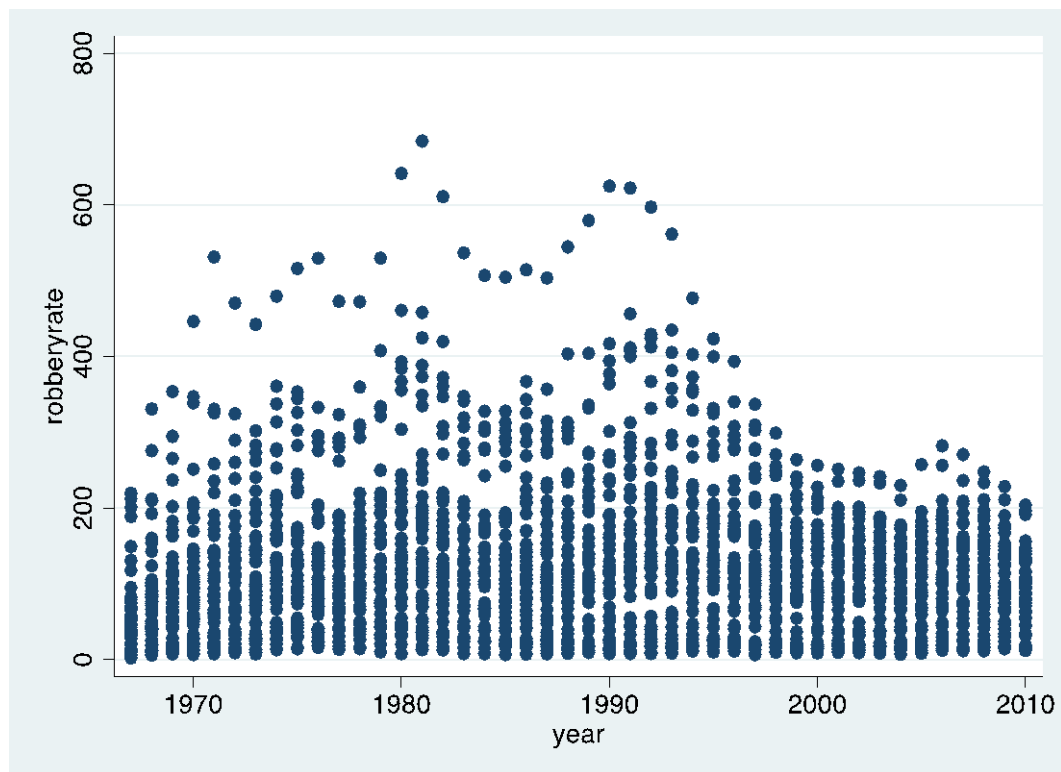
```
AR parameter: Panel-specific           Asymptotics: T -> Infinity
Panel means:   Included
Time trend:    Not included
Drift term:    Not included             ADF regressions: 0 lags
-----
```

		Statistic	p-value
Inverse chi-squared(96)	P	124.5743	0.0265
Inverse normal	Z	-1.5881	0.0561
Inverse logit t(244)	L*	-1.5866	0.0569
Modified inv. chi-squared	Pm	2.0622	0.0196

```
-----
P statistic requires number of panels to be finite.
Other statistics are suitable for finite or infinite number of panels.
-----
```

Reject the null hypothesis that all the panels contain a unit root.  
=> stationary

~Robbery Rate



```
. xtunitroot fisher robberyrate, dfuller lags(0)
```

Fisher-type unit-root test for robberyrate  
Based on augmented Dickey-Fuller tests

-----  
Ho: All panels contain unit roots                      Number of panels =        48  
Ha: At least one panel is stationary                  Number of periods =      44

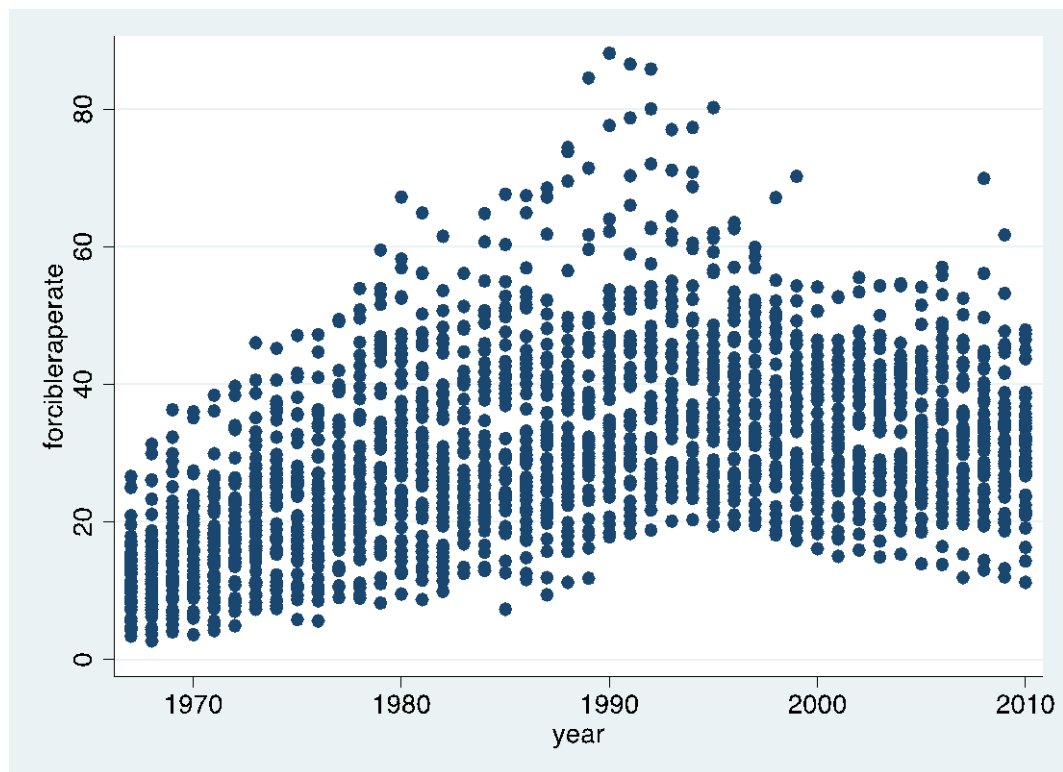
AR parameter: Panel-specific                              Asymptotics: T -> Infinity  
Panel means:    Included  
Time trend:     Not included  
Drift term:      Not included                              ADF regressions: 0 lags

		Statistic	p-value
Inverse chi-squared(96)	P	210.7856	0.0000
Inverse normal	Z	-6.6043	0.0000
Inverse logit t(244)	L*	-6.8868	0.0000
Modified inv. chi-squared	Pm	8.2839	0.0000

-----  
P statistic requires number of panels to be finite.  
Other statistics are suitable for finite or infinite number of panels.  
-----

Reject the null hypothesis that all the panels contain a unit root.  
=> stationary

~Forcible Rape Rate



```
. xtunitroot fisher forcibleraperate, dfuller lags(0)
```

Fisher-type unit-root test for forcibleraperate  
Based on augmented Dickey-Fuller tests

```
-----
Ho: All panels contain unit roots      Number of panels =    48
Ha: At least one panel is stationary   Number of periods =    44
```

```
AR parameter: Panel-specific           Asymptotics: T -> Infinity
Panel means:   Included
Time trend:    Not included
Drift term:    Not included             ADF regressions: 0 lags
-----
```

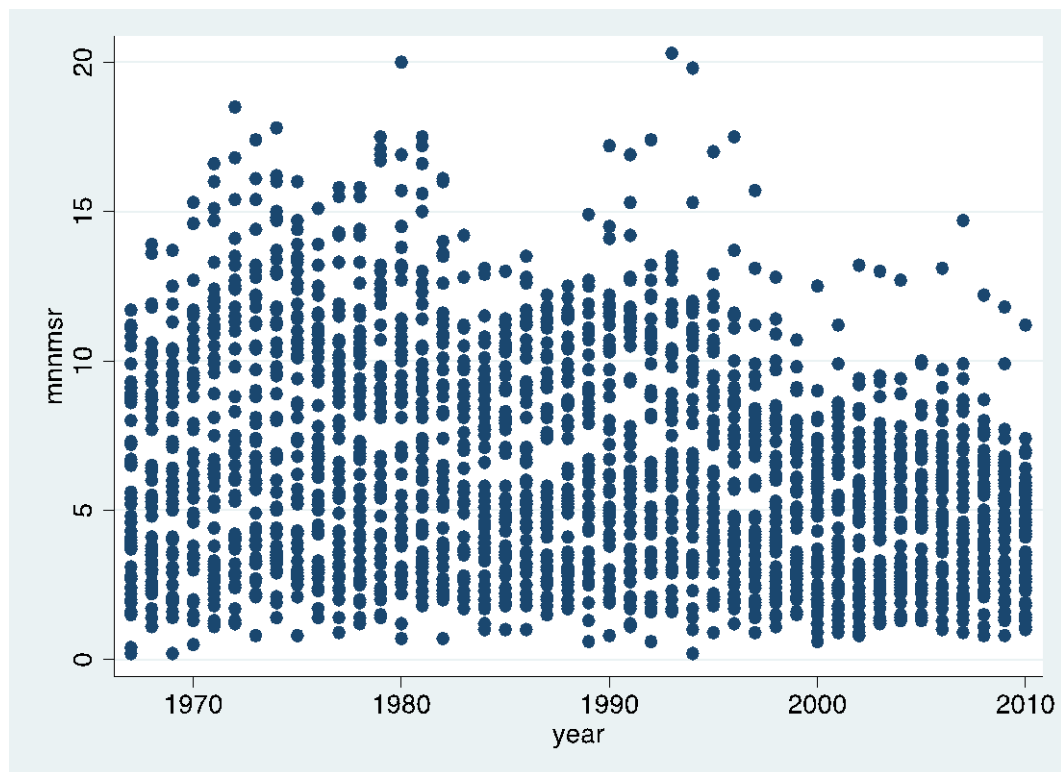
		Statistic	p-value
Inverse chi-squared(96)	P	158.0796	0.0001
Inverse normal	Z	-4.5425	0.0000
Inverse logit t(244)	L*	-4.4972	0.0000
Modified inv. chi-squared	Pm	4.4802	0.0000

```
-----
P statistic requires number of panels to be finite.
Other statistics are suitable for finite or infinite number of panels.
-----
```

**Reject the null hypothesis that all the panels contain a unit root.**  
**=> stationary**

~Murder and Non-Negligible Manslaughter Rate (mnnmsr)





```
. xtunitroot fisher mnmmsr, dfuller lags(0)
```

Fisher-type unit-root test for mnmmsr  
Based on augmented Dickey-Fuller tests

-----  
Ho: All panels contain unit roots                      Number of panels =        48  
Ha: At least one panel is stationary                  Number of periods =      44

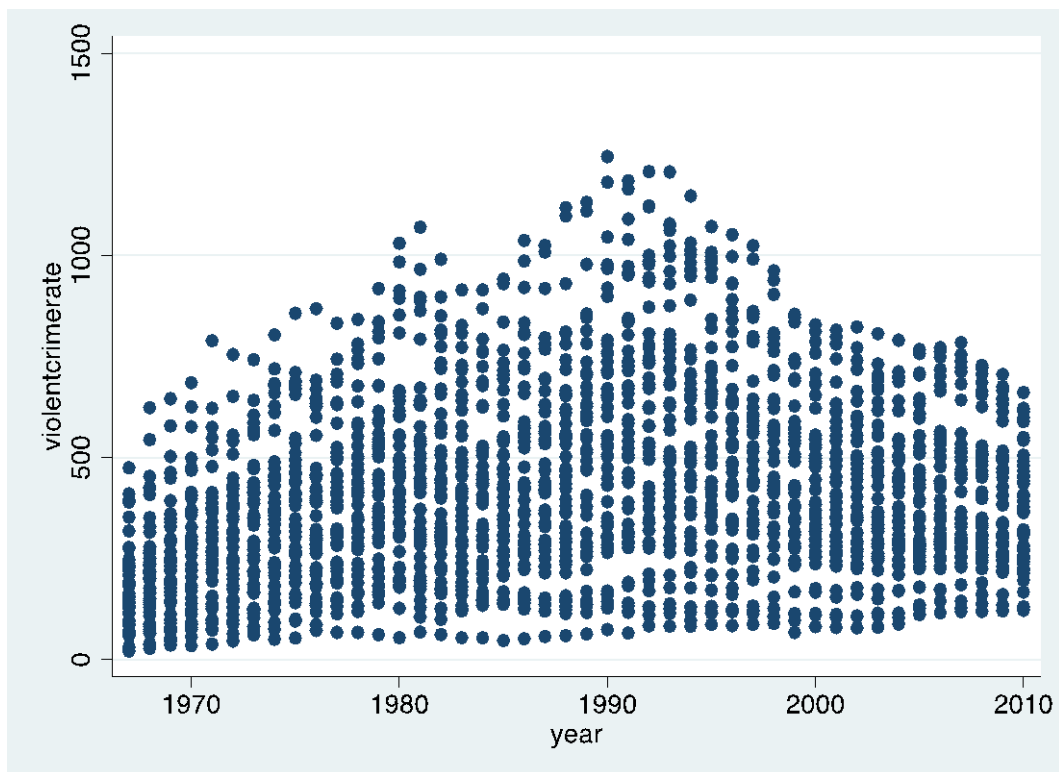
AR parameter: Panel-specific                              Asymptotics: T -> Infinity  
Panel means:    Included  
Time trend:     Not included  
Drift term:      Not included                              ADF regressions: 0 lags

		Statistic	p-value
Inverse chi-squared(96)	P	360.0734	0.0000
Inverse normal	Z	-8.6354	0.0000
Inverse logit t(244)	L*	-12.2409	0.0000
Modified inv. chi-squared	Pm	19.0579	0.0000

-----  
P statistic requires number of panels to be finite.  
Other statistics are suitable for finite or infinite number of panels.  
-----

Reject the null hypothesis that all the panels contain a unit root.  
=> stationary

~Violent Crime Rate



```
. xtunitroot fisher violentcrimerate, dfuller lags(0)
```

Fisher-type unit-root test for violentcrimerate  
Based on augmented Dickey-Fuller tests

```
-----
Ho: All panels contain unit roots      Number of panels =    48
Ha: At least one panel is stationary   Number of periods =   44
```

```
AR parameter: Panel-specific           Asymptotics: T -> Infinity
Panel means:   Included
Time trend:    Not included
Drift term:    Not included             ADF regressions: 0 lags
```

```
-----
                        Statistic      p-value
-----
Inverse chi-squared(96)  P           150.4355    0.0003
Inverse normal           Z           -4.4483    0.0000
Inverse logit t(244)     L*          -4.2178    0.0000
Modified inv. chi-squared Pm          3.9285    0.0000
-----
```

```
P statistic requires number of panels to be finite.
Other statistics are suitable for finite or infinite number of panels.
-----
```

```
Reject the null hypothesis that all the panels contain a unit root.
=> stationary
```

## Conclusion:

Despite weak results from the fixed effect 2SLS, this paper provides evidence that increasing growth rates of prison population likely has a negative relationship with unemployment, such that an increase in prison growth rate results in a decrease in the unemployment rate. This is

suggestive of what kind of response new policies directed at increased imprisonment also have a strong effect on unemployment.

However, we were not able to prove conclusively that an endogenous relationship exists between unemployment and prison population, which would have suggested that policies targeted at increasing imprisonment rates are enacted due to high unemployment.

Using VAR models we find evidence that unemployment and prison populations granger cause one another and are endogenous. However, due to weak instrumental variables we were unable accurately test endogeneity in our fixed effects model.

## **Validity Assessment:**

As in most panel data sets omitted variable bias is a concern with the dataset used in this project. The most pertinent omitted variables in our project were those that dealt with both general and prison demographics. Problematically, data on demographics of the US prison population is not readily available. This is concerning due to the generally understood ethnic imbalance in prisons. Ultimately, we were unable to control for many population demographics which would have been useful in explaining both unemployment and prison rates.

Similarly, we lacked sufficiently strong instrumental variables to conduct a valid IV 2SLS regression. We lacked variables that we sufficiently correlated with prison population growth and without correlation to the unemployment rate. One variable that would have likely been useful would be prison demographics or crime specific policy implementation.

Another concern is that parts of our data set were derived from self-reported surveys which might incentivize over or under reporting. Prior to 2004 the UCR were used to rank law enforcement agencies, which may have resulted in over and under reporting of certain crimes.

Likewise, the US prison system is rife with selection bias. For one the vast majority of prisoners are male and not white. Further, certain crimes, such as those involving sexual assault, have social implications that might prevent the victim from coming forward. This may result in false trends resulting not from increased crime rates but increased reporting rates.

Further, we make a number of potentially problematic assumptions in this paper. One critical assumption that this paper makes about those imprisoned in US correctional facilities is that they share the same propensity to pursue employment as the general US population. This is particularly problematic if crime is dependent on particular characteristics. For instance if crime is only committed by meth addicts, and presumably meth addicts have lower rates of participation in the labor force for various reasons, it would not be valid to equate the employment profile of a criminal with a non-criminal due to self selection bias.

Another assumption that may be a problem is that crime is not committed out of necessity. Which is to say that high unemployment does not cause crime through channels of necessity. This is perhaps less of a concern than the prior assumption due to the well-documented geographic

invariance of crime.<sup>1</sup> Concentrations of crime tend to be in low income transitional neighborhoods with large population turnovers. During times of economic hardship crime is not exported to higher income targets but remains geographically stagnant.

---

<sup>1</sup> [The Geography of Crime](#)

Joseph Cohen

[Annals of the American Academy of Political and Social Science](#)

Vol. 217, Crime in the United States (Sep., 1941), pp. 29-37

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