Economics of Crime

Police and Crime

1 Police and crime

Question: Does more police reduce crime?

Obvious problem - reverse causality.

If deterrent effect of the police works, then $\uparrow Police \rightarrow \downarrow Crime$. But society responds to higher crime by hiring more police, hence $\uparrow Crime \rightarrow \uparrow Police$! This leads to a source of "bad" (hardly identifiable) variation due to the reverse causality.

Another issue is relation $\uparrow Police \rightarrow \uparrow Crime$, because with more police presence more crimes gets noticed and reported in the books. Increase of police force might close a gap between actual and reported criminal activity, seemingly increasing measured crime levels. Therefore used explanatory variables for crime have to be accounted for this effect.

Earlier empirical work failed to find that more police reduces crime. But OLS is obviously upward biased.

We would need variation in *Police* that is not caused by the changes in *Crime*. New empirical toolbox in this chapter: **instrumental variables**.

EVROPSKÁ UNIE
Evropské strukturální a investiční fondy
Operační program Výzkum, vývoj a vzdělávání

MINISTERSTVO ŠKOLSTVÍ, MLÁDEŽE A TĚLOVÝCHOVY

1.1 Event studies

These studies are exploiting a large and usually short-term shock to deterrence on police presence. As mentioned above, changes in size of the police force should not be caused by crime level itself.

1.1.1 Draca, Machin, and Witt (2011)

July 2005 terrorist attacks in London led to a large increase in the number of police present on the streets of 6 central London boroughs in the six weeks afterwards (more than 30% - overtime, removed from administration, etc). Then discontinued after the danger ended. Increase in police force was unrelated to local crime levels, was responding to external thread.

Weekly data at the borough level - crime rates and police hours per 1000

Empirical design - Table 2 in the paper

- First diff-in-diff
- Use the diff-in-diff design to obtain IV estimates

Plausible elasticity of crime with respect to police hours. Concerns about the results:

- Crime rates too volatile, may have been a random shock (note a noticeable drop in the raw data). Conduct a placebo test - regression with each week as treatment (Figure 3). Only the treatment weeks have confidence intervals below zero in the crime equation.
- Terrorism changed many things that also **reduced crime** (people, including criminals, stay at home). Take the data from the London tube - huge drop in ridership, than it gradually rebounds. But police presence was discontinued abruptly, and crime abruptly rebounded.

1.1.2 Some drawbacks of the event study design

- Some do not estimate any structural relationship (Klick and Tabarrok 2005 - a terror alert is on or off; DiTella and Shargrodsky 2004 - a block has a protected building or not), just a correlation with a story.
- Substitution by criminals over time may lead to an overestimate of the results.

1.2 Studies based on Instrumental Variables

1.2.1 Levitt (AER 97): Electoral cycles in police hiring.

Number of police goes up consistently during mayoral or gubernatorial election years. In cities with elected mayors, the mayors have a full control over police resources, and being tough on crime is a candidate's selling point.
In his sample of 59 U.S. large cities during 1970-92, the mean % change in the number of sworn police officers is 2-2.1 % during election years and 0 % in other years. For the instrument to be valid, we need to determine if elections are exogenous to crime (they are). Elections obviously exogenous to crime, though they may be other policies that have a political cycles and affect crime.

Instrumental variable process:

- use $\Delta Z \rightarrow \Delta X \rightarrow \Delta Y$ to isolate the good variation
- regress change in police force on the election dummies (mayoral and gubernatorial) and other controls
- use predicted change in police in the ultimate regression of interest - run

$$Y_{ist} = \beta_1 + \beta_2 \widehat{X}_{ist} + \beta_3 \widehat{X}_{ist-1} + u_{ist}$$

- In a singe variable case, IV boils down to

$$\widehat{\beta} = \frac{cov(Y, \widehat{X})}{var(\widehat{X})} = \frac{cov(Y, \widehat{\gamma} Z)}{var(\widehat{\gamma} Z)}$$

If the conditions on Z hold, then the IV estimate is consistent and $\widehat{\beta}$ has a causal interpretation. We are using only variation in police that is caused by the election cycle.

Table 2 (1st stage), small R^2 problem. The election is a weak instrument - keeps only a small amount of variation in the number of police. About a 2% increase due to election - this little amount of variation he effectively uses to identify the causal effect of police on crime.

Tries to overcome the problem by increasing the range of instruments, allowing the effect of elections to vary by e.g. city size (interacts the two election dummy with 4 city size dummies, that creates 8 instruments), and gets (only) a 20% increase in the variation explained.

Table 3 and 4 - Regresses the crime on policemen this year and one lagged year, reports the sum.

Study finds the greatest impact on murder, quite a little on the property crime.

Cost and benefit analysis: Dirty numbers. At $1million value of life saved, he gets the cost per violent crime of $33,000. The cost of an average property crime is $1,100. The conservative estimates of the elasticities of crimes with respect to police implies that adding one policemen reduces the damage from crime by $200,000, while the average cost of a policemen is $38,000 in salary and roughly the same amount on equipment.

1.2.2 Evans and Owens: COPS and crime

In 1994 the federal government started a program disbursing large grants to cities to hire more policemen. Large program: the grants eventually paid 25-35% of city policemen. Depending on the city size, between 0.8-1.4 policemen granted per 10,000. Over 90% of cities eventually received some grant.
For this grant, cities had to apply, some of them were rejected and had to really. This created a variation in the size and timing of the grant across cities.

The grants received by the city is a instrument for the number of police officers.

Validity of the instrument:

- Obviously correlated with the regressors (save for the extreme flypaper effect, but that is rejected).
- However, may be correlated with crime (places with higher crime should logically receive more grants). This is a general problem with estimating effect of every subventions, interventions are not selected randomly by design.
  - Cities with more crime (and larger cities) received more grants.
  - But grants are uncorrelated with the pre-grant growth rates of crime or the size of the police force (Table 3). This fact is proven in data.
  - With city fixed effects, it is the changes that matter. Using fixed effect "demeans" the variable and focuses only on changes.

First stage (Table 4): Police officers as a function of the police officers granted. For each officer hired through the grant, the size of the police force increases by 0.7 (hence some of the grants were just offsets, but still a strong effect).

Second stage (Table 5, bottom panel): Crime rates as a function of predicted police officers. Plausible elasticities for most crimes (surprisingly high more murders).

1.2.3 Weisburd (2015wp): Does Police Presence Deter Crime?

The interesting aspects of the paper:

- Tries to uncover (identify) a channel through which more police cuts crime.
- Use of very detailed data.
- Also shows the importance of removing reverse causality.

Police cuts crime, but identifying the channels through which is difficult. The policemen do many things, which affect crime through different mechanisms:

- Patrolling streets proactive policing - prevention (deterring crime before it happens). But this also leads to more crime being discovered and reported.
- Responding to emergency calls - reactive policing - help victims, help identify offenders (ultimately increasing p).
- Investigation, collecting evidence - ultimately increasing p - deterrence, incapacitation.

What is important? Presence on the street at a particular place and time? Quick response times? Investigative capacity? The paper deals with the first channel - police presence and crime. Detailed location data is needed for that.

Data:

- A showcase paper of using "big data" from Dallas Police Department
- Automobile Locator System - deployed in all 873 police cars, January - December - GPS tracker of where each car is, geo location coordinates by 30 seconds
- The police work is organized along 234 beats (each about 5,000 population) (see map in paper)
- The ultimate dataset has beat-hour observation. Key variables: number of police cars present in that beat and hour.
- Key institutional factor: Patrols are assigned to "their" beat. And they should be there, unless they are called out to be in a different beat, to respond to an emergency call.

Descriptive relationship (Figure 1):

- $\uparrow$ Cars allocated $\Rightarrow$ $\uparrow$ Cars present in a beat. (The treatment is there, the police cars patrol where they should)
- $\uparrow$ Cars present $\Rightarrow$ $\uparrow$ Crime. Clear reverse causality. The police are alocated where and when the crime is.

Identifying the *causal* effect of police presence on crime:

- The police have to response to calls to help (within 8 minutes).
- Often times they are called to outside of their beat.
- Use the times when they are unexpectedly called outside of their beat to see how the crime changes when they are out.
- Construct an instrument: Response Ratio (RR) = the fraction of the time that officers allocated to a given beat spend answering calls outside of that beat. The actual presence is then determined by exogenous factors (an emergency in a nearby beat).

Results using the instrument:

- Descriptive relationship (Figure 2):
- $\uparrow$ % of the time allocated to outside beats $\Rightarrow$ $\downarrow$ cars present in the originally allocated beat
- $\uparrow$ % of the time allocated to outside beat $\Rightarrow$ $\uparrow$ crime in the originally assigned beat
- OLS regression: a positive relationship, even with location fixed effects
- IV: first stage confirms that the Response Ratio is negatively related to actual police presence in a beat (e.g. the officers are not immediately substituted)
- IV: second stage shows negative (-0.034 - -0.03) relationship between police vehicles in a beat-hour and crime. In percentage terms, a 10-percent increase in the police presence translates into a 1.2-percent reduction in crime. Or one hour of one car reduces the crime rate by 0.03, with a mean crime rate of 0.148, so by 20 percent.

- Concern about the instrument: The RR is related to crime in "own" district also through reverse causality. A call from outside → officers may not be able to come if they are dealing with a high-crime situation in their beat. Or call from outside → officers leave their beat because it is unusually quiet → the crime in "own" beat rises simply through the reversion to the mean.
- Alternative instrument: Expected Response Ratio = number of outside calls that officials were asked to answer divided by the allocated patrol time. So this is not affected by situations when they did not answer when they were busy. (Intention to treat).
- Result is even stronger. (2.5 percentage terms drop)

Finer results and issues:

- Effects by crime type: strongest for violent crime and public disturbances, surprisingly absent for burglary
- Temporal displacement: Does the fact that there is less police and less crime at this hour simply shift the crime to the next hour? Test: does police presence at hour t have a positive effect on crime at hour $t+1$? (Table 14) No effects to speak of.
- One concern remains: how is crime reporing related to police presence? More may be resolved on the spot by policemen without being recorded, while if they are not there, the incident may get recorded based on a phone call.

Overall, a remarkable paper, showing the effect of police-on-the-street. Great use of "big data".

1.2.4 Instrumental Variables - general comments and conclusions

- It would not do to put Z into the basic regression:

  $$Y = \beta_1 + \beta_2 X + u + \gamma Z$$

  Z is uncorrelated with u, it does not cause Y, so we should get $\widehat{\gamma} = 0$, while the correlation between X and u is still there.

- If most variation in X is not caused by Z, then you throw away almost all good variation too $\rightarrow$ low R^2, large standard errors, poor small sample properties.

- The instrument must be valid! If in fact $Z \rightarrow Y$, then IV is totally misleading. If the true model is

  $$Y = \beta X + \lambda Z + u$$

  you in fact run after instrumenting

  $$Y = (\beta\widehat{\gamma} + \lambda)Z + u$$

- Choice of instrument must be justified by further analysis. Its best practice to show results with and without the instrument to see the size of the effect.

- For issues as effect of police on crime, using of IV is a must. Real world is too complicated to determine the causality. Alternative is a perfect natural experiment with diff-and-diff.

Reading list for this chapter

- Draca, M, S. Machin and R. Witt: Panic on the Streets of London: Police, Crime, and the July 2005 Terror Attacks, American Economic Review 2011.
- Levitt, S. D: Using Electoral Cycles in Police Hiring to Estimate the Effect of Police on Crime, American Economic Review, Vol. 87 (3), 1997: 270-290.
- Owens, Emily G., and William N. Evans: COPS and crime, Journal of Public Economics, Vol. 91, 2007, 181-201.
- Weisburd, S. (2015). Does Police Presence Create Deterrence? Working paper, Tel Aviv University
- DiTella, S. and Shargrodsky, E: Do Police Reduce Crime? Estimates Using the Allocation of Police Forces After a Terrorist Attack, American Economic Review 2004.
- Mastrobuoni, G. (2017). Crime is terribly revealing: Information technology and police productivity.

EVROPSKÁ UNIE
Evropské strukturální a investiční fondy
Operační program Výzkum, vývoj a vzdělávání

MINISTERSTVO ŠKOLSTVÍ, MLÁDEŽE A TĚLOVÝCHOVY

Národohospodářská fakulta VŠE v Praze