# Identifying Causal Effects

**Theodore Koutmeridis**
University of Glasgow & CREATe
RCUK Centre for Copyright & New Business Models in the Creative Economy

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Behaviour, Structure & Interventions research network
Interdisciplinary PhD Workshop

## Few words about us

- **Behaviour, Structure and Interventions (BSI)** is a research network, which aims to develop and refine a methodology, at the interface of theory and empirics, that can be applied to the study of substantive issues in a variety of different settings and problems and deliver policy impact. The network is explicitly inter-disciplinary but with a disciplinary core located in economics and social sciences.

- Contacts:
  — Prof. Sayantan Ghosal (Network Co-coordinator)
  — Dr Theodore Koutmeridis (Network Co-coordinator)
  — David Wright (Networks Administrator)

- **Interdisciplinary PhD Workshop**:
  — Mini-course by **Theo Koutmeridis** (CREATe / Law & Econ)
  — 8 PhD talks, feedback, networking, collaborations, ...

## Correlations VS Causation

- In **theoretical** research, most of the time, we know how things work and what causes what.
- In the real world we observe and we derive regularities (e.g. in the natural universe stars follow patterns, in the social universe prices follow patterns).
- In **empirical** research the main task is to distinguish *correlation* from *causation*.
- In this course we are going to examine precisely this.

## Correlation / Examples

- Education and income move together (positive correlation).
- Education and health move together (positive correlation).
- Child's education and parents' education move together (positive correlation).
- Simple intuition suggests that: education increases income but income increases education too and education increases health but better health also leads to better education.
- However, we would expect parents' education to increase child's education, as the former occurred earlier than the latter. This does not mean that measuring a variable with a lag would lead to causality, as concepts are deeper than their measurement (common mistake).

## Causality / Examples I

- In order to examine if education increases wages, we should be innovative, as there are problems that bias our results:
— omitted factors (ability is hard to be measured),
— reverse causation (education increase income but income increases education too - *chicken or the egg*),
— measurement error (we might not be able to measure accurately wages / hidden income).

- Education example: Twins of the same gender have many similar (usually unobserved) characteristics. If one gets more education than the other and we can link this with differences in wages, we can argue that this gives a better estimate of the effect of education on wages compared to non-twins data.

## Causality / Examples II

- Ideally we would wish to keep everything constant and change only one thing to evaluate the impact of this change.
- Gender example I: after controlling for various factors, the examination of gender gap in twins can offer a better sense of gender wage discrimination compared to non-twins data.
- Gender example II: transgender example - women who become men earn more, while men who become women earn less (clever idea / hard to get the data)!
- Apart from such intuitive examples, there are really useful techniques in identifying causal effects.

# Outline

# Outline

## Primary VS Secondary Data

- Primary data (you collect them / used mainly in experiments)
  — advantage: may identify causal effects (together with a good design)
  — disadvantage: difficult and expensive to collect

- Secondary data (somebody else collects them / used mainly in regression analysis)
  — advantage: easy and cheap to collect
  — disadvantage: usually cannot identify causal effects (without an innovative idea or a good design)

## Primary Data and Experiments

- Control VS Treatment groups
  — Treatment is exactly the same as control, with the only difference that it is selected randomly to receive some treatment (RCT: randomised control trials).
  — Advantage: Virtue of experiment is that you control the decision making environment and are able to vary one factor keeping everything else constant.
  — Example: effectiveness of a new pill, control groups takes placebo pill, treatment group takes a new pill (ideally without knowing that / Hawthorne effect)

- Diff-in-Diff (Difference-in-Differences) approach:
  $Effect = (Treat_{After} - Treat_{Before}) - (Ctrl_{After} - Ctrl_{Before})$

# Outline

1. Intro
2. Data
3. Panel Data
4. Endogeneity
5. Instrumental Variables (IV)
6. Difference in Differences (Diff-in-Diff)
7. Regression Discontinuity Design (RDD)
8. Applications

# Data Structures and Panel Data

- Cross-sectional data
  — Observations related to many individuals at a given period.
  $Y_i = c + b_1 X_{1i} + b_2 X_{2i} + ... + e_i$

- Time series data
  — Observations related to one individual for many periods.
  $Y_t = c + b_1 X_{1t} + b_2 X_{2t} + ... + e_t$

- Panel data
  — Observations related to many individuals for many periods.
  $Y_{it} = a_i + b_1 X_{1it} + b_2 X_{2it} + ... + e_{it}$
  $a_i$: captures all time-invariant individual specific characteristics.

## Fixed Effects

- Panel data

— Observations related to many individuals for many periods.

$$Y_{it} = a_i + b_1 X_{1it} + b_2 X_{2it} + ... + e_{it}$$

$a_i$: captures all time-invariant individual specific characteristics.

**The structure of the data allows us to gain precision by controlling not only the impact of observables ($X_{1it}, X_{2it}, ...$) but also the impact of time-invariant unobservables $a_i$ (unobserved heterogeneity)!**

# Outline

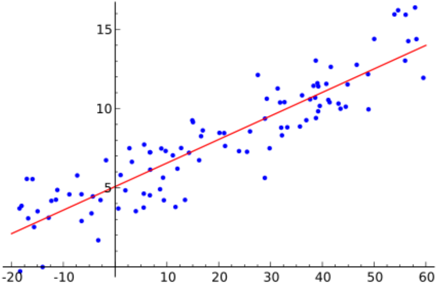
## The Problem of Endogeneity

- $Y_i = c + b_1 X_{1i} + b_2 X_{2i} + ... + e_i$
- In the equation above we wish to find the effect that $X_{1i}$ has on $Y_i$ but the variable of interest $X_{1i}$ **is correlated with the error term** $e_i$**.**
- In other words $Corr(X_{1i}, e_i) \neq 0$.

## 3 Reasons why we have Endogeneity

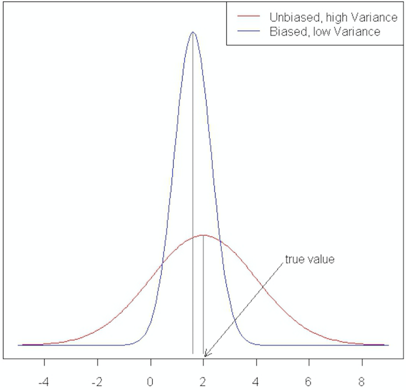
- $Y_i = c + b_1 X_{1i} + b_2 X_{2i} + ... + e_i$
- Endogeneity: $Corr(X_{1i}, e_i) \neq 0$.
- We have the problem of endogeneity for 3 reasons:
  — 1) omitted variable bias (a relevant $X$ is omitted),
  — 2) reverse causality ($X$ affects $Y$ but $Y$ also affects $X$),
  — 3) measurement error (we cannot measure variables accurately).
- Endogeneity means that the regression coefficient in an **Ordinary Least Squares (OLS)** regression is **biased**.

# Extra Slide: Ordinary Least Squares




OLS is a method for estimating the unknown parameters in a linear regression model by minimising the sum of the *square* vertical distances between data observations and the responses predicted by the linear approximation of the data. Gauss-Markov theorem: a linear regression model in which the errors have expectation zero and are uncorrelated and have equal variances, the best linear unbiased estimator (BLUE) of the coefficients is given by the OLS estimator. MVUE for non-linear.

## Extra Slide: Bias - Variance tradeoff




The **bias** relates to the mis-centring of the estimator to the true value. The **variance** relates to the imprecision of the estimator. Which one should we keep from the graph? Mean squared error:

$$\mathrm{MSE}(\hat{\theta}) = \mathrm{E}\left[(\hat{\theta} - \theta)^2\right] = \mathrm{Var}(\hat{\theta}) + \Big(\mathrm{Bias}(\hat{\theta}, \theta)\Big)^2 .$$

# Outline

## Tackling Endogeneity with Instrumental Variables

- $Y_i = b_0 + b_1 X_{1i} + b_2 X_{2i} + ... + e_i$
- Endogeneity: $Corr(X_{1i}, e_i) \neq 0$.
- When there is no direct fix, such as including omitted factors or measuring variables properly, we have to use other methods.
- Finding an **Instrumental Variable** can fix the problem of endogeneity.

## Conditions for a Valid Instrumental Variable $Z$

- $Y_i = b_0 + b_1 X_{1i} + b_2 X_{2i} + ... + e_i$
  Endogeneity: $Corr(X_{1i}, e_i) \neq 0$.

- Conditions for a valid instrument $Z_{1i}$:
  — 1) Relevance: $Corr(X_{1i}, Z_{1i}) > 0$.
  — 2) Exogeneity (exclusion restriction): $Corr(Z_{1i}, e_i) = 0$.
  — The intuition is the following: the changes in the instrument affect $Z_{1i}$, affect $Y_{1i}$ *exclusively* through $X_{1i}$.

- Examples of triples:
  — $Y_{1i}$: health; $X_{1i}$: smoking; $Z_{1i}$: taxation of tobacco.
  Problem: smoking and alcohol go nicely together and if alcohol is omitted the exclusion restriction is violated.
  — $Y_{1i}$: GDP growth; $X_{1i}$: institutions; $Z_{1i}$: settler's mortality.
  Problem: settler's mortality affects human capital and if human capital is omitted the exclusion restriction is violated again.

## Instrumental Variables / 2 Stage Least Squares

- $Y_i = b_0 + b_1 X_{1i} + b_2 X_{2i} + ... + e_i$
  Endogeneity: $Corr(X_{1i}, e_i) \neq 0$.

- Reduced form ($Z_{1i}$ instead of $X_{1i}$).
  $Y_i = b_0 + b_1 Z_{1i} + b_2 X_{2i} + ... + e_i$

- First Stage: regress $X$ on the $Z$ and all $X$s to get $\hat{X_{1i}}$
  $\widehat{X_{1i}} = \gamma_0 + \gamma_1 Z_{1i} + \gamma_2 X_{2i} + ... + u_i$

- Second Stage
  $Y_i = b_0 + b_1 \widehat{X_{1i}} + b_2 X_{2i} + ... + \epsilon_i$

  reg Y X, rob (OLS)
  reg Y Z, rob (Reduced form)
  reg X Z, rob (1st Stage)
  ivreg2 Y (X=Z), rob first (IV Structure)

# Outline

## Experiments

- Diff-in-Diff (Difference-in-Differences) approach:
  $Effect = (Treat_{After} - Treat_{Before}) - (Ctrl_{After} - Ctrl_{Before})$

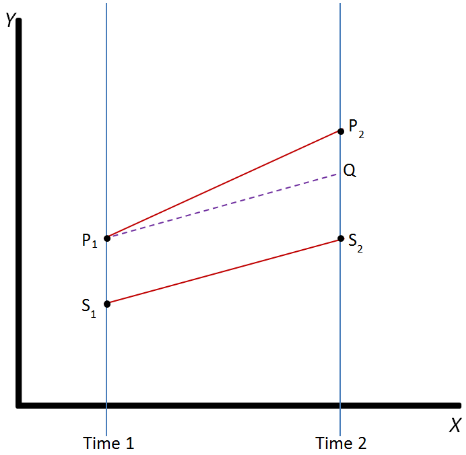
- Types of Experiments
  — Lab Experiments: laboratories, the setting is perfectly controlled but individuals know that they have been examined
  — Natural Experiments: somebody externally generates an *exogenous variation*
  — Field Experiments: similar to lab but the researcher goes to the individuals instead of them going to his lab

- See also *synthetic control* groups:
  A synthetic control group, by construction deals with the appropriateness of the control group (a synthetic control group is comprised of different individuals, countries, etc., which jointly form a group that is directly comparable to the treated group).

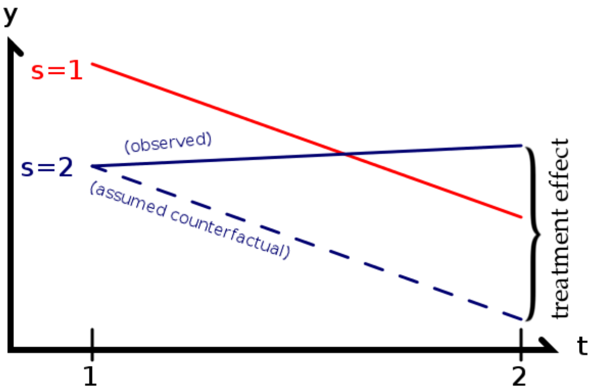
## Experiments

- Diff-in-Diff (Difference-in-Differences) approach:
  $Effect = (Treat_{After} - Treat_{Before}) - (Ctrl_{After} - Ctrl_{Before})$
  $Effect = (Treat_{After} - Ctrl_{After}) - (Treat_{Before} - Ctrl_{Before})$
- These two Diff-in-Diff equations are equivalent.
- This equivalence facilitates our understanding of the logic of this method. But graphs can also offer a good illustration.

# Diff-in-Diff graph



## Diff-in-Diff graph and counterfactual



## Diff-in-Diff table

| $y_{st}$ | $s=2$ | $s=1$ | Difference |
|---|---|---|---|
| $t=2$ | $y_{22}$ | $y_{12}$ | $y_{12}-y_{22}$ |
| $t=1$ | $y_{21}$ | $y_{11}$ | $y_{11}-y_{21}$ |
| **Change** | $y_{21}-y_{22}$ | $y_{11}-y_{12}$ | $(y_{11}-y_{21})-(y_{12}-y_{22})$ |

## Diff-in-Diff regression I

$$y = b_0 + b_1 T + b_2 S + b_3 (T \cdot S) + e$$

— where $T$ is a dummy variable for $t = 2$, and $S$ is a dummy variable for $s = 2$. The composite variable $(T \cdot S)$ is then a dummy variable indicating when S=T=1.

— the estimates in this model are:
$\hat{\beta}_0 = (y|T = 0, S = 0)$
$\hat{\beta}_1 = (y|T = 1, S = 0) - (y|T = 0, S = 0)$
$\hat{\beta}_2 = (y|T = 0, S = 1) - (y|T = 0, S = 0)$
$\hat{\beta}_3 = [(y|T = 1, S = 1) - (y|T = 0, S = 1)] -$
(y — T=1, S=0) - (y — T=0, S=0)

$$Effect = (Treat_{After} - Ctrl_{After}) - (Treat_{Before} - Ctrl_{Before})$$

# Diff-in-Diff regression II

$y = b_0 + b_1 T + b_2 S + b_3(T \cdot S) + X'\beta + e$
where $X$ can include other variables, controlling for potential pre-existing differences between the control and the randomly selected treatment group

Example: Impact of Minimum Wages on Employment
$y_{ist} = \gamma_s +_t + \delta(FA_s \cdot d_t) + X'_{ist}\beta + e_{ist}$
— where the employment $y$ of individual $i$, at state $s$, in year $t$, is affected by the interaction of the fraction of young people at each state $FA_s$ after the increase in the federal (for all the states) minimum wage \$3.35 to \$3.80, which occurred in 1990 ($d_t = 1$ for 1990 and $d_t = 0$ for 1989).
— importantly we add further covariates increasing the precision of our estimates, as $X_{ist}$ can include individual level characteristics like race or time-varying variables at the state level

## Internal VS External Validity

- In experiments and if the Diff-in-Diff approach is applied properly it is possible to derive **internally valid** results (causal relationships).

- The big challenge in experiments is to establish **external validity**, which relates to the ability to scale up the results and derive general laws that hold above and beyond the particularities of the experimental setting.

- Two recent developments on this:
  — JPAL attempts to generalise experimental results from development economics. 724 ongoing and completed randomised evaluations in 67 countries!
  — Only 1/3 to 1/2 of the major publications in psychology can be replicated! Open Science Collaboration. (2015). Estimating the reproducibility of psychological science. Science.

## Outline

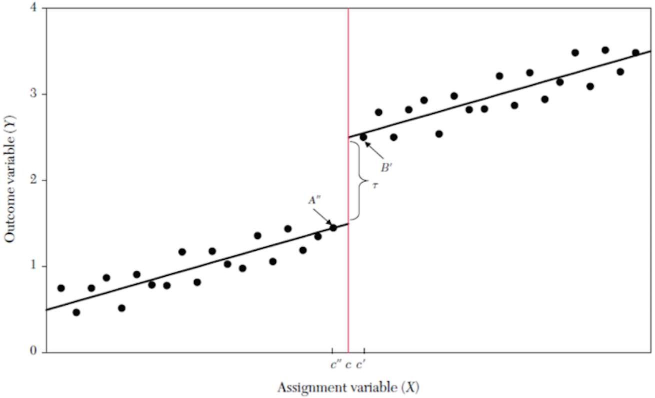
## Regression Discontinuity Design: the main idea

- Key study: Thistlethwaite, D. L., Campbell, D. T. (1960). Regression-discontinuity analysis: An alternative to the ex post facto experiment. Journal of Educational psychology, 51(6), 309.

- Regression discontinuity designs exploit the fact that some rules are quite arbitrary and therefore provide good quasi-experiments when you compare individuals who are just affected by the rule with people who are just not affected by the rule.

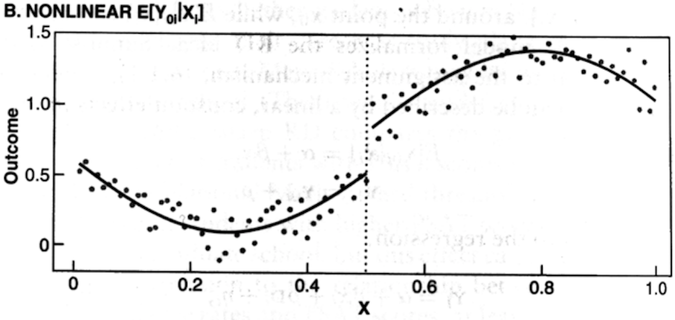
- Examples: just got a scholarship, just got a distinction, just got aid, etc.

## Linear RDD




$$Y_i = a + bX_i + \rho D_i + e_i$$

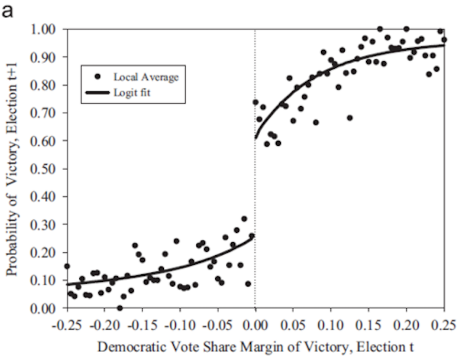
## Non-linear RDD




$p^{th}$ polynomial

$Y_i = a + b_1 X_i + b_2 X_i^2 + ... + b_p X_i^p + \rho D_i + e_i$

# Example RDD




Lee (2008): The Effect of Winning the Previous Election on The Probability of Winning Current Election - He analyses the probability of winning the election in year $t$ by comparing candidates who just won compared to candidates who just lost the election in year $t-1$.

# Outline

# Applications from the Economics of Crime

- We have offered an overview of the basic methods to identify causal effects.
- We now shift our attention to applications from the economics of crime.
- Applications have their own importance and they do not always need to appear as extras next to theories. This is why we will examine several applications.
- Apart from the importance of crime for society, this example offers an interesting exposition and tests a central theory using data and empirical methods.

## The economic theory of crime

**Theory:** Consider the basic model of the criminal decision following Becker (1968), Ehrlich (1973) or Freeman (1999):

$$\text{SuccessProb*IllegalGains} - \text{CaughtProb*Sanctions} > \text{LegalGains}$$
$$(1-\pi) * U(W_C) \; - \; \pi * U(S) \; > \; U(W_L)$$

**Topics:** Key Determinants of Crime
— $U(W_L)$**:** labor markets (wages, unemployment)
— $U(S)$**:** punishment, sanctions, sentences
— $\pi$**:** policing, detection/protection technology
— $U(W_C)$**:** returns from crime, illegal gains

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## 1. Labor markets and crime

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**Freeman (1999)** shows that unemployment has, if something, a weak but increasing effect on crime. Wage decreases at the bottom of the distribution seem to have a stronger and increasing effect on crime.

# 1. Labor markets and crime: OLS

Table 6: Effects of Economic Conditions on Crime Rates. Ten Year Differences, 1979-1989. Weighted Least Squares Estimates.

| | Overall Crime Index | Property Crime Index | Auto Theft | Burglary | Larceny | Violent Crime Index | Aggravated Assault | Murder | Robbery | Rape |
|---|---|---|---|---|---|---|---|---|---|---|
| Change in Mean Log Household Income in MA | 0.692** | 0.671** | 2.088** | 0.207 | 0.566** | 0.770** | 1.050** | 0.679 | 0.853** | -0.860** |
| | (0.187) | (0.190) | (0.300) | (0.221) | (0.195) | (0.266) | (0.346) | (0.578) | (0.378) | (0.399 |
| | [6.0] | [5.8] | [18.2] | [1.8] | [4.9] | [6.7] | [9.1] | [5.9] | [7.4] | [-7.5] |
| Change in Mean Log Weekly Wage of Non-College Men in MA (Residuals) | -1.008** | -1.015** | -2.282** | -0.976** | -0.785** | -0.784** | -0.861** | 0.065 | -1.016** | 0.774** |
| | (0.207) | (0.210) | (0.333) | (0.244) | (0.216) | (0.295) | (0.384) | (0.640) | (0.419) | (0.442) |
| | [13.8] | [13.9] | [31.3] | [13.4] | [10.8] | [10.7] | [11.8] | [-0.9] | [13.9] | [-10.6] |
| Unemployment Rate of Non-College Men | 2.102** | 2.226** | 2.516** | 2.540** | 2.160** | 0.776 | 0.694 | 0.805 | 2.920** | -1.874* |
| | (0.463) | (0.471) | (0.746) | (0.548) | (0.484) | (0.661) | (0.860) | (1.435) | (0.939) | (0.992) |
| | [1.3] | [1.4] | [1.6] | [1.6] | [1.3] | [0.5] | [0.4] | [0.5] | [1.8] | [-1.2] |
| Observations | 582 | 582 | 582 | 582 | 582 | 582 | 582 | 582 | 582 | 582 |
| Partial $R^2$ | 0.074 | 0.075 | 0.108 | 0.072 | 0.056 | 0.019 | 0.017 | 0.005 | 0.028 | 0.014 |

** indicates significance at the 5% level. * indicates significance at the 10% level. Standard errors in parentheses. Numbers in brackets represent the "predicted" percent increase of the crime rate due to the mean change in the independent variable, computed by multiplying the coefficient estimate by the mean change in the independent variable between 1979-1989 (multiplied by 100). Dependent variable is log change in crime rate from 1979-1989 in county. Sample consists of 582 counties. Regressions include county and time fixed effects and demographic controls (percent of population age 10-19, age 20-29, age 30-39, age 40-49, age 50-64, and age 65 and over, percent male, percent black, and percent non-black and non-white). Regressions weighted by mean of population size of each county. Partial R-squares are after controlling for county and time fixed effects, and demographic controls. Wage residuals control for educational attainment, a quartic in potential experience, Hispanic background, black, and marital status.

# 1. Labor markets and crime: Scatterplot

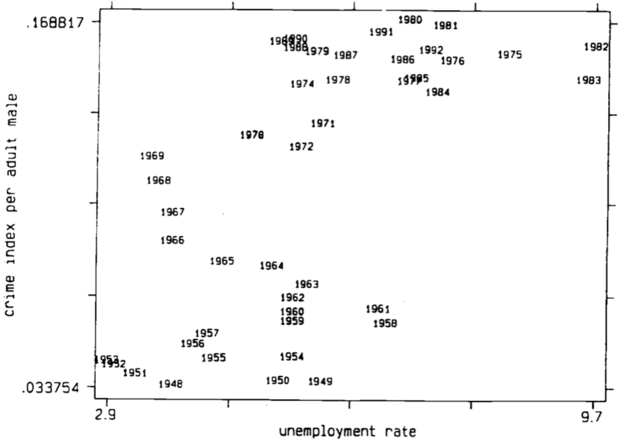


FIGURE 6: CRIMES PER ADULT MALE AND UNEMPLOYMENT 1948-1992

## 2. Crime and punishment

**Theory:** Consider the basic model of the criminal decision following Becker (1968), Ehrlich (1973) or Freeman (1999):

SuccessProb*IllegalGains−CaughtProb*Sanctions>LegalGains

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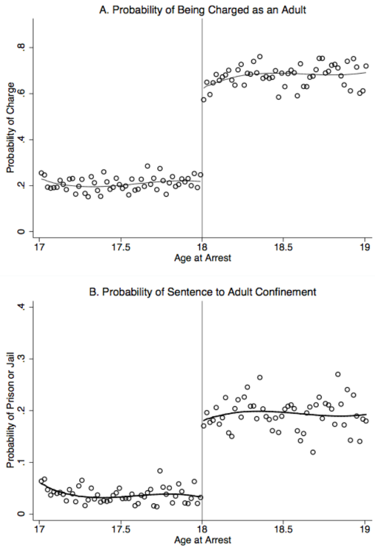
**Lee and McCrary (2009)** show that sanctions do not act as important deterrents for criminals, as there is only a 2% decline in crime just before and just after the age of 18, while sanctions increase by 230%. However, Bell et al. (2014) suggest that criminals respond to changes in the severity of sanctions and substitute away from types of crime that are penalized with tougher sentences.

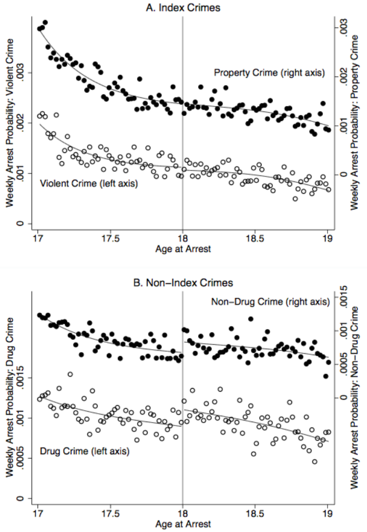
# 2. Crime and punishment: Regression Discontinuity (RD)

FIGURE 2. TRANSFER AND PUNITIVENESS BY AGE



# 2. Crime and punishment: Regression Discontinuity (RD)

FIGURE 3. CRIMINAL PROPENSITY BY TYPE OF OFFENSE



## 3. Crime and policing

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## 3. Crime and policing - two ideas

**Theory:** Consider the basic model of the criminal decision following Becker (1968), Ehrlich (1973) or Freeman (1999):

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$$(1-\pi) * U(W_C) \; - \; \pi * U(S) \; > \; U(W_L)$$

**Topics:** Key Research Questions

**Blanes i Vidal & Kirchmaier:** do faster police responses increase the likelihood of detecting crimes?

**Mastrobuoni:** does IT innovation via predictive policing increase police's productivity?

**Data:** Police Datasets / Methods used

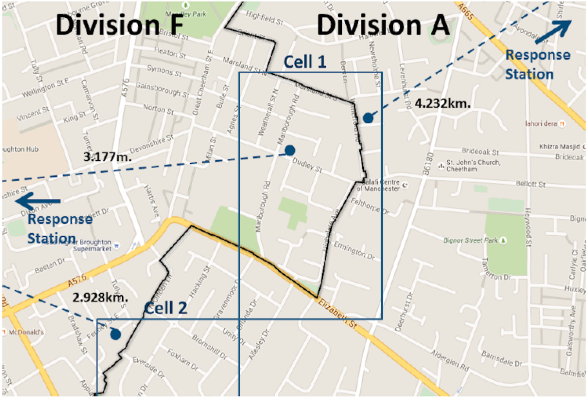
**Blanes i Vidal & Kirchmaier:** Manchester Police / IV

**Mastrobuoni:** Milan Police / DiD

## *"The Effect of Police Response Time on Crime Detection"* *Jordi Blanes i Vidal and Tom Kirchmaier*

**Puzzle:** Does Rapid Response Policing work?

**Data :** Unique crime data / nice design with distance as IV.



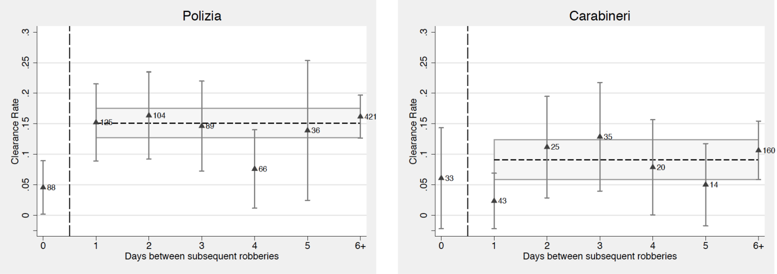
## Blanes i Vidal and Kirchmaier (2015) - Results

- Establishes a causal effect of police response time on crime detection, which is large and strongly significant.
- The effect holds on the extensive margin (likelihood of detection) as well as on the intensive margin (time to detection).
- Stronger effects for thefts than for violent offenses, although the effects are large for every type of crime.
- One of the mechanisms through which "police response time" operates: the likelihood that a victim or witness will name a suspect to the police.

# *"Crime is Terribly Revealing: Information Technology and Police Productivity"* *Giovanni Mastrobuoni*

**Puzzle:** Does IT innovation via predictive policing work?

**Data :** Unique crime data / nice design with Diff-in-Diff.



## **Mastrobuoni (2015)** - Results

- Using a quasi-random assignment of crimes to Polizia (adopted new IT innovation) or Carabinieri, provides evidence that IT-related predictive policing leads to an increase in the probability of clearing bank robberies.

- Consistent with this argument there is no effect in the first robbery but significant differences for consequent robberies between Polizia (adopted new IT innovation) and Carabinieri.

- Diff-in-Diff results are confirmed with “donut” RDD. All interviews take place at 10am. For robberies 3 hours before 10am similar effects but for robberies 3 hours after clearance rates increase by 10% only for Polizia.

# 4. Returns from Crime

**Theory:** Consider the basic model of the criminal decision following Becker (1968), Ehrlich (1973) or Freeman (1999):

$$\text{SuccessProb*IllegalGains} - \text{CaughtProb*Sanctions} > \text{LegalGains}$$
$$(1-\pi) * U(W_C) \; - \; \pi * U(S) \; > \; U(W_L)$$

**Topics:** Key Determinants of Crime

— $U(W_L)$**:** labor markets (wages, unemployment)

— $U(S)$**:** punishment, sanctions, sentences

— $\pi$**:** policing, detection/protection technology

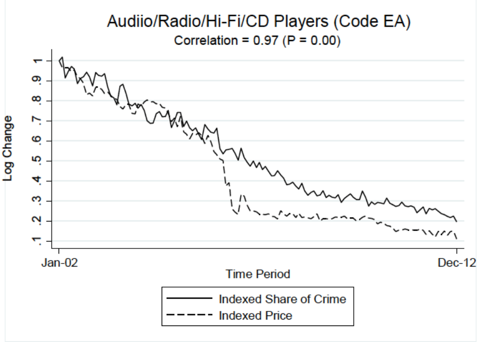
— $U(W_C)$**:** returns from crime, illegal gains

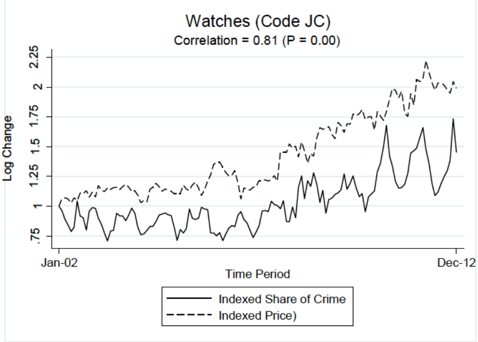
**Draca, Koutmeridis, Machin (2015)**, henceforth DKM, analyze how crime responds to economic incentives by estimating crime-price elasticities. They find evidence of significant positive crime-price elasticities in a panel of consumer goods, then focus on commodity related goods, finding sizable elasticities when they instrument local prices by exogenous shifts in global commodity prices.

# *"The Changing Returns to Crime: Do Criminals Respond to Prices?" with Mirko Draca (Warwick) and Stephen Machin (UCL)*

**Puzzle:** How criminals react when the prices of products change?

**Data :** Unique crime data / we know what was stolen / we match it with prices.



## **DKM** - Main Idea

**Theory:** Consider the basic model of the criminal decision following Becker (1968), Ehrlich (1973) or Freeman (1999):
SuccessProb*IllegalGains−CaughtProb*Sanctions>LegalGains

$$(1-\pi) * U(W_C) \ - \ \pi * U(S) \ > \ U(W_L)$$

**Dataset:** We match monthly crime data from the London Metropolitan Police Service to product prices from the ONS
– Unique feature: we know what was stolen / we build a panel of data and isolate product specific characteristics.

**Method:** We show how criminals respond to price changes in two ways
**Approach 1:** *Fixed effects* estimates reveal a positive elasticity.
**Approach 2:** *Instrumental Variable* estimates reveal a positive elasticity too. "Global commodity metal prices" used as instruments for "London scrap metal prices".

## DKM - A Simple Model of Crime

$$(1 - \pi_{g,i}) * P_g \; - \; \pi_{g,i} * S_g \; > \; W_i$$

$\pi$: probability of being caught
$P$: Price / value / returns from crime
$S$: Sanctions / sentences / punishment
$W$: Wages / returns from legitimate labor

$P_g$: Each product $g$ yields the same return for all
$S_g$: Crime for each product $g$ is punished equally for all
$W_i$: Wages depends on the skills of each individual

**Homogeneous agent / Heterogeneous goods**
Our data concern several different goods but we do not have much information regarding criminals.

## **DKM** - Homogeneous agent/Heterogeneous goods: equilibrium

When the inequality below holds, individuals commit crime:

$$(1 - \pi_1) * P_1 \; - \; \pi_1 * S_1 \; > \; W$$

The probability of being caught rises when the stolen quantity rises. *Low-hanging fruit explanation*: $\pi = kQ_1$, where $k > 0$

In equilibrium the expression above holds with equality. This gives equilibrium stolen quantity for given prices.

$$(1 - kQ_1) * P_1 \; - \; kQ_1 * S_1 \; = \; W$$

Rearranging: $Q_1 = (P_1 - W)/[k(P_1 + S)]$

## **DKM** - Homogeneous agent / Heterogeneous goods: Elasticity

$$Q_1 = (P_1 - W)/[k(P_1 + S)] \qquad (*)$$

Taking the partial derivative of (*) with respect to price gives:
$\partial Q_1/\partial P_1 = (S + W)/[k(P_1 + S)^2]$

Thus the associated crime-price elasticity is:
$(\partial Q_1/\partial P_1)(P_1/Q_1) = \{(S + W)/[k(P_1 + S)^2]\}(P_1/Q_1)$

The elasticity can be re-written as:
$(\partial Q_1/\partial P_1)(P_1/Q_1) = \partial \log Q_1/\partial \log P_1 \equiv b$

Where the **elasticity** $b$ is given by the following expression:
**Theory:** $\log Q_{1t} = constant + b \log P_1$

**Data:** $\log(Crime)_{gt} = \alpha_g + \alpha_t + \beta \log(Price)_{gt} + \epsilon_{gt}$

## DKM - Crime Data Description

- Crime by property type (theft, robbery, burglary) - with key feature of what was stolen.
- Administrative monthly data between January 2002 and December 2012 from the Crime Record Information System (CRIS) of the London Metropolitan Police Service (MPS) - this is the MPS standard reporting format for crimes.
- Property types coded at 2-digit level (203 of them in 19 one-digit groups). Some are non-market goods (passport, documents etc.) and some are housing infrastructure (gates, fireplaces etc.).
- We will also complement these data with victimisation data from the British Crime Survey over the same time period.

## DKM - Price Data Description

- These are matched to ONS data on prices (used to compute retail and consumer price index) at monthly level between January 2002 and December 2012.
- End up with panel of 44 groups matched to prices in balanced panel (of 12 months by 11 years). This covers 78 percent of the market goods.
- The metal group M is going to be of particular interest (for reasons that will become clear). We have matched these to scrap metal prices (from letsrecycle.com) which we instrument using international commodity prices.

## DKM - More Data

- We also complement our analysis with data on what was reported stolen in crime victimizations reported in the British Crime Survey (BCS).
- The BCS is an annual survey of around 40,000 households in England and Wales.
- For our purposes, it contains data on what was stolen, its (replacement) value and on reporting patterns to the police.

| (1) CODE | (2) DESCRIPTION | (3) NUMBER OF TWO-DIGIT PRODUCTS | (4) SHARE OF TOTAL CRIME (Full Period) | (5) SHARE OF TOTAL CRIME (2002 Only) | (6) SHARE OF TOTAL CRIME (2012 Only) | (7) SHARE MATCHED (Within 1-digit) |
|---|---|---|---|---|---|---|
| A | Clothing | 10 | 0.036 | 0.040 | 0.034 | 0.877 |
| B | Publications | 4 | 0.003 | 0.004 | 0.002 | 0.802 |
| C | Currency and Official Documents | 13 | 0.261 | 0.288 | 0.210 | na |
| D | Cosmetics and Drugs | 4 | 0.017 | 0.172 | 0.015 | 0.972 |
| E | Electronic and Electrical | 21 | 0.194 | 0.191 | 0.232 | 0.804 |
| F | Weapons | 5 | 0.001 | 0.001 | 0.000 | na |
| G | Food and Drink (inc Alcohol) | 7 | 0.024 | 0.024 | 0.026 | 0.862 |
| H | Furnishing & Household Accessories | 22 | 0.018 | 0.026 | 0.012 | 0.665 |
| J | Jewellery | 10 | 0.060 | 0.055 | 0.083 | 0.887 |
| K | Personal Bags and Cases | 8 | 0.101 | 0.107 | 0.086 | na |
| L | Leisure Equipment / Vehicle Accessories | 19 | 0.056 | 0.038 | 0.072 | 0.505 |
| M | Metal Commodities | 7 | 0.003 | 0.001 | 0.006 | 1.000 |
| N | Personal and Vehicle Documents | 12 | 0.091 | 0.089 | 0.080 | na |
| P | Office and Art Materials | 8 | 0.004 | 0.005 | 0.003 | na |
| R | Building Materials | 16 | 0.002 | 0.001 | 0.002 | 0.525 |
| S | Photographic and Scientific Equipment | 5 | 0.030 | 0.029 | 0.024 | 0.309 |
| T | Building Tools | 10 | 0.030 | 0.037 | 0.036 | 0.816 |
| V | Pets and Animals | 7 | 0.000 | 0.000 | 0.000 | na |
| W | Public Property, Fuel and Miscellaneous | 15 | 0.071 | 0.050 | 0.078 | 0.148 |
| | **OVERALL STATISTICS** | | | | | |
| | (1) Share Matched (balanced panel) | | 0.368 | | | |
| | (2) Share Non-Matched (unbalanced) | | 0.108 | | | |
| | (3) Share Rare / Unusual | | 0.033 | | | |
| | (4) Share Non-Market | | 0.492 | | | |

## APPENDIX A: ADDITIONAL TABLES

**Table A1: Example of Matching Metropolitan Police Service (MPS) Goods Categories to Office of National Statistics (ONS) Item Codes.**

| (A) MPS GOODS CLASSIFICATIONS FOR CLOTHING. | | (B) ONS MATCH FOR CHILDRENSWEAR 2-DIGIT MPS CODE. | |
|---|---|---|---|
| **MPS Goods Code (2-digit)** | **MPS Category Label Description** | **ONS Product Item id** | **ONS Item ID Label Description** |
| AA | Ladies wear | 510324 | Trousers (suitable for school) |
| AB | Menswear | 510328 | Boy's Jeans (5-15 years) |
| **AC** | **CHILDRENSWEAR** | 510330 | Babygro or Sleep Suit |
| AD | Sportswear | 510336 | Girl's Skirt (5-15 years) |
| AE | Protective Clothing | 510340 | Girl's Fashion Top (12-15 years) |
| AF | Fur | 510341 | Child's Trousers (18 months – 4 years) |
| AG | Footwear | 510342 | Girl's Summer Jacket |
| AH | Clothing Fabric | 510343 | Girl's Winter Jacket |
| AJ | Uniform | 510344 | Girl's Trouser (not denim) |
| | | 510345 | Boy's Branded Sports Top |
| | | 510346 | Childs Jumper |

Notes: This table shows an example of how we have matched the MPS goods categories codes to the ONS retail price index item id codes. Panel (A) shows the level of 2-digit detail available within the overall 1-digit Clothing category within the MPS data. Panel (B) then shows an example of the 6-digit item ids that have been matched to the MPS "Childrenswear" category. Hence our matching by label description process is facilitated by the level of detail available in the ONS data, which allows us to make fine distinctions for appropriate item matches against the MPS data.

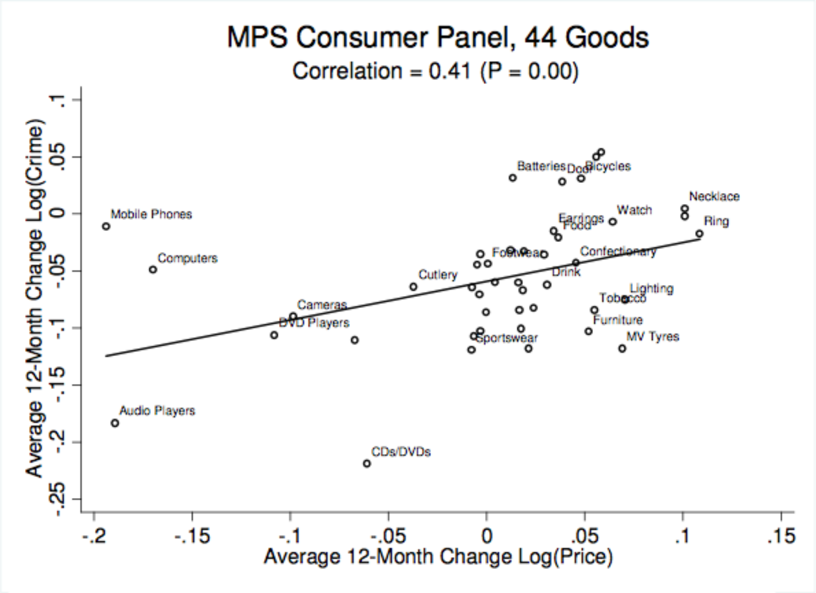
# DKM - Changes in the Share of Property Crime: **Top 10 Goods**

| (1)<br>PROPERTY TYPE CODE | (2)<br>PROPERTY TYPE DESCRIPTION | (3)<br>ANNUALISED GROWTH (QUANTITIES) | (4)<br>10-YEAR CHANGE IN SHARE (%) | (5)<br>FINAL SHARE IN 2012 (%) |
|---|---|---|---|---|
| ET | Mobile Phones | -0.011 | 8.8 | 31.6 |
| | | (0.125) | | |
| LA | Bicycles and Accessories | 0.031 | 4.6 | 8.8 |
| | | (0.109) | | |
| JA | Necklace / Pendant | 0.005 | 1.9 | 5.1 |
| | | (0.103) | | |
| JC | Watch | -0.006 | 1.3 | 4.2 |
| | | (0.087) | | |
| JB | Ring | -0.016 | 1.0 | 4.3 |
| | | (0.097) | | |
| JD | Bracelets | -0.006 | 1.0 | 2.9 |
| | | (0.087) | | |
| | Earrings | -0.013 | 0.5 | 1.9 |
| JE | | (0.114) | | |
| | Hand Tool – Power | -0.034 | 0.5 | 5.9 |
| TA | | (0.126) | | |
| | Foodstuff | -0.020 | 0.3 | 1.7 |
| GA | | (0.130) | | |
| ER | Battery / Charger | 0.031 | 0.2 | 0.4 |
| | | (0.055) | | |

# DKM - Changes in the Share of Property Crime: **Bottom 10 Goods**

| PROPERTY TYPE CODE | PROPERTY TYPE DESCRIPTION | ANNUALISED GROWTH (QUANTITIES) | 10-YEAR CHANGE SHARE (%) | FINAL SHARE (%) (LEVEL ) |
|---|---|---|---|---|
| EA | Audio/Radio/Hi-Fi/CD | -0.183 | -8.5 | 2.8 |
| | | (0.076) | | |
| HA | Records/CDs/Tapes/DVDs | -0.216 | -2.9 | 0.6 |
| | | (0.084) | | |
| EB | TV/Video/DVD/Projectors | -0.105 | -1.9 | 2.3 |
| | | (0.076) | | |
| SB | Optical Equipment | -0.089 | -1.0 | 1.8 |
| | | (0.057) | | |
| TB | Hand Tool – Mechanical | -0.103 | -0.8 | 1.0 |
| | | (0.117) | | |
| AA | Ladieswear | -0.064 | -0.6 | 2.6 |
| | | (0.046) | | |
| GD | Drink – Alcoholic | -0.067 | -0.6 | 2.2 |
| | | (0.056) | | |
| DA | Cosmetics / Toiletries | -0.060 | -0.6 | 3.3 |
| | | (0.046) | | |
| AB | Menswear | -0.059 | -0.5 | 3.3 |
| | | (0.071) | | |
| AD | Toiletries | -0.119 | -0.5 | 0.5 |
| | | (0.094) | | |

## **DKM** - Panel: Between Goods Correlations (Jan 2002–Dec 2012)



## DKM - Empirical Modelling Framework I

- How to specify time effects?
  Starting point: $f(t)$ = month dummies ($\alpha_m$) and year dummies ($\alpha_y$) separately, then full set of month ($m$) by year ($y$) dummies, $\alpha_t (= \alpha_y * \alpha_m)$

  $$\log C_{gt} = \alpha_g + \beta log P_{gt} + \alpha_t + u_{gt}$$

- Seasonality of crime (and possibly prices).
  Generalise further to include month specific fixed effects, $\alpha_g * \alpha_m$

  $$\log C_{gt} = \alpha_g * \alpha_m + \beta log P_{gt} + \alpha_t + u_{gt}$$

# DKM - Empirical Modelling Framework II

- Measuring prices:
  — Mostly going to use retail prices, but if what is stolen is to be sold on it is resale prices that criminals are interested in. The price measure we first use (consumer prices as given by the ONS) is obviously an imperfect proxy for this. However, if we think of the relationship between consumer prices and resale value as following a simple linear markdown function, like $Resale_{gt} = (1 - \lambda)Price_{gt}$, then it is evident that if the re-sale price faced by criminals is some constant fraction $(1 - \lambda)$ of the retail price we measure, it is captured by the product fixed effects. Indeed, if it further varies seasonally, the seasonally adjusted model will also control for this.
  — In our British Crime Survey analysis, we have data on replacement cost of what was stolen.
  — In our metal prices analysis, we have scrap metal prices as direct measures of the resale price.

# DKM - Empirical Modelling Framework III

- Detection probabilities:
  Recall, that criminals make decisions on the basis of $(1 - \pi_g)P_g$, the price weighed by the probability of not being caught committing a crime. So if detection technologies change this may affect this (we will discuss this in the metal prices part). Would expect this to be captured by the product fixed effects, unless product specific changes to crime matter.

- Crime types:
  Heterogeneity in products and in crime may be important (especially if goods with changing prices are more associated with particular types of crime). Can address this possibility by looking separately at different property crimes (we have data on thefts/burglary/robbery).

# DKM - Panel: Crime-Price Elasticities (within good), 2002-12

(1): $\log(Crime)_{gt} = \alpha_g + \tau_m + \tau_y + \beta \log(Price\ Index)_{gt} + \epsilon_{gt}$

(2): $\log(Crime)_{gt} = \alpha_g + \tau_m X \tau_y + \beta \log(Price\ Index)_{gt} + \epsilon_{gt}$

(3): $\log(Crime)_{gt} = \alpha_g X \tau_m + \tau_m X \tau_y + \beta \log(Price\ Index)_{gt} + \epsilon_{gt}$

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | Log(Crime) | | | Log(Theft) | Log(Burglary + Robbery) | Log(Crime) |
| Log(Price) | 0.348 | 0.348 | 0.346 | 0.413 | 0.254 | 0.106 |
| | (0.130) | (0.132) | (0.138) | (0.155) | (0.123) | (0.047) |
| Lagged Dependent Variable | | | | | | 0.692 |
| | | | | | | (0.061) |
| Long-Run Elasticity | | | | | | 0.342 |
| | | | | | | (0.140) |
| Goods Fixed Effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Month Fixed Effects | Yes | No | No | No | No | No |
| Year Fixed Effects | Yes | No | No | No | No | No |
| Month*Year Fixed Effects | No | Yes | Yes | Yes | Yes | Yes |
| Month*Goods Fixed Effects | No | No | Yes | Yes | Yes | Yes |
| Number of Products | 44 | 44 | 44 | 44 | 44 | 44 |
| Number of Observations | 5,808 | 5,808 | 5,808 | 5,808 | 5,808 | 5,764 |

# **DKM** - Panel: Crime-Price Elasticities (within good), 2002-12

$$(1): \log(Crime)_{gt} = \alpha_g + \tau_m + \tau_y + \beta \log(Price\ Index)_{gt} + \epsilon_{gt}$$

$$(2): \log(Crime)_{gt} = \alpha_g + \tau_m X \tau_y + \beta \log(Price\ Index)_{gt} + \epsilon_{gt}$$

$$(3): \log(Crime)_{gt} = \alpha_g X \tau_m + \tau_m X \tau_y + \beta \log(Price\ Index)_{gt} + \epsilon_{gt}$$

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | | Log(Crime) | | Log(Theft) | Log(Burglary + Robbery) | Log(Crime) |
| Log(Price) | 0.348 | 0.348 | 0.346 | 0.413 | 0.254 | 0.106 |
| | (0.130) | (0.132) | (0.138) | (0.155) | (0.123) | (0.047) |
| Lagged Dependent Variable | | | | | | 0.692 |
| | | | | | | (0.061) |
| Long-Run Elasticity | | | | | | 0.342 |
| | | | | | | (0.140) |
| Goods Fixed Effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Month Fixed Effects | Yes | No | No | No | No | No |
| Year Fixed Effects | Yes | No | No | No | No | No |
| Month*Year Fixed Effects | No | Yes | Yes | Yes | Yes | Yes |
| Month*Goods Fixed Effects | No | No | Yes | Yes | Yes | Yes |
| Number of Products | 44 | 44 | 44 | 44 | 44 | 44 |
| Number of Observations | 5,808 | 5,808 | 5,808 | 5,808 | 5,808 | 5,764 |

# DKM - Panel: Crime-Price Elasticities (within good), 2002-12

$$(1): \log(Crime)_{gt} = \alpha_g + \tau_m + \tau_y + \beta \log(Price\ Index)_{gt} + \epsilon_{gt}$$
$$(2): \log(Crime)_{gt} = \alpha_g + \tau_m X \tau_y + \beta \log(Price\ Index)_{gt} + \epsilon_{gt}$$
$$(3): \log(Crime)_{gt} = \alpha_g X \tau_m + \tau_m X \tau_y + \beta \log(Price\ Index)_{gt} + \epsilon_{gt}$$

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | | Log(Crime) | | Log(Theft) | Log(Burglary + Robbery) | Log(Crime) |
| Log(Price) | 0.348<br>(0.130) | 0.348<br>(0.132) | 0.346<br>(0.138) | 0.413<br>(0.155) | 0.254<br>(0.123) | 0.106<br>(0.047) |
| Lagged Dependent Variable | | | | | | 0.692<br>(0.061) |
| Long-Run Elasticity | | | | | | 0.342<br>(0.140) |
| Goods Fixed Effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Month Fixed Effects | Yes | No | No | No | No | No |
| Year Fixed Effects | Yes | No | No | No | No | No |
| Month*Year Fixed Effects | No | Yes | Yes | Yes | Yes | Yes |
| Month*Goods Fixed Effects | No | No | Yes | Yes | Yes | Yes |
| Number of Products | 44 | 44 | 44 | 44 | 44 | 44 |
| Number of Observations | 5,808 | 5,808 | 5,808 | 5,808 | 5,808 | 5,764 |

# DKM - Panel / Lags: Crime-Price Elasticities (within good), 2002-12

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | Log(Crime) | | | |
| Log(Price) | 0.346 | 0.193 | 0.165 | 0.164 |
| | (0.138) | (0.138) | (0.086) | (0.085) |
| $\text{Log(Price)}_{(t-1)}$ | | 0.156 | 0.087 | 0.085 |
| | | (0.101) | (0.077) | (0.078) |
| $\text{Log(Price)}_{(t-2)}$ | | | 0.099 | 0.091 |
| | | | (0.080) | (0.045) |
| $\text{Log(Price)}_{(t-3)}$ | | | | 0.004 |
| | | | | (0.091) |
| Long-Run Elasticity | 0.346 | 0.351 | 0.352 | 0.352 |
| | (0.138) | (0.140) | (0.140) | (0.142) |
| Goods Fixed Effects | Yes | Yes | Yes | Yes |
| Month * Year Fixed Effects | Yes | Yes | Yes | Yes |
| Month * Goods Fixed Effects | Yes | Yes | Yes | Yes |
| Number of Products | 44 | 44 | 44 | 44 |
| Number of Observations | 5,676 | 5,676 | 5,676 | 5,676 |

# DKM - Panel / Lags: Crime-Price Elasticities (within good), 2002-12

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | Log(Crime) | | | |
| Log(Price) | 0.346 | 0.193 | 0.165 | 0.164 |
| | (0.138) | (0.138) | (0.086) | (0.085) |
| Log(Price)$_{(t-1)}$ | | 0.156 | 0.087 | 0.085 |
| | | (0.101) | (0.077) | (0.078) |
| Log(Price)$_{(t-2)}$ | | | 0.099 | 0.091 |
| | | | (0.080) | (0.045) |
| Log(Price)$_{(t-3)}$ | | | | 0.004 |
| | | | | (0.091) |
| Long-Run Elasticity | 0.346 | 0.351 | 0.352 | 0.352 |
| | (0.138) | (0.140) | (0.140) | (0.142) |
| Goods Fixed Effects | Yes | Yes | Yes | Yes |
| Month * Year Fixed Effects | Yes | Yes | Yes | Yes |
| Month * Goods Fixed Effects | Yes | Yes | Yes | Yes |
| Number of Products | 44 | 44 | 44 | 44 |
| Number of Observations | 5,676 | 5,676 | 5,676 | 5,676 |

## DKM - Identification Issues

1. Investment in Security: protect valuable goods / downward bias
2. Police Responses: these occur with a lag / monthly data
3. Resale Value: measurement error probably a downward bias
4. Endogenous Reporting: report mainly valuable goods
5. Demand Shocks: rising demand boost prices & goods stock

# DKM - Identification Issues

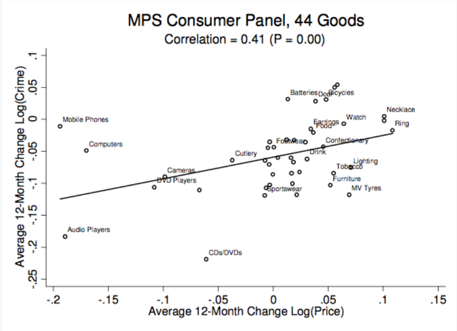
1. Investment in Security: protect valuable goods / downward bias
2. Police Responses: these occur with a lag / monthly data
3. Resale Value: measurement error probably a downward bias
4. **Endogenous Reporting**: report mainly valuable goods
5. Demand Shocks: rising demand boost prices & goods stock

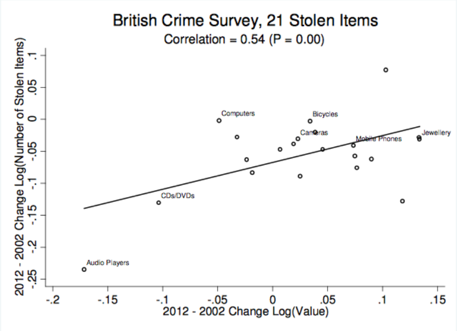
## British Crime Survey, 2002 & 2012

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | Share of Reported Crimes | | Log(Crime) | |
| | Levels | (1) + Product Fixed Effects | Reported Incidents | All Incidents |
| Log(Value) | 0.118 | 0.018 | 0.421 | 0.518 |
| | (0.026) | (0.023) | (0.216) | (0.278) |
| Product Fixed Effects | No | Yes | Yes | Yes |
| Year Fixed Effect | Yes | Yes | Yes | Yes |
| Number of Products | 21 | 21 | 21 | 21 |
| Number of Observations | 42 | 42 | 42 | 42 |

# **DKM** - Identification: Endogenous Reporting: report valuable goods

2002-12: Similar results with reported MET (left) & surveyed BCS (right) data




—BUT **demand shocks** still boost both prices & the stock of goods.
—We deal with this endogeneity issue by using Instrumental Variables.
—"Global metal commodity prices" are highly correlated with "London scrap metal prices", but uncorrelated with $\epsilon_t$, so suitable instruments.

## DKM - Commodity Related Goods

- Demand shocks: Focus on a set of commodity-related goods for which the source of demand shocks is known, in that prices set on global markets (and so are exogenous).

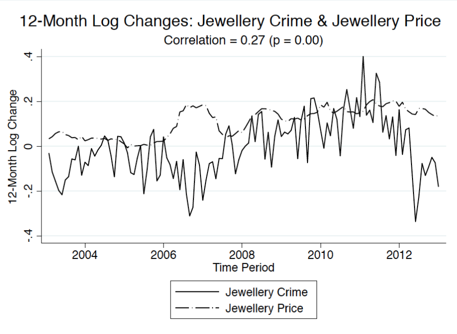
- Two groups
  1. "Consumer Prices": we estimate separately by OLS and IV.
     — Fuel and Energy: relate to oil prices;
     — Jewellery: relate to gold prices.
  2. Metals group: we estimate scrap price models by OLS and IV. All metals and place specific focus on copper crimes. Have direct resale value available (scrap metal dealers).

- Study individual time series for jewellery/fuel and metals/copper.
  — Set up as quasi-experiment: prices change exogenously due to global demand shocks - e.g. rapidly rising copper prices related to recent economic growth in China.
  — Estimate seasonally (12 month) differenced IV models using world commodity prices as instruments for prices.

# DKM - IV Part 1: Jewellery & Fuel Crime & Prices (12-month diffs)

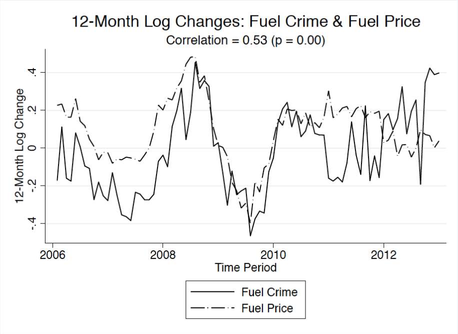
## Jewellery

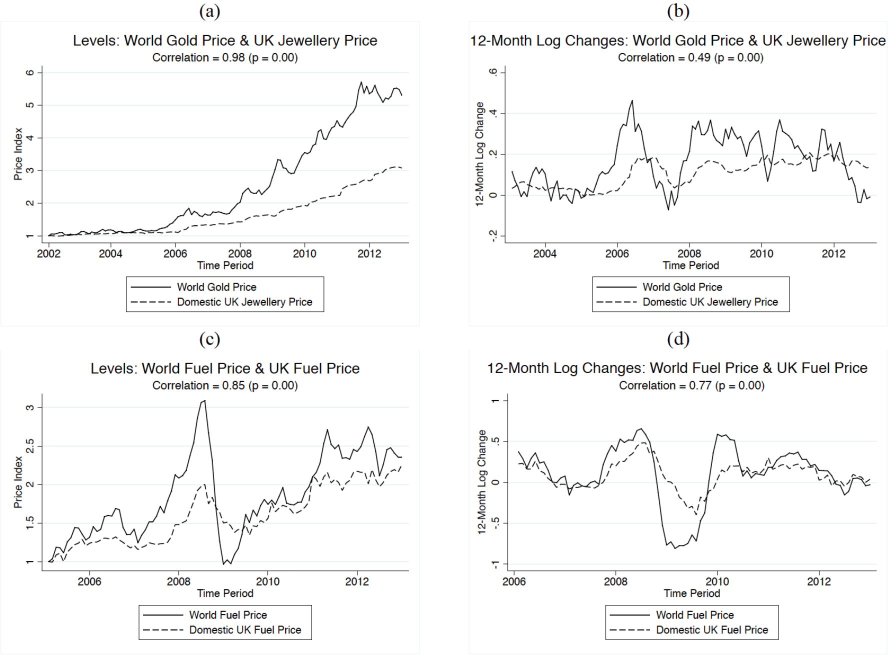
(a)




## Fuel

(b)




(a)
Levels: World Gold Price & UK Jewellery Price
Correlation = 0.98 (p = 0.00)
Price Index
Time Period
World Gold Price
Domestic UK Jewellery Price
(b)
12-Month Log Changes: World Gold Price & UK Jewellery Price
Correlation = 0.49 (p = 0.00)
12-Month Log Change
Time Period
World Gold Price
Domestic UK Jewellery Price
(c)
Levels: World Fuel Price & UK Fuel Price
Correlation = 0.85 (p = 0.00)
Price Index
Time Period
World Fuel Price
Domestic UK Fuel Price
(d)
12-Month Log Changes: World Fuel Price & UK Fuel Price
Correlation = 0.77 (p = 0.00)
12-Month Log Change
Time Period
World Fuel Price
Domestic UK Fuel Price

$$(1):\ \Delta\log(Crime)_{mt} = \delta_1 + \theta_1\Delta\log(Local\ Price)_{mt} + \psi_1 Time + \alpha_m + \omega_{1mt}$$
$$(3):\ \Delta\log(Local\ Price)_{mt} = \delta_3 + \theta_3\Delta\log(World\ Price)_{mt} + \psi_3 Time + \alpha_m + \omega_{3mt}$$
$$(4):\ \Delta\log(Crime)_{mt} = \delta_4 + \theta_4\Delta\log(Local\ Price)_{mt} + \psi_4 Time + \alpha_m + \omega_{4mt}$$

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| | OLS | OLS Reduced Form | First Stage | IV Structural Form | OLS | OLS Reduced Form | First Stage | IV Structural Form |
| | $\Delta_{12}$Log(Crime) | $\Delta_{12}$Log(Crime) | $\Delta_{12}$Log(Price) | $\Delta_{12}$Log(Crime) | $\Delta_{12}$Log(Crime) | $\Delta_{12}$Log(Crime) | $\Delta_{12}$Log(Price) | $\Delta_{12}$Log(Crime) |
| **A. Jewellery** | | | | | | | | |
| $\Delta_{12}$Log(Price) | 0.563 | | | 1.248 | -0.205 | | | 1.479 |
| | (0.168) | | | (0.395) | (0.314) | | | (0.898) |
| $\Delta_{12}$Log(World Price) | | 0.304 | 0.244 | | | 0.191 | 0.129 | |
| | | (0.089) | (0.037) | | | (0.104) | (0.026) | |
| F-Statistic | | | 43.90 | | | | 24.39 | |
| Time Trend | No | No | No | No | Yes | Yes | Yes | Yes |
| Number of Observations | 120 | 120 | 120 | 120 | 120 | 120 | 120 | 120 |
| **B. Fuel** | | | | | | | | |
| $\Delta_{12}$Log(Price) | 0.699 | | | 0.626 | 0.708 | | | 0.657 |
| | (0.096) | | | (0.110) | (0.098) | | | (0.106) |
| $\Delta_{12}$Log(World Price) | | 0.229 | 0.365 | | | 0.240 | 0.366 | |
| | | (0.050) | (0.046) | | | (0.052) | (0.046) | |
| F-Statistic | | | 63.77 | | | | 62.20 | |
| Time Trend | No | No | No | No | Yes | Yes | Yes | Yes |
| Number of Observations | 84 | 84 | 84 | 84 | 84 | 84 | 84 | 84 |

$$(1):\ \Delta\log(Crime)_{mt} = \delta_1 + \theta_1 \Delta\log(Local\ Price)_{mt} + \psi_1 Time + \alpha_m + \omega_{1mt}$$
$$(3):\ \Delta\log(Local\ Price)_{mt} = \delta_3 + \theta_3 \Delta\log(World\ Price)_{mt} + \psi_3 Time + \alpha_m + \omega_{3mt}$$
$$(4):\ \Delta\log(Crime)_{mt} = \delta_4 + \theta_4 \Delta\log(Local\ Price)_{mt} + \psi_4 Time + \alpha_m + \omega_{4mt}$$

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| | OLS | OLS Reduced Form | First Stage | IV Structural Form | OLS | OLS Reduced Form | First Stage | IV Structural Form |
| | $\Delta_{12}$Log(Crime) | $\Delta_{12}$Log(Crime) | $\Delta_{12}$Log(Price) | $\Delta_{12}$Log(Crime) | $\Delta_{12}$Log(Crime) | $\Delta_{12}$Log(Crime) | $\Delta_{12}$Log(Price) | $\Delta_{12}$Log(Crime) |
| **A. Jewellery** | | | | | | | | |
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| | (0.168) | | | (0.395) | (0.314) | | | (0.898) |
| $\Delta_{12}$Log(World Price) | | 0.304 | 0.244 | | | 0.191 | 0.129 | |
| | | (0.089) | (0.037) | | | (0.104) | (0.026) | |
| F-Statistic | | | 43.90 | | | | 24.39 | |
| Time Trend | No | No | No | No | Yes | Yes | Yes | Yes |
| Number of Observations | 120 | 120 | 120 | 120 | 120 | 120 | 120 | 120 |
| **B. Fuel** | | | | | | | | |
| $\Delta_{12}$Log(Price) | 0.699 | | | 0.626 | 0.708 | | | 0.657 |
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| $\Delta_{12}$Log(World Price) | | 0.229 | 0.365 | | | 0.240 | 0.366 | |
| | | (0.050) | (0.046) | | | (0.052) | (0.046) | |
| F-Statistic | | | 63.77 | | | | 62.20 | |
| Time Trend | No | No | No | No | Yes | Yes | Yes | Yes |
| Number of Observations | 84 | 84 | 84 | 84 | 84 | 84 | 84 | 84 |

$$(1):\ \Delta \log(\mathit{Crime})_{mt} = \delta_1 + \theta_1 \Delta \log(\mathit{Local\ Price})_{mt} + \psi_1 \mathit{Time} + \alpha_m + \omega_{1mt}$$
$$(3):\ \Delta \log(\mathit{Local\ Price})_{mt} = \delta_3 + \theta_3 \Delta \log(\mathit{World\ Price})_{mt} + \psi_3 \mathit{Time} + \alpha_m + \omega_{3mt}$$
$$(4):\ \Delta \log(\mathit{Crime})_{mt} = \delta_4 + \theta_4 \Delta \log(\mathit{Local\ Price})_{mt} + \psi_4 \mathit{Time} + \alpha_m + \omega_{4mt}$$

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| | OLS | OLS Reduced Form | First Stage | IV Structural Form | OLS | OLS Reduced Form | First Stage | IV Structural Form |
| | $\Delta_{12}$Log(Crime) | $\Delta_{12}$Log(Crime) | $\Delta_{12}$Log(Price) | $\Delta_{12}$Log(Crime) | $\Delta_{12}$Log(Crime) | $\Delta_{12}$Log(Crime) | $\Delta_{12}$Log(Price) | $\Delta_{12}$Log(Crime) |
| **A. Jewellery** | | | | | | | | |
| $\Delta_{12}$Log(Price) | 0.563 | | | 1.248 | -0.205 | | | 1.479 |
| | (0.168) | | | (0.395) | (0.314) | | | (0.898) |
| $\Delta_{12}$Log(World Price) | | 0.304 | 0.244 | | | 0.191 | 0.129 | |
| | | (0.089) | (0.037) | | | (0.104) | (0.026) | |
| F-Statistic | | | 43.90 | | | | 24.39 | |
| Time Trend | No | No | No | No | Yes | Yes | Yes | Yes |
| Number of Observations | 120 | 120 | 120 | 120 | 120 | 120 | 120 | 120 |
| **B. Fuel** | | | | | | | | |
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| Time Trend | No | No | No | No | Yes | Yes | Yes | Yes |
| Number of Observations | 84 | 84 | 84 | 84 | 84 | 84 | 84 | 84 |

$$(1):\ \Delta\log(Crime)_{mt} = \delta_1 + \theta_1\Delta\log(Local\ \ Price)_{mt} + \psi_1 Time + \alpha_m + \omega_{1mt}$$
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$$(4):\ \Delta\log(Crime)_{mt} = \delta_4 + \theta_4\Delta\log(Local\ \ Price)_{mt} + \psi_4 Time + \alpha_m + \omega_{4mt}$$

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| | OLS | OLS Reduced Form | First Stage | IV Structural Form | OLS | OLS Reduced Form | First Stage | IV Structural Form |
| | $\Delta_{12}$Log(Crime) | $\Delta_{12}$Log(Crime) | $\Delta_{12}$Log(Price) | $\Delta_{12}$Log(Crime) | $\Delta_{12}$Log(Crime) | $\Delta_{12}$Log(Crime) | $\Delta_{12}$Log(Price) | $\Delta_{12}$Log(Crime) |
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| | (0.168) | | | (0.395) | (0.314) | | | (0.898) |
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| | | (0.089) | (0.037) | | | (0.104) | (0.026) | |
| F-Statistic | | | 43.90 | | | | 24.39 | |
| Time Trend | No | No | No | No | Yes | Yes | Yes | Yes |
| Number of Observations | 120 | 120 | 120 | 120 | 120 | 120 | 120 | 120 |
| **B. Fuel** | | | | | | | | |
| $\Delta_{12}$Log(Price) | 0.699 | | | 0.626 | 0.708 | | | 0.657 |
| | (0.096) | | | (0.110) | (0.098) | | | (0.106) |
| $\Delta_{12}$Log(World Price) | | 0.229 | 0.365 | | | 0.240 | 0.366 | |
| | | (0.050) | (0.046) | | | (0.052) | (0.046) | |
| F-Statistic | | | 63.77 | | | | 62.20 | |
| Time Trend | No | No | No | No | Yes | Yes | Yes | Yes |
| Number of Observations | 84 | 84 | 84 | 84 | 84 | 84 | 84 | 84 |

$$(1):\ \Delta \log(Crime)_{mt} = \delta_1 + \theta_1 \Delta \log(Local\ \ Price)_{mt} + \psi_1 Time + \alpha_m + \omega_{1mt}$$
$$(3):\ \Delta \log(Local\ \ Price)_{mt} = \delta_3 + \theta_3 \Delta \log(World\ \ Price)_{mt} + \psi_3 Time + \alpha_m + \omega_{3mt}$$
$$(4):\ \Delta \log(Crime)_{mt} = \delta_4 + \theta_4 \Delta \log(Local\ \ Price)_{mt} + \psi_4 Time + \alpha_m + \omega_{4mt}$$

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| | OLS | OLS Reduced Form | First Stage | IV Structural Form | OLS | OLS Reduced Form | First Stage | IV Structural Form |
| | $\Delta_{12}$Log(Crime) | $\Delta_{12}$Log(Crime) | $\Delta_{12}$Log(Price) | $\Delta_{12}$Log(Crime) | $\Delta_{12}$Log(Crime) | $\Delta_{12}$Log(Crime) | $\Delta_{12}$Log(Price) | $\Delta_{12}$Log(Crime) |
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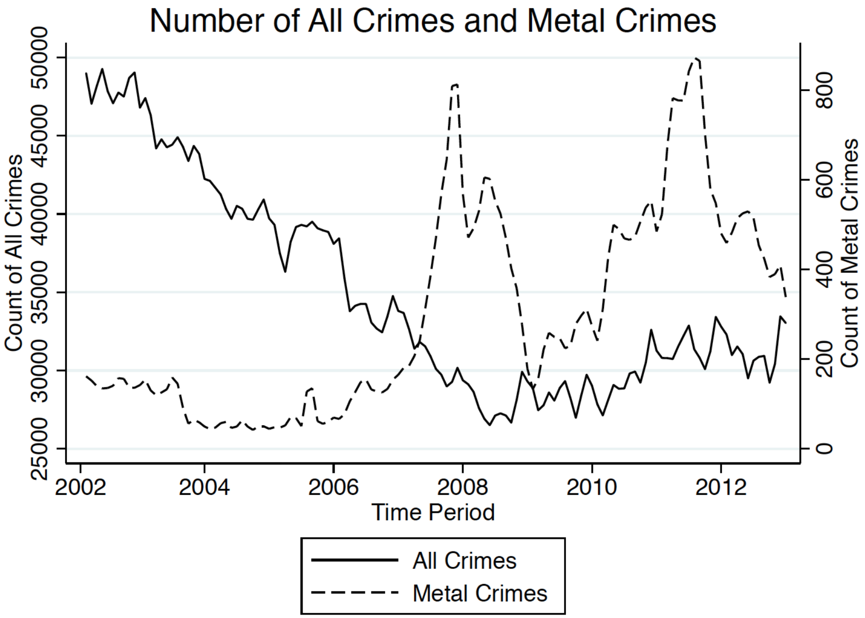
| | (0.168) | | | (0.395) | (0.314) | | | (0.898) |
| $\Delta_{12}$Log(World Price) | | 0.304 | 0.244 | | | 0.191 | 0.129 | |
| | | (0.089) | (0.037) | | | (0.104) | (0.026) | |
| F-Statistic | | | 43.90 | | | | 24.39 | |
| Time Trend | No | No | No | No | Yes | Yes | Yes | Yes |
| Number of Observations | 120 | 120 | 120 | 120 | 120 | 120 | 120 | 120 |
| **B. Fuel** | | | | | | | | |
| $\Delta_{12}$Log(Price) | 0.699 | | | 0.626 | 0.708 | | | 0.657 |
| | (0.096) | | | (0.110) | (0.098) | | | (0.106) |
| $\Delta_{12}$Log(World Price) | | 0.229 | 0.365 | | | 0.240 | 0.366 | |
| | | (0.050) | (0.046) | | | (0.052) | (0.046) | |
| F-Statistic | | | 63.77 | | | | 62.20 | |
| Time Trend | No | No | No | No | Yes | Yes | Yes | Yes |
| Number of Observations | 84 | 84 | 84 | 84 | 84 | 84 | 84 | 84 |


Number of All Crimes and Metal Crimes
Count of All Crimes
50000
45000
40000
35000
30000
25000
Count of Metal Crimes
800
600
400
200
0
2002
2004
2006
2008
2010
2012
Time Period
All Crimes
Metal Crimes

# DKM - Metal Crimes

- These crimes are of even more particular interest as they have risen sharply over time, and have been very common and often costly. The goods are stolen for the value of their constituent metals.
- There are many anecdotes of “lifting lead from churches” and “cable theft from tube trains and stations”. These crimes can yield a very high return and one that is higher now than in the past.
- They also have sizeable additional costs and are taking a heavy toll on businesses, homeowners and on the police .
- According to the MPS, metal cable theft alone costs 770 million pounds per year, while Bennett (2008) offers further UK examples and estimates that “240,000 passenger minutes lost in 2006” due to delays caused by copper cable theft. Metals have now become a category in police recorded crime statistics.

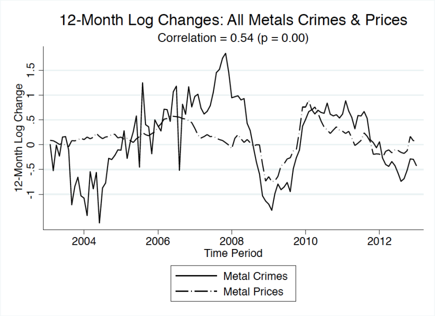
## **DKM** - Metal Crimes: (Selected) 2012 Example Headlines

- "Metal theft costs Church of England 10 million".
- "Czech metal thieves dismantle 10-ton bridge".
- "Bishop condemns theft of IRA Warrington bomb plaque for scrap".
- "5bn scrap metal industry told to '*clean up act over thefts crime wave*' ".
- "Metal thieves now target cages at animal hospital".

# DKM - IV Part 2: Metals Crime-Prices (12-month diffs)

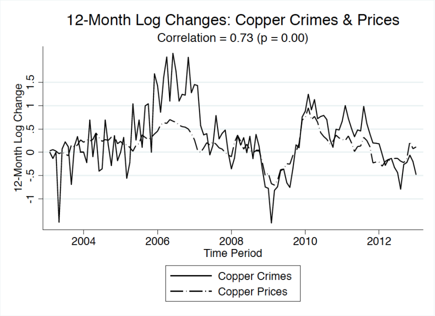
## All Metals

(a)

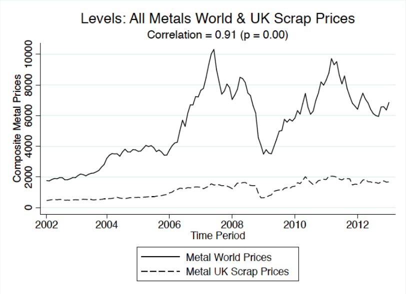



## Copper

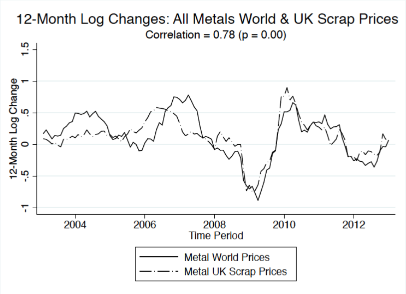
(b)



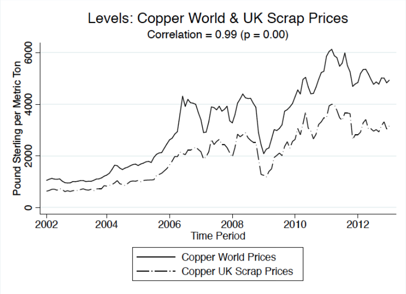
(a)


Levels: All Metals World & UK Scrap Prices
Correlation = 0.91 (p = 0.00)
Composite Metal Prices
0
2000
4000
6000
8000
10000
2002
2004
2006
2008
2010
2012
Time Period
Metal World Prices
Metal UK Scrap Prices

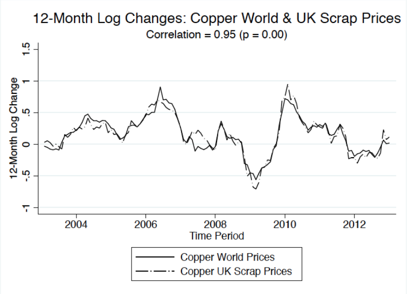
(b)


12-Month Log Changes: All Metals World & UK Scrap Prices
Correlation = 0.78 (p = 0.00)
12-Month Log Change
-1
-.5
0
.5
1
1.5
2004
2006
2008
2010
2012
Time Period
Metal World Prices
Metal UK Scrap Prices

(c)


Levels: Copper World & UK Scrap Prices
Correlation = 0.99 (p = 0.00)
Pound Sterling per Metric Ton
0
2000
4000
6000
2002
2004
2006
2008
2010
2012
Time Period
Copper World Prices
Copper UK Scrap Prices

(d)


12-Month Log Changes: Copper World & UK Scrap Prices
Correlation = 0.95 (p = 0.00)
12-Month Log Change
-1
-.5
0
.5
1
1.5
2004
2006
2008
2010
2012
Time Period
Copper World Prices
Copper UK Scrap Prices

$$(1):\ \Delta\log(\mathit{Crime})_{mt} = \delta_1 + \theta_1 \Delta\log(\mathit{Scrap\ Price})_{mt} + \psi_1 \mathit{Time} + \alpha_m + \omega_{1mt}$$
$$(3):\ \Delta\log(\mathit{Scrap\ Price})_{mt} = \delta_3 + \theta_3 \Delta\log(\mathit{World\ Price})_{mt} + \psi_3 \mathit{Time} + \alpha_m + \omega_{3mt}$$
$$(4):\ \Delta\log(\mathit{Crime})_{mt} = \delta_4 + \theta_4 \Delta\log(\mathit{Scrap\ Price})_{mt} + \psi_4 \mathit{Time} + \alpha_m + \omega_{4mt}$$

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| | OLS | OLS Reduced Form | First Stage | IV Structural Form | OLS | OLS Reduced Form | First Stage | IV Structural Form |
| | $\Delta_{12}$Log(Crime) | $\Delta_{12}$Log(Crime) | $\Delta_{12}$Log(Scrap Price) | $\Delta_{12}$Log(Crime) | $\Delta_{12}$Log(Crime) | $\Delta_{12}$Log(Crime) | $\Delta_{12}$Log(Scrap Price) | $\Delta_{12}$Log(Crime) |
| **A. All Metals** | | | | | | | | |
| $\Delta_{12}$Log(Scrap Price) | 1.349 | | | 1.320 | 1.427 | | | 1.493 |
| | (0.114) | | | (0.143) | (0.133) | | | (0.143) |
| $\Delta_{12}$Log(World Price) | | 1.333 | 1.010 | | | 1.587 | 1.063 | |
| | | (0.151) | (0.050) | | | (0.148) | (0.051) | |
| F-Statistic | | | 412.85 | | | | 422.13 | |
| Time Trend | No | No | No | No | Yes | Yes | Yes | Yes |
| Number of Observations | 120 | 120 | 120 | 120 | 120 | 120 | 120 | 120 |
| **B. Copper** | | | | | | | | |
| $\Delta_{12}$Log(Scrap Price) | 1.657 | | | 1.756 | 1.700 | | | 1.812 |
| | (0.128) | | | (0.146) | (0.136) | | | (0.154) |
| $\Delta_{12}$Log(World Price) | | 1.752 | 0.997 | | | 1.811 | 0.999 | |
| | | (0.134) | (0.040) | | | (0.136) | (0.042) | |
| F-Statistic | | | 636.99 | | | | 578.61 | |
| Time Trend | No | No | No | No | Yes | Yes | Yes | Yes |
| Number of Observations | 120 | 120 | 120 | 120 | 120 | 120 | 120 | 120 |

$$(1):\ \Delta\log(Crime)_{mt} = \delta_1 + \theta_1 \Delta\log(Scrap\ Price)_{mt} + \psi_1 Time + \alpha_m + \omega_{1mt}$$
$$(3):\ \Delta\log(Scrap\ Price)_{mt} = \delta_3 + \theta_3 \Delta\log(World\ Price)_{mt} + \psi_3 Time + \alpha_m + \omega_{3mt}$$
$$(4):\ \Delta\log(Crime)_{mt} = \delta_4 + \theta_4 \Delta\log(Scrap\ Price)_{mt} + \psi_4 Time + \alpha_m + \omega_{4mt}$$

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| | OLS | OLS Reduced Form | First Stage | IV Structural Form | OLS | OLS Reduced Form | First Stage | IV Structural Form |
| | $\Delta_{12}$Log(Crime) | $\Delta_{12}$Log(Crime) | $\Delta_{12}$Log(Scrap Price) | $\Delta_{12}$Log(Crime) | $\Delta_{12}$Log(Crime) | $\Delta_{12}$Log(Crime) | $\Delta_{12}$Log(Scrap Price) | $\Delta_{12}$Log(Crime) |
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| | (0.114) | | | (0.143) | (0.133) | | | (0.143) |
| $\Delta_{12}$Log(World Price) | | 1.333 | 1.010 | | | 1.587 | 1.063 | |
| | | (0.151) | (0.050) | | | (0.148) | (0.051) | |
| F-Statistic | | | 412.85 | | | | 422.13 | |
| Time Trend | No | No | No | No | Yes | Yes | Yes | Yes |
| Number of Observations | 120 | 120 | 120 | 120 | 120 | 120 | 120 | 120 |
| **B. Copper** | | | | | | | | |
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| Time Trend | No | No | No | No | Yes | Yes | Yes | Yes |
| Number of Observations | 120 | 120 | 120 | 120 | 120 | 120 | 120 | 120 |

$$(1):\ \Delta\log(Crime)_{mt} = \delta_1 + \theta_1\Delta\log(Scrap\ Price)_{mt} + \psi_1 Time + \alpha_m + \omega_{1mt}$$
$$(3):\ \Delta\log(Scrap\ Price)_{mt} = \delta_3 + \theta_3\Delta\log(World\ Price)_{mt} + \psi_3 Time + \alpha_m + \omega_{3mt}$$
$$(4):\ \Delta\log(Crime)_{mt} = \delta_4 + \theta_4\Delta\log(Scrap\ Price)_{mt} + \psi_4 Time + \alpha_m + \omega_{4mt}$$

| | (1) OLS | (2) OLS Reduced Form | (3) First Stage | (4) IV Structural Form | (5) OLS | (6) OLS Reduced Form | (7) First Stage | (8) IV Structural Form |
|---|---|---|---|---|---|---|---|---|
| | $\Delta_{12}$Log(Crime) | $\Delta_{12}$Log(Crime) | $\Delta_{12}$Log(Scrap Price) | $\Delta_{12}$Log(Crime) | $\Delta_{12}$Log(Crime) | $\Delta_{12}$Log(Crime) | $\Delta_{12}$Log(Scrap Price) | $\Delta_{12}$Log(Crime) |
| **A. All Metals** | | | | | | | | |
| $\Delta_{12}$Log(Scrap Price) | 1.349 | | | 1.320 | 1.427 | | | 1.493 |
| | (0.114) | | | (0.143) | (0.133) | | | (0.143) |
| $\Delta_{12}$Log(World Price) | | 1.333 | 1.010 | | | 1.587 | 1.063 | |
| | | (0.151) | (0.050) | | | (0.148) | (0.051) | |
| F-Statistic | | | 412.85 | | | | 422.13 | |
| Time Trend | No | No | No | No | Yes | Yes | Yes | Yes |
| Number of Observations | 120 | 120 | 120 | 120 | 120 | 120 | 120 | 120 |
| **B. Copper** | | | | | | | | |
| $\Delta_{12}$Log(Scrap Price) | 1.657 | | | 1.756 | 1.700 | | | 1.812 |
| | (0.128) | | | (0.146) | (0.136) | | | (0.154) |
| $\Delta_{12}$Log(World Price) | | 1.752 | 0.997 | | | 1.811 | 0.999 | |
| | | (0.134) | (0.040) | | | (0.136) | (0.042) | |
| F-Statistic | | | 636.99 | | | | 578.61 | |
| Time Trend | No | No | No | No | Yes | Yes | Yes | Yes |
| Number of Observations | 120 | 120 | 120 | 120 | 120 | 120 | 120 | 120 |

$$(1):\ \Delta \log(Crime)_{mt} = \delta_1 + \theta_1 \Delta \log(Scrap\ Price)_{mt} + \psi_1 Time + \alpha_m + \omega_{1mt}$$
$$(3):\ \Delta \log(Scrap\ Price)_{mt} = \delta_3 + \theta_3 \Delta \log(World\ Price)_{mt} + \psi_3 Time + \alpha_m + \omega_{3mt}$$
$$(4):\ \Delta \log(Crime)_{mt} = \delta_4 + \theta_4 \Delta \log(Scrap\ Price)_{mt} + \psi_4 Time + \alpha_m + \omega_{4mt}$$

| | (1) OLS | (2) OLS Reduced Form | (3) First Stage | (4) IV Structural Form | (5) OLS | (6) OLS Reduced Form | (7) First Stage | (8) IV Structural Form |
|---|---|---|---|---|---|---|---|---|
| | $\Delta_{12}$Log(Crime) | $\Delta_{12}$Log(Crime) | $\Delta_{12}$Log(Scrap Price) | $\Delta_{12}$Log(Crime) | $\Delta_{12}$Log(Crime) | $\Delta_{12}$Log(Crime) | $\Delta_{12}$Log(Scrap Price) | $\Delta_{12}$Log(Crime) |
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| $\Delta_{12}$Log(Scrap Price) | 1.349 | | | 1.320 | 1.427 | | | 1.493 |
| | (0.114) | | | (0.143) | (0.133) | | | (0.143) |
| $\Delta_{12}$Log(World Price) | | 1.333 | 1.010 | | | 1.587 | 1.063 | |
| | | (0.151) | (0.050) | | | (0.148) | (0.051) | |
| F-Statistic | | | 412.85 | | | | 422.13 | |
| Time Trend | No | No | No | No | Yes | Yes | Yes | Yes |
| Number of Observations | 120 | 120 | 120 | 120 | 120 | 120 | 120 | 120 |
| **B. Copper** | | | | | | | | |
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| | (0.128) | | | (0.146) | (0.136) | | | (0.154) |
| $\Delta_{12}$Log(World Price) | | 1.752 | 0.997 | | | 1.811 | 0.999 | |
| | | (0.134) | (0.040) | | | (0.136) | (0.042) | |
| F-Statistic | | | 636.99 | | | | 578.61 | |
| Time Trend | No | No | No | No | Yes | Yes | Yes | Yes |
| Number of Observations | 120 | 120 | 120 | 120 | 120 | 120 | 120 | 120 |

$$(1):\ \Delta\log(Crime)_{mt} = \delta_1 + \theta_1 \Delta\log(Scrap\ Price)_{mt} + \psi_1 Time + \alpha_m + \omega_{1mt}$$
$$(3):\ \Delta\log(Scrap\ Price)_{mt} = \delta_3 + \theta_3 \Delta\log(World\ Price)_{mt} + \psi_3 Time + \alpha_m + \omega_{3mt}$$
$$(4):\ \Delta\log(Crime)_{mt} = \delta_4 + \theta_4 \Delta\log(Scrap\ Price)_{mt} + \psi_4 Time + \alpha_m + \omega_{4mt}$$

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| | OLS | OLS Reduced Form | First Stage | IV Structural Form | OLS | OLS Reduced Form | First Stage | IV Structural Form |
| | $\Delta_{12}$Log(Crime) | $\Delta_{12}$Log(Crime) | $\Delta_{12}$Log(Scrap Price) | $\Delta_{12}$Log(Crime) | $\Delta_{12}$Log(Crime) | $\Delta_{12}$Log(Crime) | $\Delta_{12}$Log(Scrap Price) | $\Delta_{12}$Log(Crime) |
| **A. All Metals** | | | | | | | | |
| $\Delta_{12}$Log(Scrap Price) | 1.349 | | | 1.320 | 1.427 | | | 1.493 |
| | (0.114) | | | (0.143) | (0.133) | | | (0.143) |
| $\Delta_{12}$Log(World Price) | | 1.333 | 1.010 | | | 1.587 | 1.063 | |
| | | (0.151) | (0.050) | | | (0.148) | (0.051) | |
| F-Statistic | | | 412.85 | | | | 422.13 | |
| Time Trend | No | No | No | No | Yes | Yes | Yes | Yes |
| Number of Observations | 120 | 120 | 120 | 120 | 120 | 120 | 120 | 120 |
| **B. Copper** | | | | | | | | |
| $\Delta_{12}$Log(Scrap Price) | 1.657 | | | 1.756 | 1.700 | | | 1.812 |
| | (0.128) | | | (0.146) | (0.136) | | | (0.154) |
| $\Delta_{12}$Log(World Price) | | 1.752 | 0.997 | | | 1.811 | 0.999 | |
| | | (0.134) | (0.040) | | | (0.136) | (0.042) | |
| F-Statistic | | | 636.99 | | | | 578.61 | |
| Time Trend | No | No | No | No | Yes | Yes | Yes | Yes |
| Number of Observations | 120 | 120 | 120 | 120 | 120 | 120 | 120 | 120 |

## How much of the falling trend in crime is explained by prices?

- The property crime we study in London (thefts, burglaries and robberies) fell by 3.5 percent a year between 2002 an 2012.
- The overall consumer price index rose by 2.9 percent per year, but the prices of the 44 goods we study rose by only 1.4 percent a year. Thus their real value fell by 1.5 percent a year.
- 1.5 times the average crime-price elasticity of 0.35 predicts a 0.53 percent a year drop in crime, or *15 percent of the crime drop*.
- The London 10th percentile weekly wage grew by 3.6 percent a year, so the goods prices fell by 2.2 percent relative to that. Benchmarking to the 10th percentile wage predicts a slightly bigger 0.81 percent a year fall, or *23 percent of the overall crime drop*.

## How much of the falling trend in crime is explained by prices?

- What about big price decreases and increases?
- The real price of **audio-visual** goods dropped by a huge 11.9(=9.0+2.9) percent a year - conducting the counterfactual exercise for audio-visual goods reveals that *38 percent* of the crime drop of 8 percent a year is attributable to lower prices.
- For **copper** the real price rose by 12.4 percent a year, which combined with the estimated elasticity of 1.8 predicts a 22.4 percent a year increase, or *76 percent* of the 29.3 percent a year increase in copper crimes.

# DKM - Crime, Prices and other factors

**Table 8: Prices and Labour Market Variables, London Monthly Data, 2002-2012**

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | $\Delta_{12}$Log(Crime) | $\Delta_{12}$Log(Crime) | $\Delta_{12}$Log(Crime) | $\Delta_{12}$Log(Crime) |
| $\Delta_{12}$Log(Price) | 0.600*** | | | 0.411*** |
| | (0.105) | | | (0.112) |
| $\Delta_{12}$Log($10^{th}$ Percentile Wage) | | -0.248*** | | -0.176*** |
| | | (0.047) | | (0.050) |
| $\Delta_{12}$Log(Male Unemployment Rate) | | | 0.189*** | 0.044 |
| | | | (0.038) | (0.043) |
| Time Trend | Yes | Yes | Yes | Yes |
| Number of Observations | 120 | 120 | 120 | 120 |

Notes: Robust standard errors in parentheses.

## **DKM, The Changing Returns to Crime** - Conclusion

- We uncover a strong positive relationship between prices and crime across a wide range of goods.
- This suggests that, as potential takings from crime rise with prices, criminals react to changing economic incentives by switching into crimes that yield a higher return.
- Thus, economic incentives working through relative price shifts act as an important determinant of criminal behaviour.

## The key message

- Identifying causal effects is difficult and costly.
- If the data are not appropriate, you have to be innovative (e.g. clever IV - more art than science).
- In order to get data appropriate for the identification of causal effects you need to spend money / effort / time.
- Identify causal effects to understand how society works but also how we can make it better. With your research you can inform policy interventions based on evidence and generate impact. This is the goal of our research network: **Behaviour, Structure and Interventions (BSI)**.

# References


- **Main Textbooks:**
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# Identifying Causal Effects

**Theodore Koutmeridis**
University of Glasgow & CREATe
RCUK Centre for Copyright & New Business Models in the Creative Economy

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Behaviour, Structure & Interventions research network
Interdisciplinary PhD Workshop