

Econometric Evaluation and Climate Change
Policies

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Background

During the last 10-15 years the Climate Change Issue has trickled down from a high level policy debate into a vast array of different policy initiatives on the ground aiming to mitigate Greenhouse Gas (GHG) pollution. Examples from the UK:

- ▶ UK Climate Change Levy and Climate Change Agreements
- ▶ EU ETS
- ▶ Renewable Obligation
- ▶ Carbon Trust
- ▶ Enhanced Capital Allowance¹
- ▶ Energy Reduction Commitment²
- ▶ Energy Technology Institute³
- ▶ Carbon Emission Reduction Target⁴

The need for econometric evaluation

- ▶ To inform future Climate Change Policy making we need know the *causal* effect of these policies.
- ▶ Many of those policies have the following structure:
 - ▶ Large number of individuals/businesses/households receive policy treatment
 - ▶ Some don't
- ▶ We can rely on a rich econometric toolkit developed in the labour economics literature to analyse such polices.
- ▶ Labour economics examples:
 - ▶ Effect of education on wage outcomes
 - ▶ Effect of hospital treatment on health
 - ▶ Effect of Military service on wage outcomes
 - ▶ The effect of children on labour market prospects of women.

Outline

- ▶ Methodology of Econometric Evaluation
- ▶ Some existing examples in more detail
- ▶ Practical issues
- ▶ Some ideas for the future

First however an example on how not to do it.....

Drugs, Sex and ... iphones

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Want to have sex with more people? Buy an iPhone (and stay away from Android)

Relaxnews
Thursday, 12 August 2010

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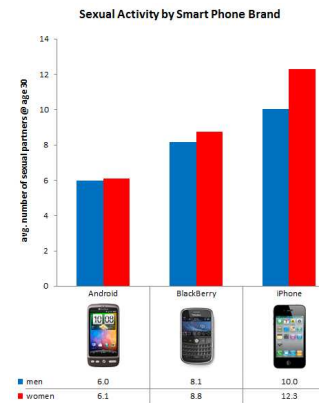
A new study conducted by online dating service OkCupid.com has revealed iPhone users have sex with twice the number of partners their Android-using counterparts have.

By the age of 30, men with an iPhone have had around 10 different partners. Their BlackBerry counterparts average around 8.1 partners.



Drugs, Sex and ... iphones

- ▶ So what's wrong with the okcupid study?
- ▶ Exploits correlation between sex and iphone usage
- ▶ Implied causality: iphone to sex
- ▶ But: why not sex to iphone?
- ▶ So what to do?

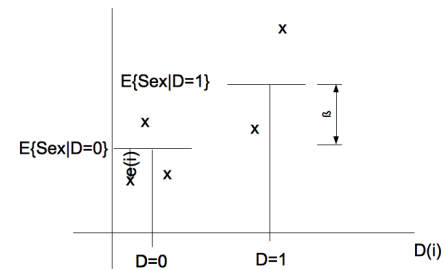


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A bit of methodology

- ▶ A more formal way of expressing the problem:
- ▶ $S_i = \beta_0 + \beta \times D_i + e_i$
- ▶ To Compute β we can use
- ▶ $\beta = \frac{\text{Cov}(S_i, D_i)}{\text{Var}(D_i)}$



To see last results note that:

$$\text{Cov}(S_i, D_i) = \frac{1}{N} \sum_i (S_i - \bar{S})(D_i - \bar{D}) = \frac{1}{N} \sum_i S_i D_i - \bar{S} \bar{D}.$$

Note that $\bar{S} = E[S_i | D_i = 1]P(D = 1) + E[S_i | D_i = 0](1 - P(D = 1))$

and $\frac{1}{N} \sum_i S_i D_i = E[S_i | D_i = 1]P(D = 1)$.

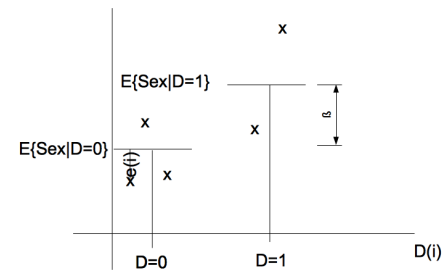
Hence $\text{Cov}(S_i, D_i) = (E[S_i | D_i = 1] - E[S_i | D_i = 0])P(D = 1)(1 - P(D = 1))$.

Similarly we can show that $\text{Var}(D_i) = P(D = 1)(1 - P(D = 1))$

From correlation to causality

$$S_i = \beta_0 + \beta \times D_i + e_i$$

- ▶ When can we interpret β as the causal effect of iphone usage on sex?
- ▶ Note that by construction we have that
- ▶ $E[e_i|D_i] = 0$



- ▶ Thus, β has a causal interpretation if the same is true for the actual process generating the data:
- ▶ $S_i = b \times D_i + \varepsilon_i$
- ▶ $E[\varepsilon_i|D_i] = E[\varepsilon_i] = 0$

How to violate $E[\varepsilon_i|D_i] = E[\varepsilon_i] = 0$?

- ▶ If both D_i and S_i are caused by something else or causality goes both ways; e.g.
- ▶ $\varepsilon_i = -\rho \times Nerd_i + \eta_i t$ and $E[D_i|Nerd_i = 1] < E[D_i|Nerd_i = 0]$
- ▶ then $E[\varepsilon_i|D_i = 1] > 0 > E[\varepsilon_i|D_i = 0]$
- ▶ So what to do?
 - ▶ Selection on observables: Controlling for other factors
 - ▶ Differences in Differences/Fixed Effects: Using time series variation to get rid of unobserved factors
 - ▶ Randomised Experiments: give me the iphone pill
 - ▶ Natural Experiments
 - ▶ Regression discontinuity
- ▶ Let's discuss each in turn

Selection on observables

- ▶ Suppose we have variables that can control for confounding factors; e.g. academic subject of individual.
- ▶ We can include them in a multivariate regressions:
$$S_i = \beta D_i + \beta_{a_1} \text{Subject}_i + \eta_i$$
- ▶ Rather than $E[\varepsilon_i | D_i] = 0$ we only need $E[\eta_i | D_i] = 0$ for causality.
- ▶ However: is academic subject sufficient to capture nerdiness?

Using time variation to get rid of un-observed factors

- ▶ Suppose we have time series data for individuals (Panel Data)
- ▶ Suppose that unobserved factors affect treatment and control group in the same way over time; i.e.
- ▶ $Sex_{it} = \beta D_{it} + \alpha_i + \eta_{it}$
- ▶ Can use (e.g.) first differences to get rid of α :
 $Sex_{it} - Sex_{it-1} = \beta(D_{it} - D_{it-1}) + \eta_{it} - \eta_{it-1}$
- ▶ Could be problematic if differences are not fixed over time; e.g. nerds are becoming cooler over time.
- ▶ Time series data might not be available.

Randomised Trials - The Gold Standard

- ▶ Follow the example of Drug Trials
- ▶ Give a **random** sample of participants iphones.
- ▶ Force a control group not to get iphones
- ▶ Compare before and after
- ▶ Best practice to isolate the effect of a specific measure.
- ▶ Not without problems, however:
 - ▶ Non compliance
 - ▶ Applicability beyond trial group?
 - ▶ General equilibrium effects?
 - ▶ (Moral) reservations: withholding goodies from some people.
- ▶ More moral design options; e.g. delay distribution of goodies to control group

Natural Experiments - Randomised trials designed by the gods and/or circumstance

- ▶ Sometimes we don't need to do experiments ourselves.
- ▶ Requires often detailed knowledge of circumstances of a policies. A bit of a treasure hunt.
- ▶ Example: exploit the fact that iphone was not available on all networks. Could examine if people who were on O2 (which covered iphone first in the UK) **before** iphone introduction had more sex after iphone introduction
- ▶ In practice we embedd this in an instrumental variable regression approach where O2 network becomes an instrument for identifying the causal effect of treatment on the outcome

The Instrumental Variable Approach

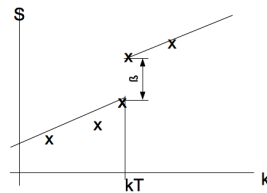
- ▶ Requirements for an instrument:
 1. Not correlated with unobserved factors (i.e. O2 users should not have more or less sex for reasons other than the early iphone arrival on O2)
 2. Correlated with the treatment (iphone usage)
- ▶ The IV approach then consists of a first stage regression:
 $D_i = \pi z_i + \delta_i$ (allows to test requirement 2)
- ▶ And a second stage: $S_i = \beta \pi z_i + \varepsilon_i$
- ▶ Implies that we estimate $\beta = \frac{\text{Cov}(S_i, z_i)}{\text{Cov}(D_i, z_i)}$
- ▶ If z_i and D_i are binary: $\beta = \frac{E[S_i|Z_i=1] - E[S_i|Z_i=0]}{E[D_i|Z_i=1] - E[D_i|Z_i=0]}$
i.e. how much more sex (pre iphone) O2 users have scaled with the difference in iphone usage between O2 and other network users

Maybe our analysis comes to LATE?

- ▶ What if treatment effect varies across i : β_i instead of β
- ▶ IV estimator identifies the Local Average Treatment Effect (LATE)
- ▶ Average β_i for those i that change their treatment status in response to z_i
- ▶ i.e. those (pre iphone) O2 users that that would not have changed to the iphone if they had been on a non O2 network.
- ▶ as opposed to never compliers (O2 users that did not switch to iphone) or always compliers (people who moved to O2 just because of iphone)
- ▶ Important special case: Instrument captures eligibility; e.g. if people were not allowed to change networks, (pre iphone) phone network membership would be an eligibility instrument.
- ▶ Thus: No always takers. IV identifies Average Treatment Effect for the Treated (ATT).

Regression discontinuity

- ▶ If un-observed factors change smoothly but policy treatment does not



- ▶ A bit like controlling with observables
- ▶ But: we only need to capture confounding factors well around the discontinuity
- ▶ Examples: Test scores that lead to selection in different schools; Geographical boundaries that lead to exclusion from treatment but nothing else (e.g. school catchment areas, tax districts)

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UK Climate Change Levy (CCL)⁶

- ▶ Energy Tax for Industry introduced in 2001
- ▶ Some firms can join Climate Change Agreements (CCA) to be exempt
- ▶ Hence we can compare outcomes (energy usage, employment etc) in firms that are exempt and those that are not.
- ▶ However: CCA participation voluntary.
There might be un-observed differences between firms that are joining and those that are not.
- ▶ Solution: 1. use differences 2. use instrument based on eligibility
- ▶ The model: $y_{it} = \beta D_{it} + \alpha_i + \eta_{it}$
- ▶ Use differences to get rid of α
- ▶ Eligibility was based on pre 2001 pollution control legislation.
Thus, we suggest that post 2001 outcome shocks are not correlated with eligibility

UK CCL – First Stage

| | (1) | (2) | (3) | (4) |
|---------------------------|---------------------|---------------------|---------------------|----------------------|
| Dependent variable | | | <i>CCL</i> | |
| Time period | 2001 | 2001 | 2000-2004 | 2001 |
| Method | OLS | Probit | FE | Probit |
| <i>NEPER</i> | 0.320*** (0.036) | 0.312*** (0.048) | 0.439*** (0.041) | |
| lnGO(t-1) | | | | 0.030*** (0.011) |
| lnK(t-1) | | | | -0.038*** (0.008) |
| lnEE(t-1) | | | | -0.042*** (0.007) |
| lnL(t-1) | | | | 0.003*** (0.003) |
| Age controls | yes | yes | yes | yes |
| Sector controls | yes | yes | no | yes |
| Region-by-year controls | yes | yes | yes | yes |
| Plant fixed effects | no | no | yes | no |
| R-squared | 0.29 | 0.29 | 0.81 | 0.38 |
| Observations | 1207 | 1102 | 17257 | 1082 |

UK CCL – Pre treatment differences?

| Variable | CCA=0 | CCA=1 | Significant? |
|--------------------|--------|--------|--------------|
| Age | 13.55 | 17.53 | *** |
| Employment | 151.49 | 536.44 | *** |
| Energy Expenditure | 0.22 | 1.95 | *** |
| Output | 19.08 | 86.08 | *** |
| Plants | 8282 | 1050 | |

| Variable | EPER=0 | EPER=1 | Significant? |
|--|--------|--------|--------------|
| $\Delta\ln(\text{Employment})$ | -0.021 | -0.016 | |
| $\Delta\ln(\text{Energy Expenditure})$ | 0.034 | 0.026 | |
| $\Delta\ln(\text{Output})$ | 0.026 | 0.037 | |

UK CCL – Some Results

| | (1) | (2) | (3) | (4) | (5) |
|--|---------------------|---------------------|----------------------|----------------------|-------------------------|
| Dependent variable | OLS | FE | r.f. (FE) | IV (FE) | obs./ plants |
| Energy share in gross output $\Delta \ln(\text{EE}/\text{GO})$ | -0.024* (0.013) | -0.027 (0.020) | -0.098** (0.040) | -0.223** (0.092) | 14,534 4,262 |
| Energy share in var. costs $\Delta \ln(\text{EE}/\text{VCost})$ | -0.027** (0.013) | -0.019 (0.018) | -0.121*** (0.038) | -0.275*** (0.089) | 14,534 4,262 |
| Energy expenditure $\Delta \ln(\text{EE})$ | -0.021* (0.013) | -0.039** (0.018) | -0.065** (0.029) | -0.149** (0.067) | 14,534 4,262 |

| | (1) | (2) | (3) | (4) | (5) |
|--|------------------|-------------------|-------------------|-------------------|-------------------------|
| Dependent variable | OLS | FE | r.f. (FE) | IV (FE) | obs./ plants |
| Employment $\Delta \ln(\text{L})$ | 0.006 (0.011) | -0.021 (0.015) | 0.020 (0.035) | 0.046 (0.081) | 14,534 4,262 |
| Real gross output $\Delta \ln(\text{Real GO})$ | 0.003 (0.011) | -0.012 (0.015) | 0.032 (0.034) | 0.074 (0.077) | 14,534 4,262 |
| Total factor productivity $\Delta \ln(\text{GO})-\text{inputs}$ | 0.002 (0.006) | 0.006 (0.010) | -0.010 (0.026) | -0.023 (0.059) | 14,467 4,262 |

Experiments are real

Hunt Allcott, "Social Norms and Energy Conservation"
(<http://web.mit.edu/allcott/www/Allcott>)

- ▶ US electric utility services company (OPower) mailed energy reports to a random sample of households
- ▶ Energy saving tips; information on electricity consumption of comparable households
- ▶ Population 78,492 household, 39,212 households in treatment group
- ▶ Random Treatment Group of
- ▶ 2.3% reduction in electricity consumption

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Practical issues

- ▶ Talk to policy makers/government departments for two main reasons:
 - ▶ Will help you find natural experiments
 - ▶ Will provide you with necessary data
- ▶ Encourage policy makers to keep data and facilitate matching
- ▶ Encourage policy makers to allow more randomisation
- ▶ ONS Micro Data
(<http://www.ons.gov.uk/about/who-we-are/our-services/vml>)

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Future Plans

- ▶ UK Carbon Trust Energy Audits. What's the causal effects?
- ▶ EU ETS. A discontinuity design?
- ▶ Your ideas? Let's talk

In conclusion: hopefully you don't buy an iphone in order to have more sex.

Thanks for listening - r.martin@lse.ac.uk

Notes

¹<http://www.eca.gov.uk/>

²http://www.decc.gov.uk/en/content/cms/what_we_do/lc_uk/crc/crc.aspx

³<http://www.energytechnologies.co.uk/Home.aspx>

⁴http://www.decc.gov.uk/en/content/cms/what_we_do/consumers/saving_energ

⁵For further reading see Angrist and Pischke (2009) "Mostly Harmless Econometrics"; Michael Greenstone and Ted Gayer "Quasi-Experimental and Experimental Approaches to Environmental Economics" RFF DP 07-22

⁶For details see Martin et al., 2009, <http://cep.lse.ac.uk/pubs/download/dp0917.pdf>