Partial Compliance and Essential Heterogeneity: Challenges for Impact Evaluation of Index Insurance

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I-4/FAO Conference: Economics of Index Insurance
January 15-16, 2010
Rome

Caveats

- This is just a starting point to get us started thinking about particular challenges of impact evaluation.
- Many other empirical approaches feasible beyond randomization and encouragement design.
- Many other practical issues I won't address:
  - Optimal level of randomization;
  - Risk of weak instruments;
  - Power calculations and minimum sample sizes;
  - …

Essential Heterogeneity

- There are many farmer characteristics that are difficult to measure and affect farmers' valuation of insurance
  - β_i, wealth, risk preferences, risk sharing networks, …

- This unobserved heterogeneity thus drives heterogeneity in:
  - Farmers' insurance purchase decision;
  - Farmer-specific impact of insurance.

- Causes problem in estimating casual impact of insurance
  - Farmers self select into purchasing insurance;
  - Uninsured are systematically different -- and thus not good CF -- for insured.

Partial Compliance

- Doesn't randomization of the treatment solve this problem?
- Yes…if we had ***full*** compliance:
  - Everyone in the treatment group actually gets treated;
  - No one in the control group gets treated.
- Might expect full compliance in some situations:
  - CCT's:
    - Treatment is receiving money, so everyone in treatment group takes it;
    - Govt. has ability to deny access to similar people in control communities;
- But full compliance very unlikely with insurance programs:
  - We've already seen demand-side reasons:
    - Take-up rates are low, even with subsidized premiums → many in "treatment" group *don't* take the treatment;
  - Institutional/supply-side reasons:
    - Hard to convince insurers to deny insurance to farmers in control group → some in "control" group *do* take treatment (Pisco example from this morning).

Encouragement Design

- So if we want to learn about the impacts of insurance, we must deal with partial compliance.
- One strategy is to use *encouragement design*.
- Instead of randomizing the treatment, we randomize the distribution of incentives ("instruments") that affect the probability that farmers buy insurance.
- Examples of potential instruments:
  - Invitations to participate in educational sessions Marketing intensity (radio ads in some areas but not others)
  - Coupons (price variation)

Rest of talk:
Elements of a Research Design

- Demonstrate essential heterogeneity via simple model of insurance demand;

- Use this simple model to introduce basic idea of encouragement design;
  - In particular, what characteristics do we need in our "instruments" in order to be able to really attribute impact to insurance.

- Pitfalls and limitations of encouragement design, especially when essential heterogeneity is large (lots of non-linearities in impact function).

Model of Insurance Demand (Miranda 1991)

- Assume farmers' only source of income and consumption is farming;
- Yield is only source of risk;
- Yield is exogenous → Farmers' only choice is to purchase insurance or not;
- Farmers differ only in basis risk.
- Basis risk represents essential heterogeneity. It determines the value of insurance to the farmer and thus:
  - Whether or not she'll buy it and;
  - Impact of insurance on farmer.

Uninsured Income, y_i^U

- We can decompose uninsured income into:

$$y_i^U = \mu_i + \beta_i \varepsilon_c + \varepsilon_i$$

  - μ_i : Mean income;
  - ε_c *:* Deviation of index (area yield) from its mean;
  - ε_i *:* Idiosyncratic risk uncorrelated with the index
    - Health shocks, plot specific pests..
    - Assume this part of basis risk is same for all farmers;
  - $\beta_i = Cov(y_i^U , \varepsilon_c)/Var(\varepsilon_c)$: Degree of co-movement between farmer *i*' s yield and the index.
    - Higher is β_i , lower is basis risk (varies across farmers)

Insured Income, y_i^I

- Farmers have access to index (area yield) insurance contract with:
  - Indemnity, I, paid when index falls below strikepoint;
  - Actuarially fair premium, p;
  - Loading, L;
  - Coupon that gives price discount c_i if farmer buys insurance.
- Insured income is thus:

$$y_i^I = y_i^U + c_i - p - L + I$$

Insurance Demand

- Farmer buys insurance if $Eu(y_i^I) \geq Eu(y_i^U)$
- Assume $Eu(y) = \mu - \gamma Var(y)$ (mean-variance utility)
- Can show that farmer buys insurance if:

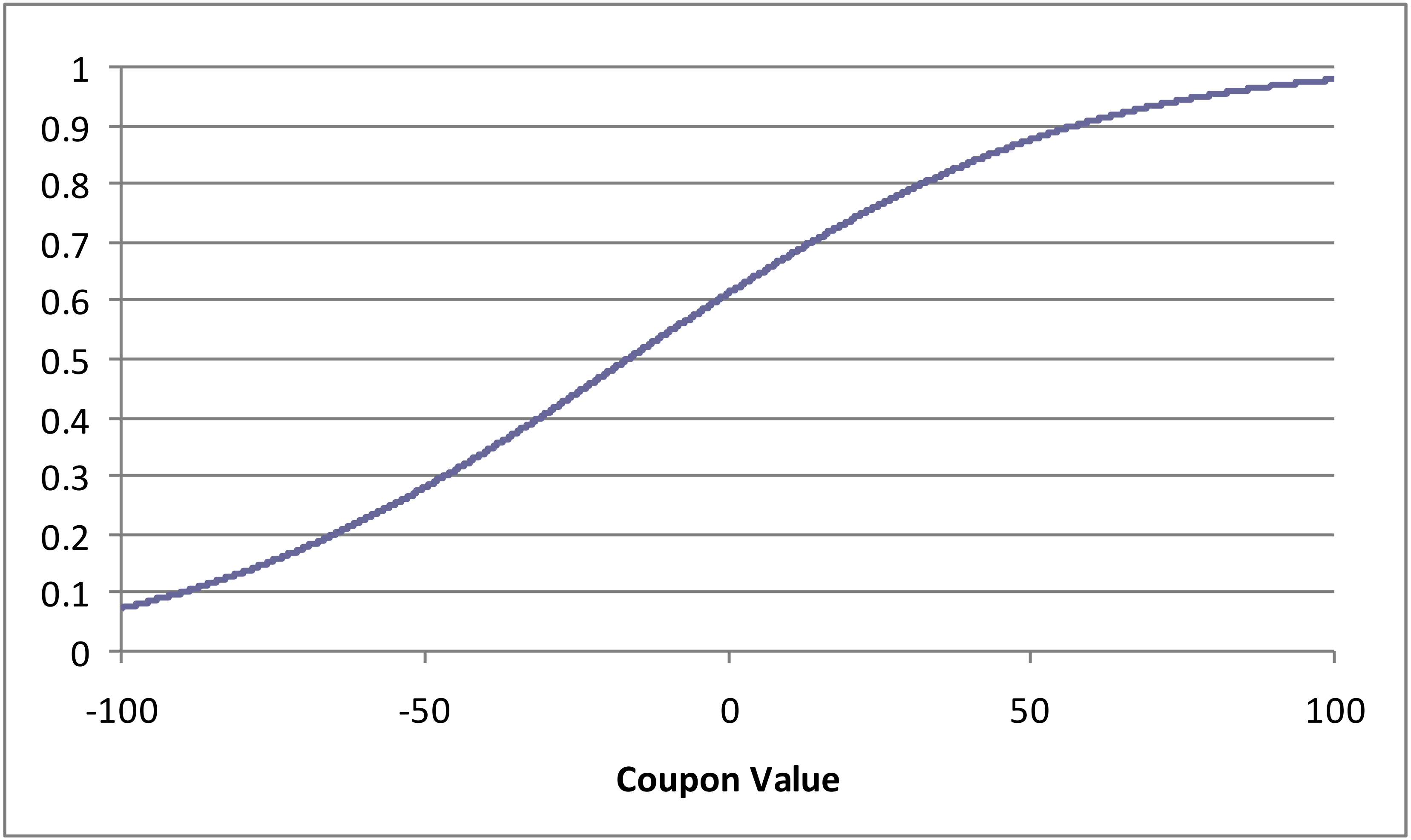
$$\beta_i \geq \beta^*(c_i) = \frac{c_i - L - \gamma Var(I)}{2\gamma Cov(\varepsilon_c, I)}$$

- So $\beta^*(c)$ Defines a critical threshold splitting all those farmers with coupon value c into purchasers and non-purchasers.
- A closer look at $\beta^*(c)$ …

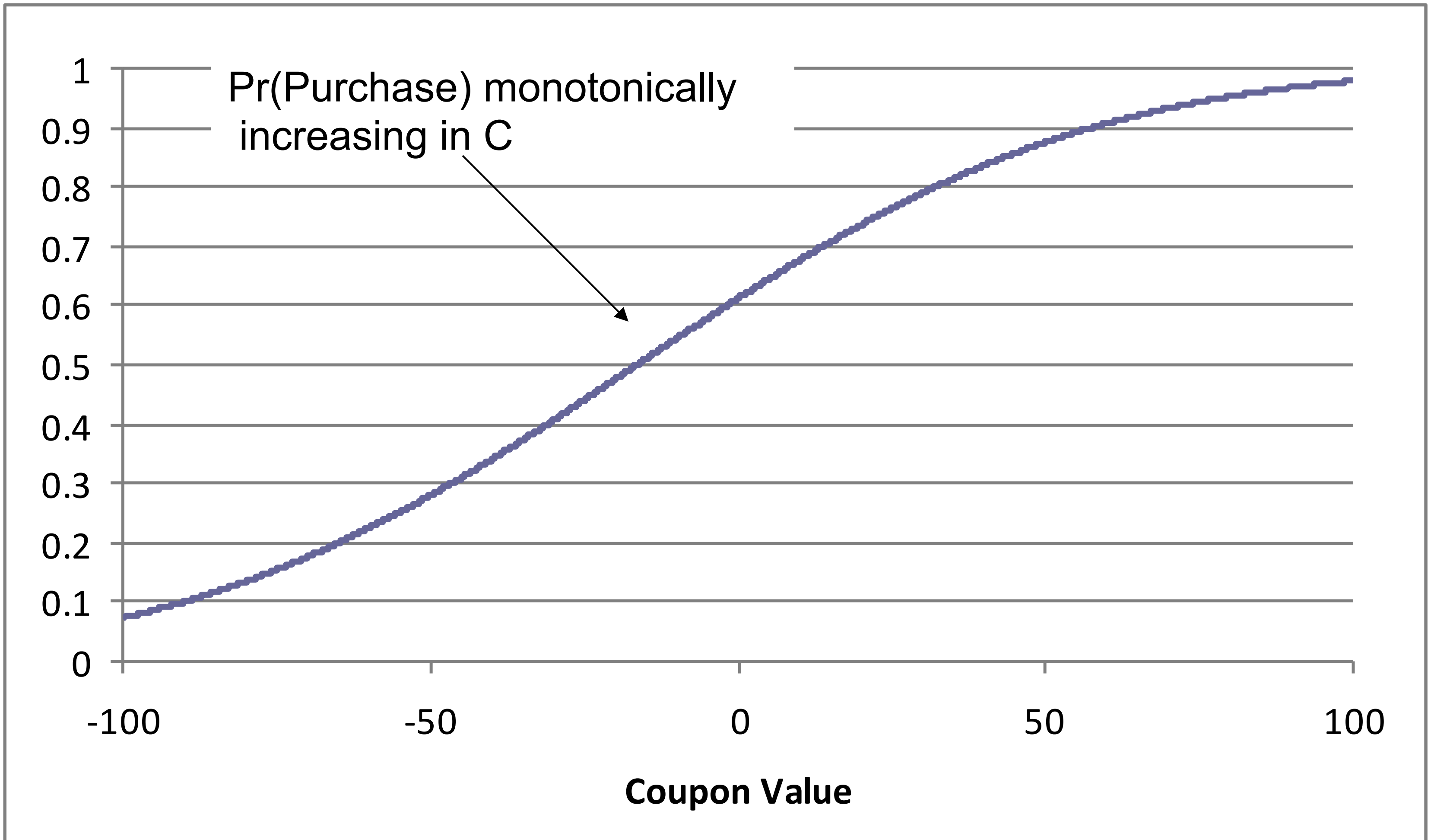
Intuition Behind $\beta^*(c_i) = \dfrac{c_i - L - \gamma Var(I)}{2\gamma Cov(\varepsilon_c, I)}$

- Among farmers with coupon size c_i those with:
  - $\beta_i \geq \beta^*(c_i)$: Insurance provides sufficient consumption smoothing (variance reduction) to warrant buying it.
  - $\beta_i < \beta^*(c_i)$: Insurance provides insufficient consumption smoothing, so don't buy.
- Manipulating coupon allows us to affect Pr(Purchase)
  - $\partial \beta^* / \partial c = c/(2\gamma Cov(I, \varepsilon_c)) < 0$
  - As the coupon rises (price falls) the minimum amount of consumption smoothing needed to buy insurance falls;
  - Thus fraction of farmers purchasing insurance is increasing in c_i
- Illustration: simulate our model using parameters (with some tweaking) from Peru…

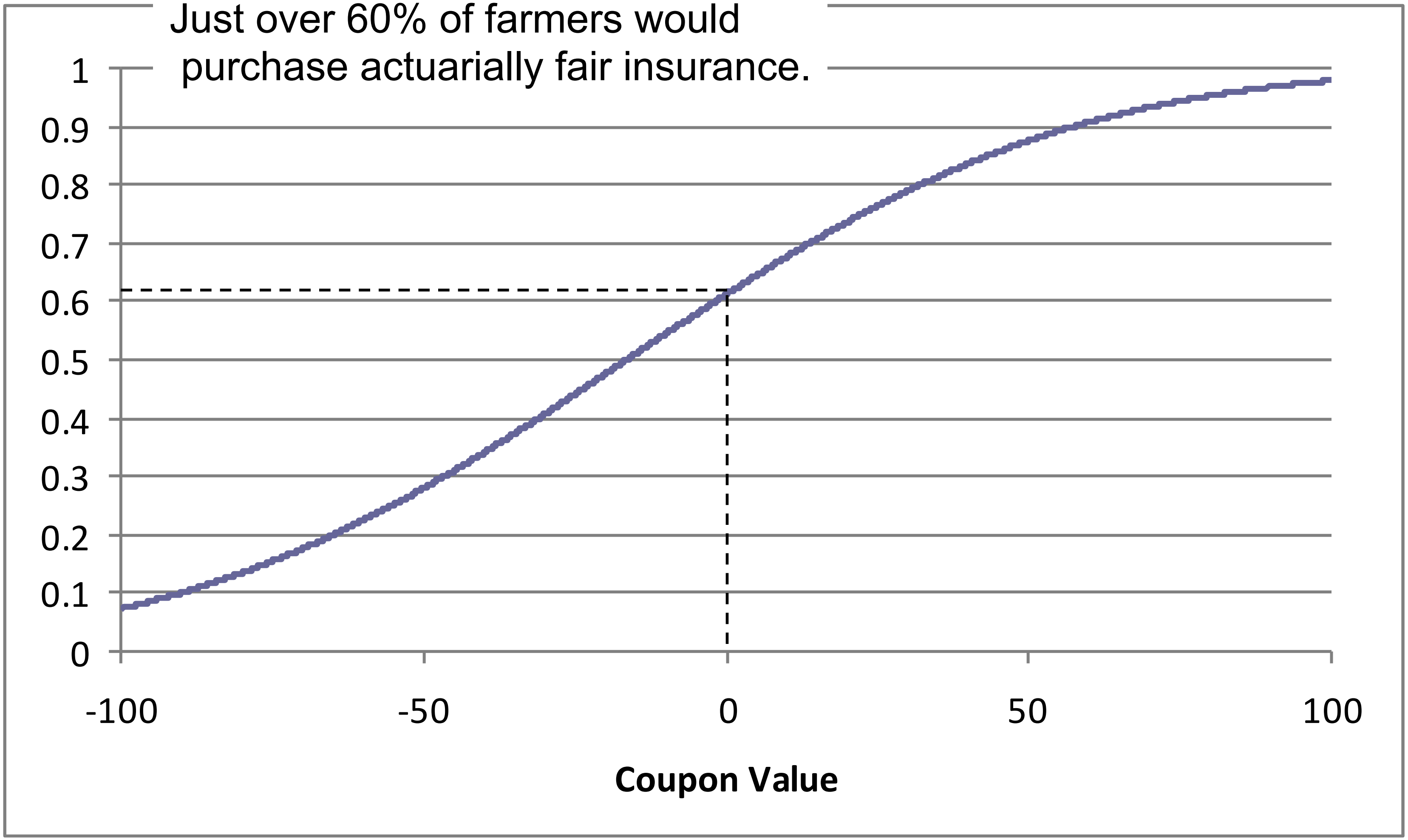
Probability of Insurance Purchase as function of Coupon Size



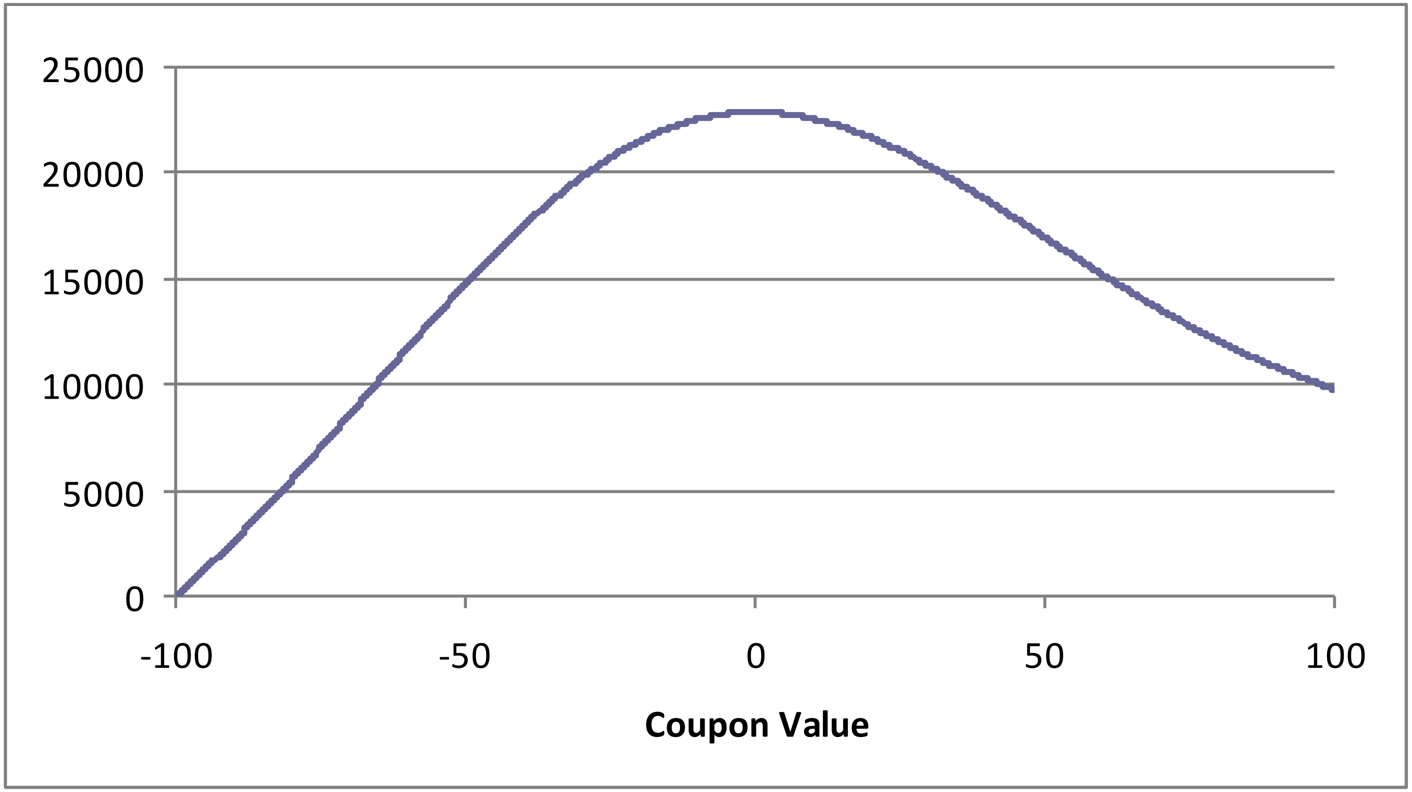
Probability of Insurance Purchase as function of Coupon Size



Probability of Insurance Purchase as function of Coupon Size

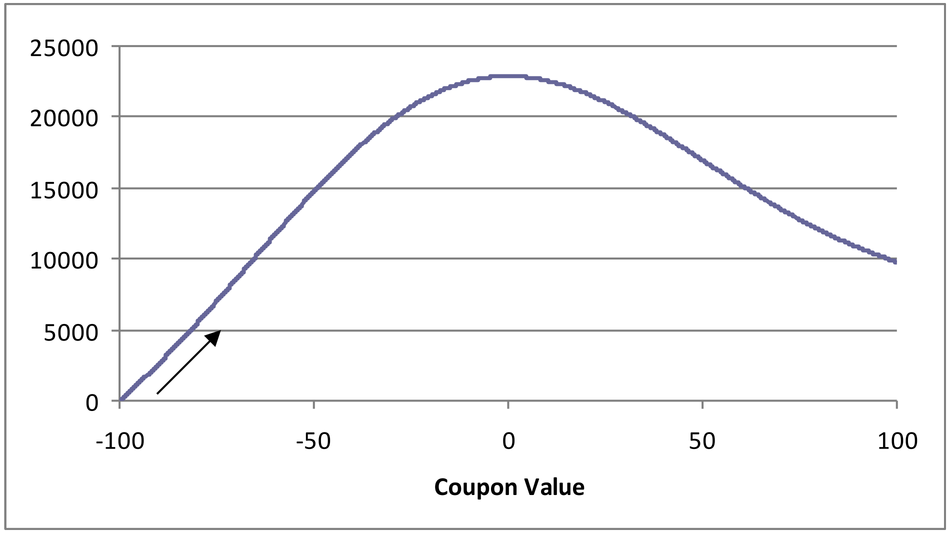


Initial Look at Impact Heterogeneity



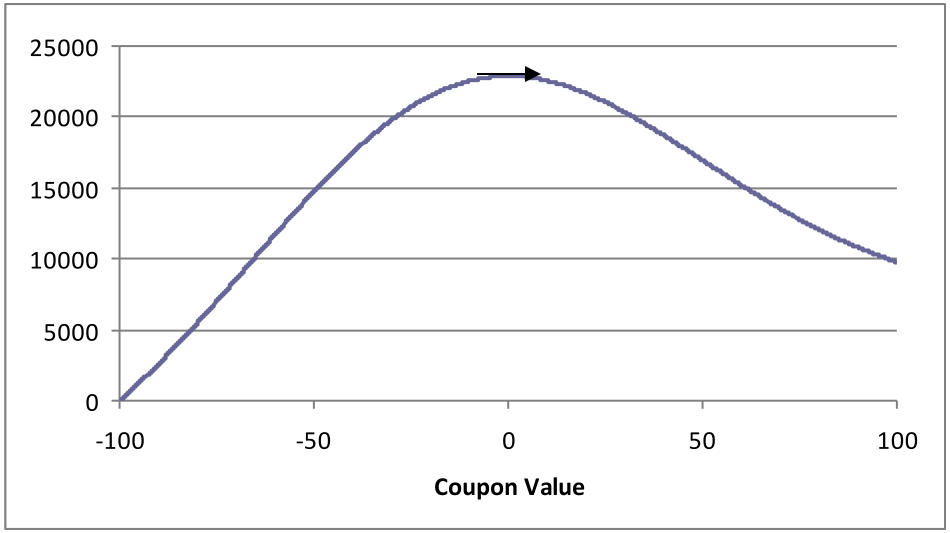
- Vertical axis is average *Eu* across all farmers (purchasers and non-purchasers) with given coupon size;
- *Eu* is net of coupon value → So we can evaluate impact of actuarially fair insurance.

Initial Look at Impact Heterogeneity



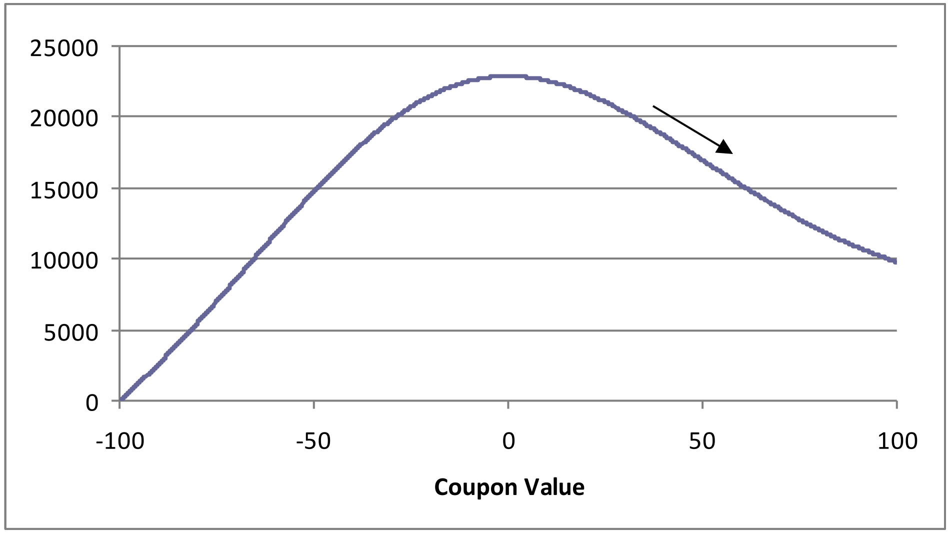
- For c << *0*: Insurance VERY expensive.
- Only the few farmers who get huge variance reduction from insurance buy it.
- A slight reduction in price (increase in coupon) induces some farmers to buy.
- Since price is still very high, new entrants still require large variance reduction
- Since we're netting out c, average expected utility increases. (expected income remains constant but average variance falls)

Initial Look at Impact Heterogeneity



- For $c = 0$: Insurance is actuarially fair.
- Indifferent farmer has same income variance with versus without insurance.
- Marginal change in coupon has no impact on average expected utility.

Initial Look at Impact Heterogeneity



- For $c > 0$: Insurance is subsidized (cheaper than actuarially fair).
- The indifferent farmer willing to accept higher income variance *with* insurance because the subsidy raises her expected income.
- Further increases in coupon lower price further, drawing in farmers with even lower β_i → average income variance increases and thus average EU across all farmers decreases.

Part II. An Empirical Strategy

- Partial compliance suggests use of encouragement design to learn about average impacts of insurance.

- Heterogeneous impacts (non-linear Expected Outcome curve) → challenges and limitations to what we can learn about impacts.

- To see this and think about implications for research design, we'll adopt framework from Moffit's "Estimating Marginal Treatment Effects in Heterogeneous Populations" (2008).

- Let's walk through that framework.

Potential Outcome Framework

- Outcome variable is $Eu(y_i)$
  - Assume we have "Utility-meter" to measure $Eu(y_i)$
  - (Of course we could use more realistic outcome variable such as investment, income, credit market participation…)
  - Observed $Eu(y_i)$ is either:
    - $Eu(y_i^U)$: Without insurance
    - $Eu(y_i^I)$: With insurance (netting out c_i)
  - d_i is again binary insurance purchase decision.

- Then we can rewrite our model as:

$$Eu(y_i) = \alpha_i + \Delta_i * d_i \qquad (4)$$

$$d_i = \begin{cases} 1 & if \ \beta_i \geq \beta^*(c_i) \\ 0 & if \ \beta_i < \beta^*(c_i) \end{cases} \qquad (5)$$

- Where:
  - $\alpha_i = Eu(y_i^U)$
  - $\Delta_i = Eu(y_i^I) - Eu(y_i^U)$
- So in Equation 4:
  - α_i is outcome without insurance;
  - $\alpha_i + \Delta_i$ is outcome with insurance;
  - Δ_i is individual-specific impact of insurance.
  - We can't observe Δ_i, but we want to learn about its distribution.
- Now condition on the instrument value, c, and take expectations over all farmers…

Identifying Assumptions

$$E[Eu(y_i) \mid c_i = c] = E\left(\alpha_i \mid c_i = c\right) + E\left(\Delta_i \mid d_i = 1, c_i = c\right) P\left(d_i = 1 \mid c_i = c\right) \qquad (6)$$

$$E\left(d_i \mid c_i = c\right) = P\left(d_i = 1 \mid c_i = c\right) = P\left(\beta_i \geq \beta^*(c_i)\right) \qquad (7)$$

- Encouragement design relies on 4 assumptions about instrument (c) to identify treatment effects.
- $(A1) \qquad E(\alpha_i \mid c_i = c) = \alpha$
  - <u>Independence</u>: Outcome without insurance is independent of the instrument (value of the coupon).
  - Randomization helps a lot, but not sufficient:
    - Dean's point: Game sessions as instrument for insurance impact? Could affect risk perceptions and behavior of participants who don't buy insurance.

Identifying Assumptions

$$E[Eu(y_i) \mid c_i = c] = E\left(\alpha_i \mid c_i = c\right) + E\left(\Delta_i \mid d_i = 1, c_i = c\right) P\left(d_i = 1 \mid c_i = c\right) \qquad (6)$$

$$E\left(d_i \mid c_i = c\right) = P\left(d_i = 1 \mid c_i = c\right) = P\left(\beta_i \geq \beta^*(c_i)\right) \qquad (7)$$

- $(A2) \qquad E(\Delta_i \mid d_i = 1, c_i = c) = g(P(d_i = 1 \mid c_i = c))$
  - Exclusion restriction.
  - Average impact of insurance among purchasers is only a function of composition of purchasers.
  - Instrument has no direct impact on outcome.
  - Randomization help a lot, but not sufficient
    - Example: Insurance information sessions as instrument
    - If sessions also provide technical assistance, then instrument would have a direct impact on outcome variable.

Identifying Assumptions

$$E[Eu(y_i)\,|\,c_i = c] = E\left(\alpha_i\,|\,c_i = c\right) + E\left(\Delta_i\,|\,d_i = 1, c_i = c\right)P\left(d_i = 1\,|\,c_i = c\right) \qquad (6)$$

$$E\left(d_i\,|\,c_i = c\right) = P\left(d_i = 1\,|\,c_i = c\right) = P\left(\beta_i \geq \beta^*(c_i)\right) \qquad (7)$$

- $(A3) \qquad Cov(c_i, d_i) \neq 0$
  - <u>*Relevance*</u>: Instrument has predictive power with respect to insurance purchase decision. (Pisco coupons not so good!)
- (A4) $\forall$ c such that $c^j \leq c^k$, $\left(d_i = 1\,|\,c_i = c^j\right) \leq \left(d_i = 1\,|\,c_i = c^k\right)\ \forall\ i.$
  - <u>Monotonicity</u>: We can order the values of the instrument such that moving from one value to the next weakly increases the probability of buying insurance for everyone (or weakly decreases it for everyone).

Estimable Equations

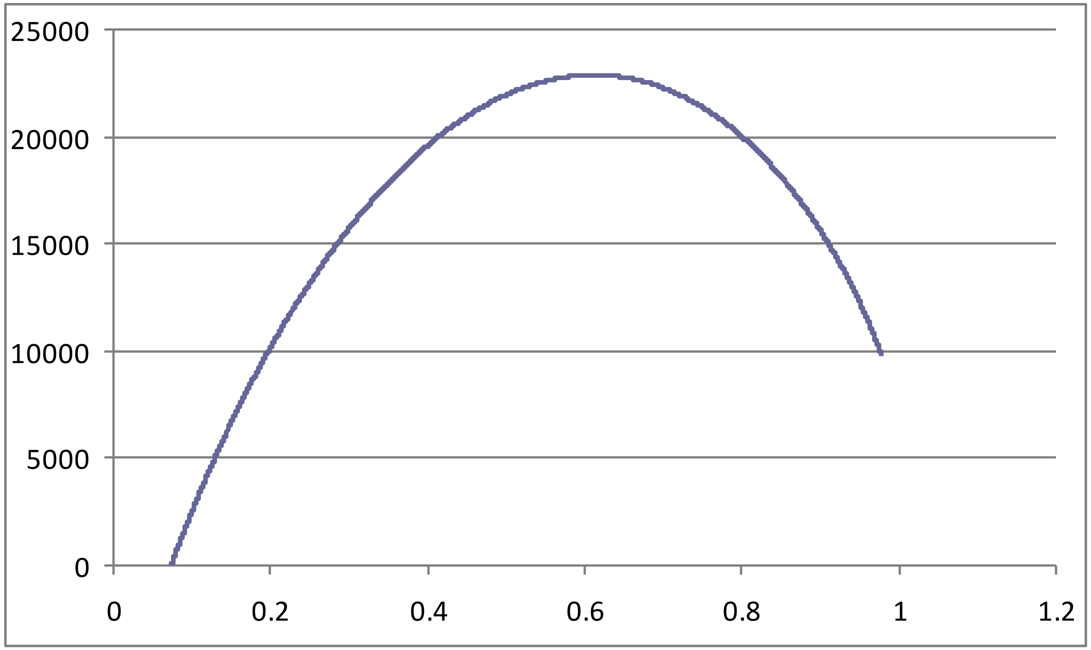
$$Eu(y_i) = \alpha + g(P(d_i = 1 | c_i = c)) * P(d_i = 1 | c_i = c) + e_i \qquad (11)$$

$$d_i = P(d_i = 1 | c_i = c) + u_i \qquad (12)$$

- The value of $Eu(y_i)$ for everyone assigned c_i equals:
  - Mean outcome without insurance, α plus;
  - Average impact of insurance among purchasers in sub-population assigned $c_i = c$ weighed by;
  - Share of this sub-population buying insurance plus;
  - (A1) – (A4) → error terms, conditional on c_i well behaved.
- Use our parameters from Peru to plot the average of equation 11 as we vary c, and thus the probability of purchasing insurance…

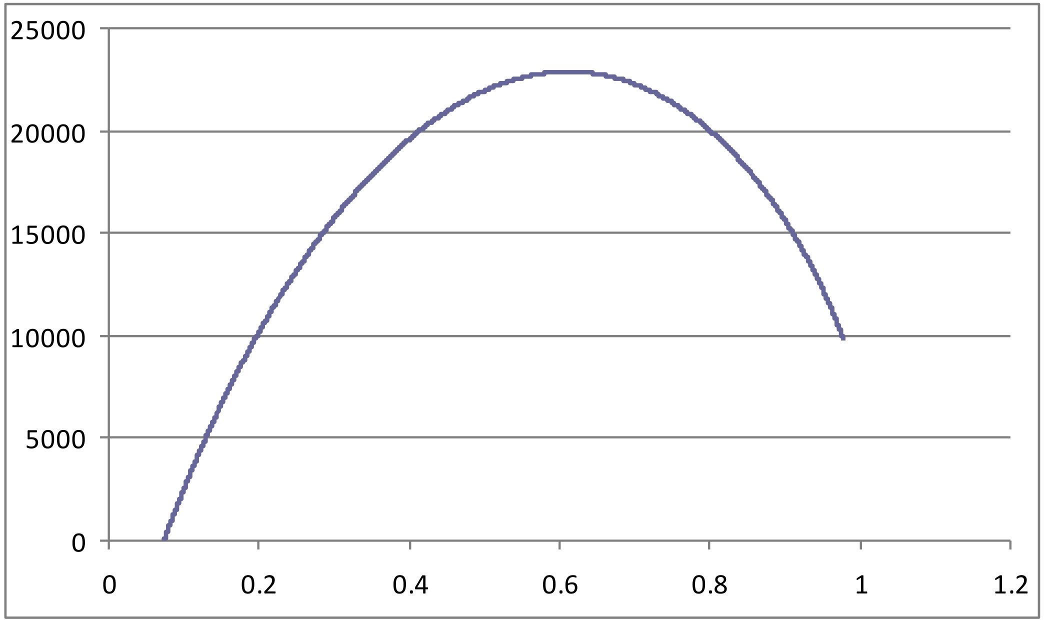
Expected Outcome Function

- Vertical axis is E[Eu];
- Horizontal axis is Pr(purchas);
- Coupon increasing from left to right.
- Turning point at .6 (was probability of purchase for c = 0)



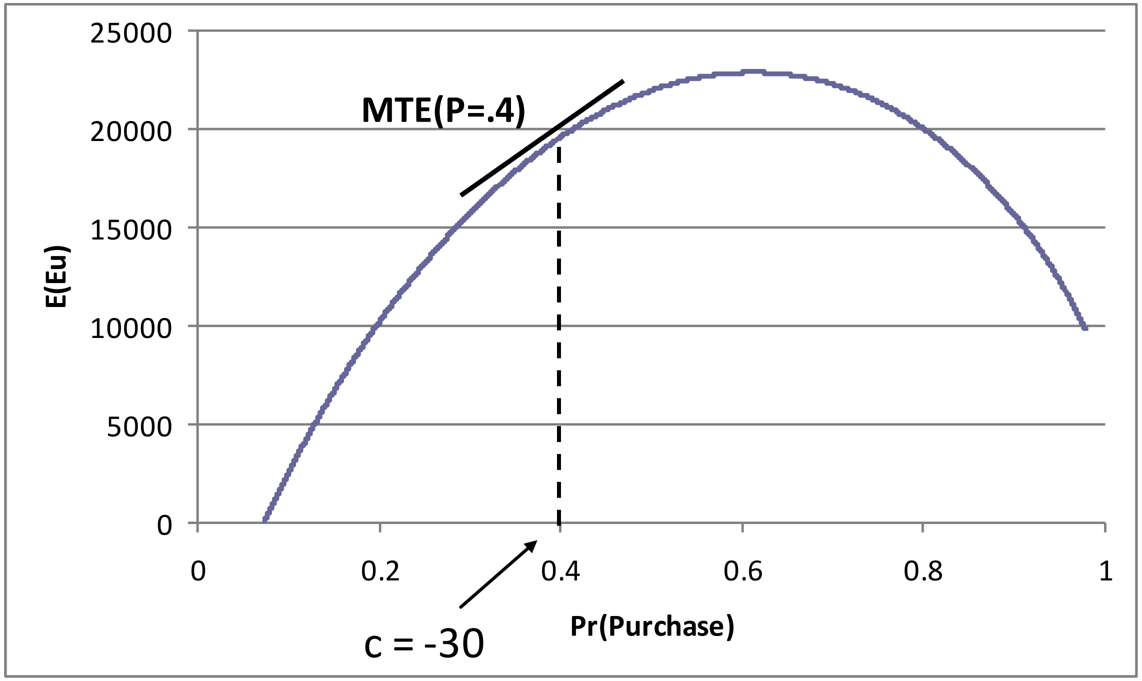
What Types of Impacts Might we Measure?

- Ideally, we would trace out entire curve.
- Non-linearity and partial compliance make that hard.
- So what things can we learn?



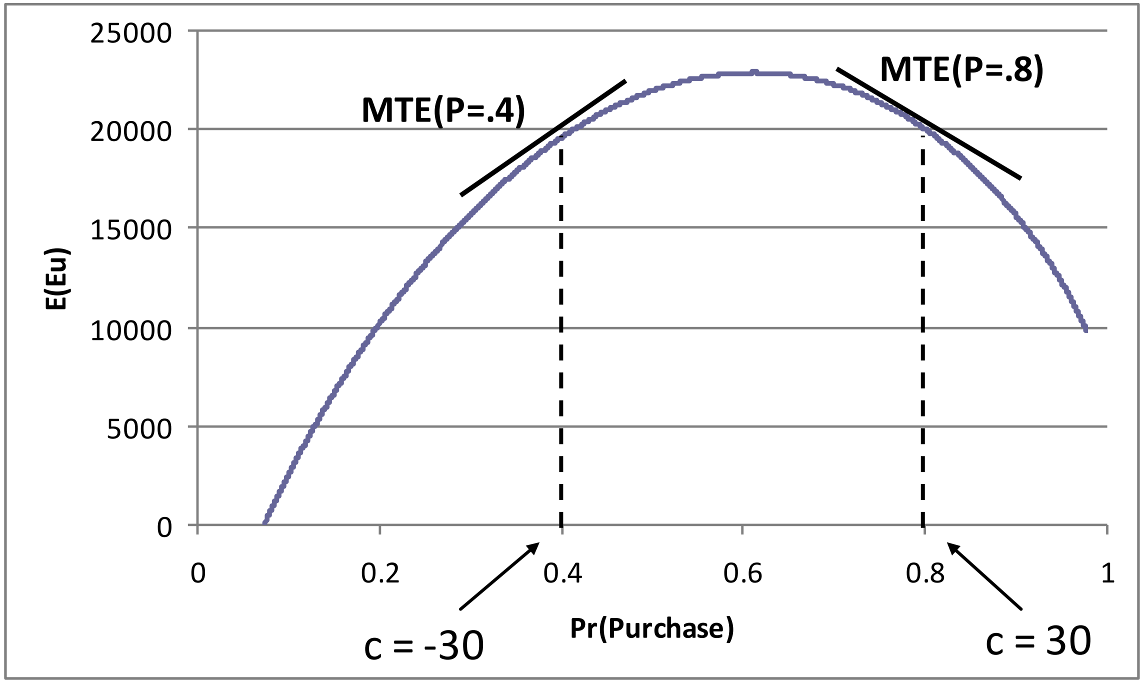
Marginal Treatment Effect (MTE)

- Instantaneous change in average outcome due to arbitrarily small change in probability of purchasing insurance.
- MTE tells us impact of insurance on very specific type of farmer: Those who are induced to buy when coupon increases from -30 → -30 + epsilon



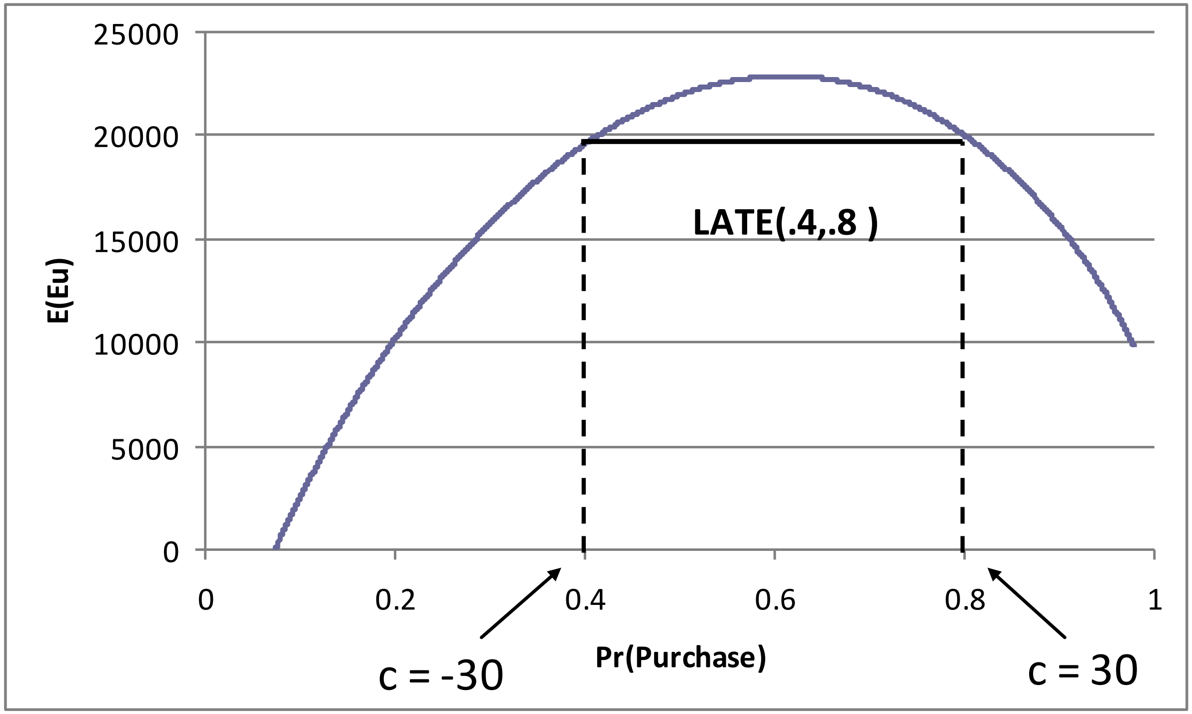
Marginal Treatment Effect (MTE)

- Essential heterogeneity → this impact is different across different groups.
- Those induced to purchase when coupon goes from 30 to 30 + epsilon have much lower β (higher basis risk).



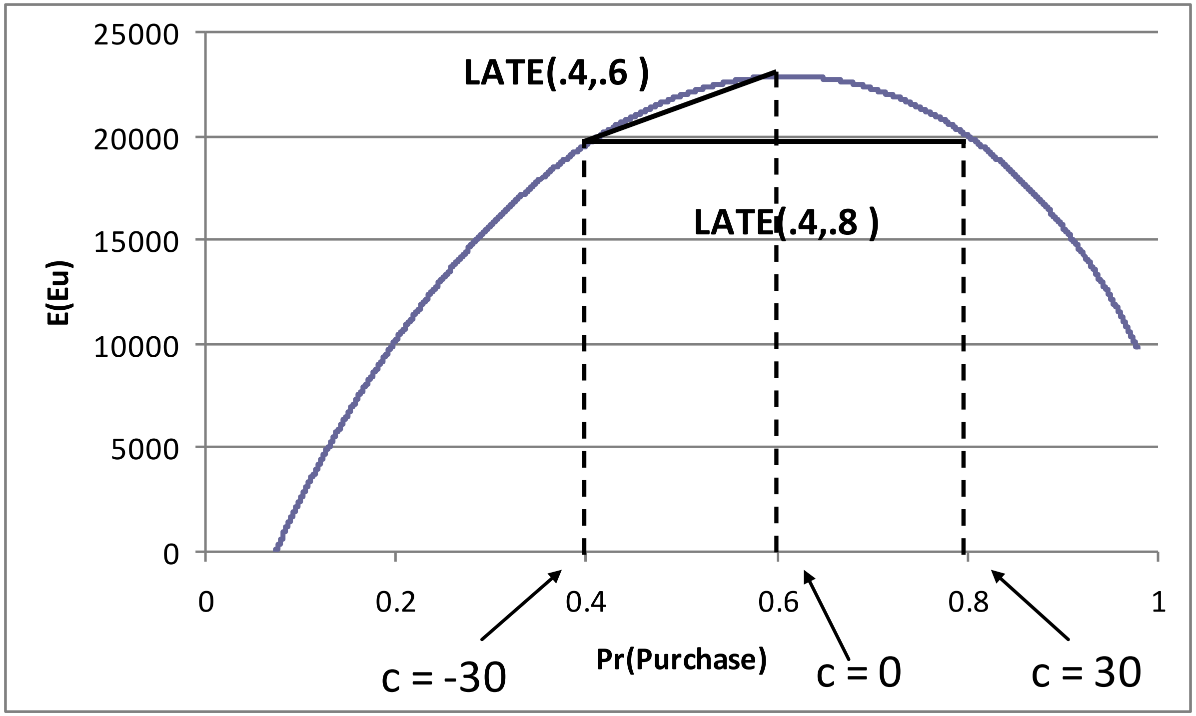
Local Average Treatment Effect (LATE)

- Discrete version of MTE between two points.
- LATE tells us the average impact of insurance on the compliers – those who would not buy insurance at the higher price (c = -30) but would buy at the lower price (c = 30)



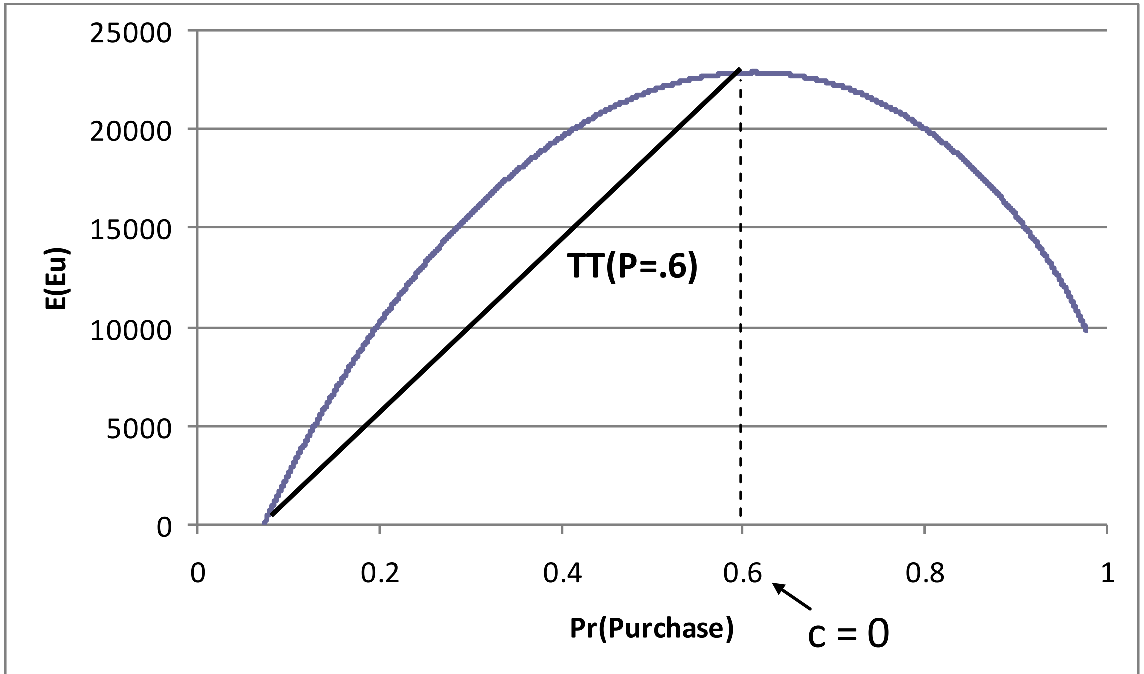
Local Average Treatment Effect (LATE)

- Essential heterogeneity (non-linearity) → LATE will differ depending on the values of the instrument at which it's evaluated.



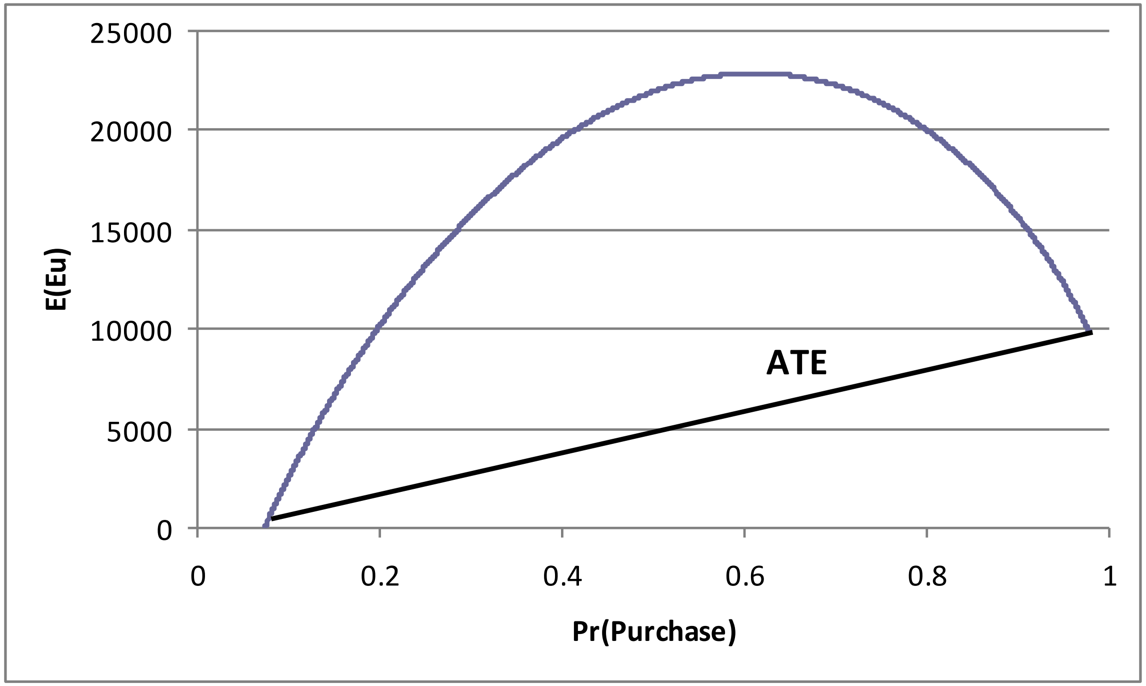
Treatment Effect on Treated (TT)

- TT gives the average effect of buying insurance on those who bought it.
- To estimate TT, empirical support must include Pr(Purchase) = 0.
- Figure shows TT if we randomize offer of actuarially fair insurance and strictly deny access to a control group (may not be feasible).



Average Treatment Effect (ATE)

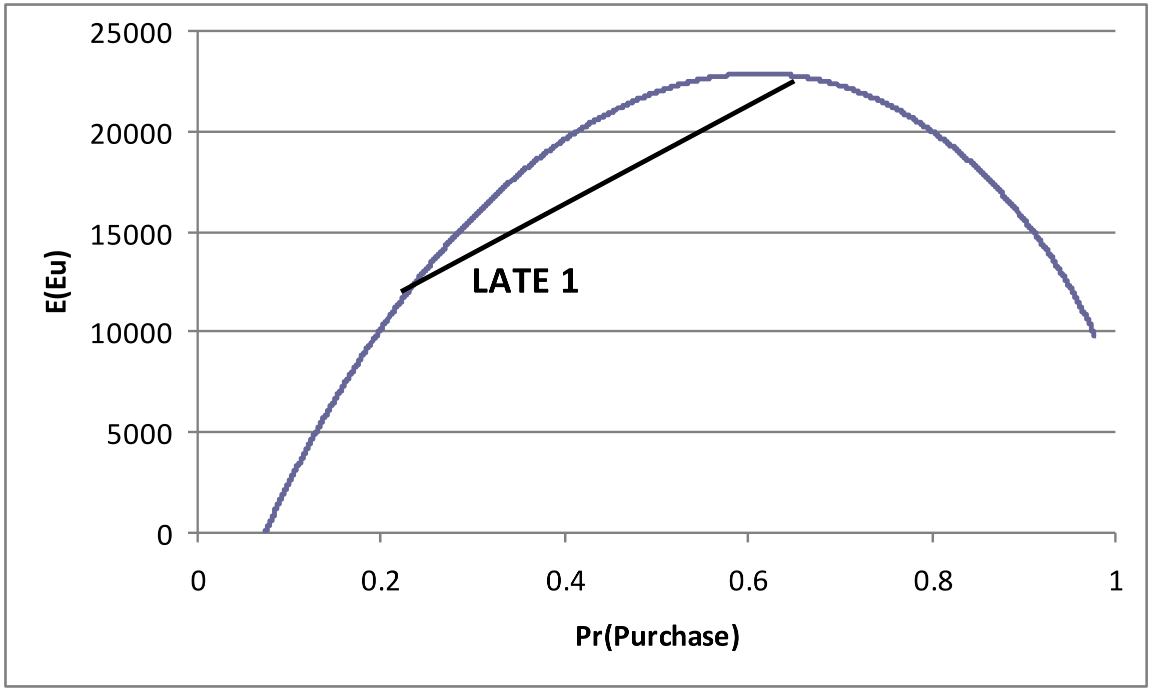
- ATE tells us the average effect if everyone were to buy insurance.
- To estimate ATE, empirical support must include Pr(Purchase) = 0 *and* Pr(Purchase) = 1.
- Very unlikely in insurance programs.



Discussion: Implications for Research Design

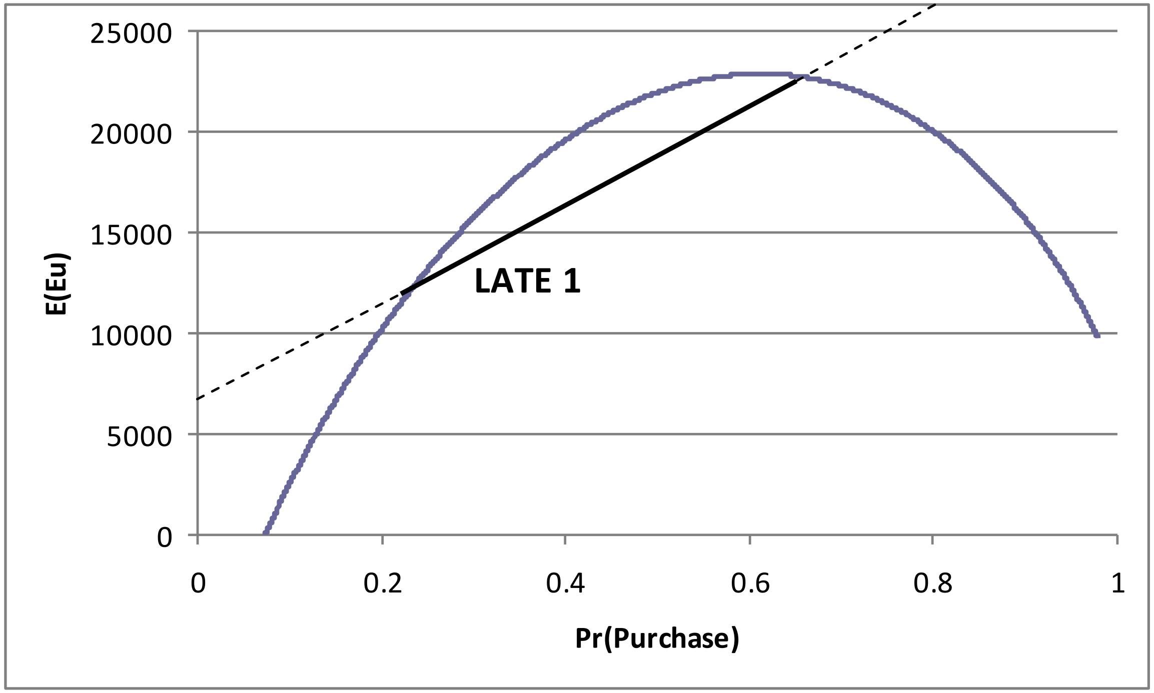
Multi-value Instruments are Important

- Say choose only two coupon values underlying this picture.
- Can do a good job estimating LATE1
- But say we wanted to use these data to estimate full curve?



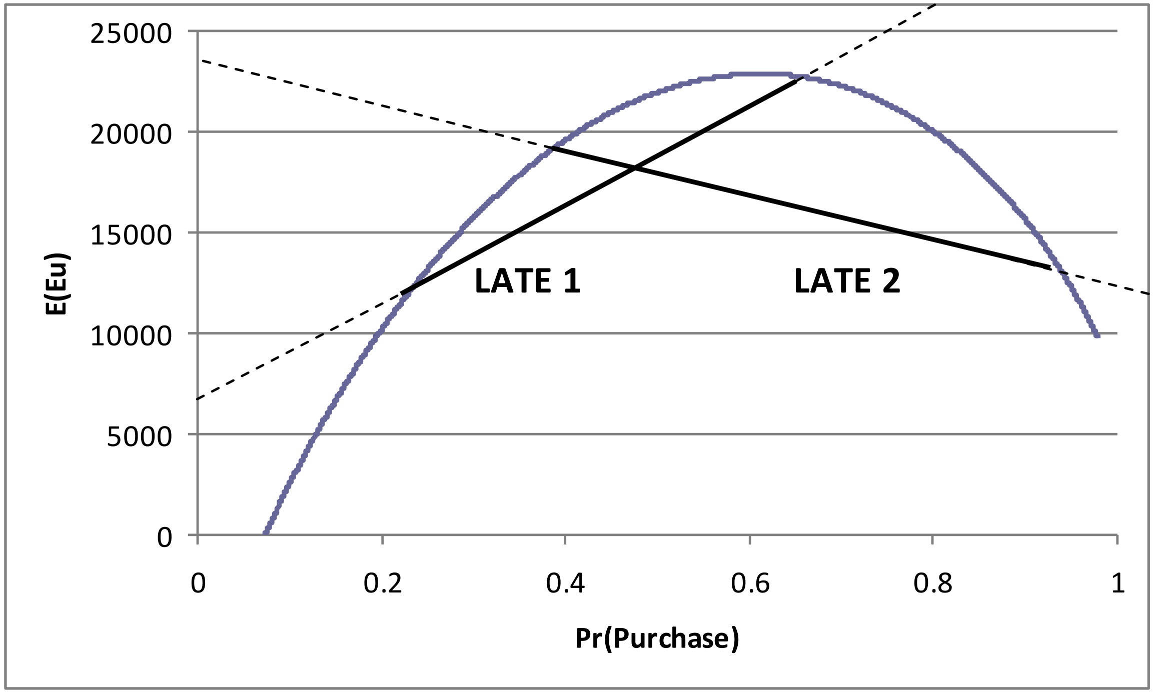
Multi-value Instruments are Important

- Could extrapolate as below
- But that would be pretty misleading.



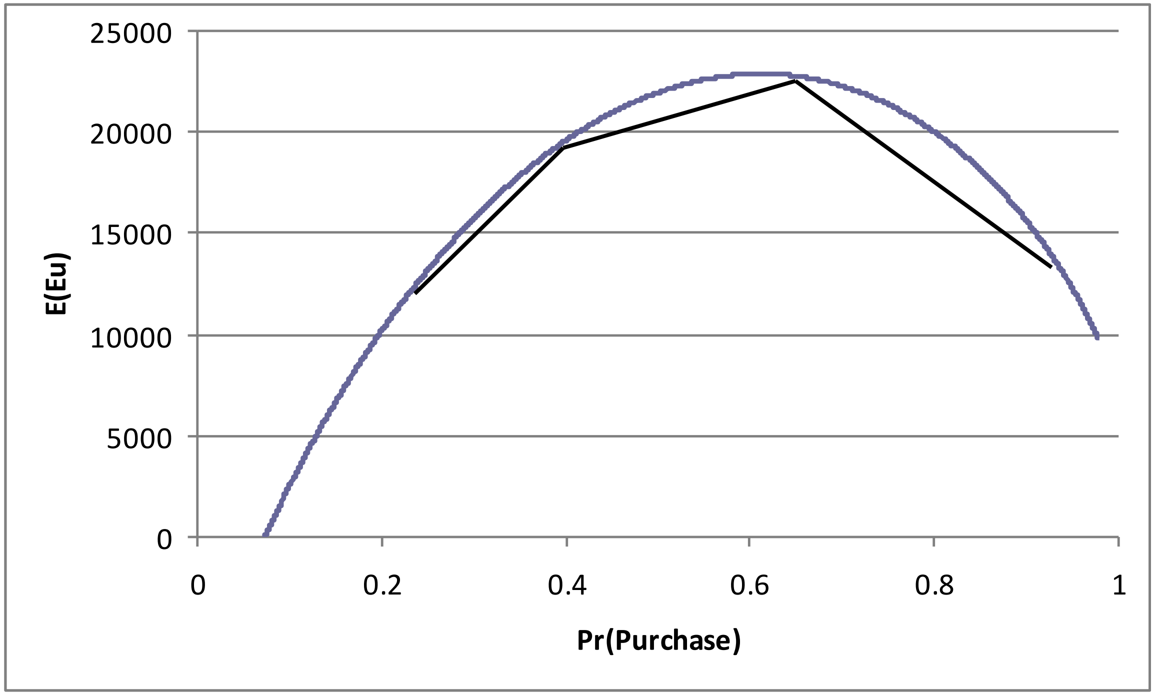
Multi-value Instruments are Important

- And if we had instead used two different coupons (giving LATE2), our extrapolation would have wildly different.



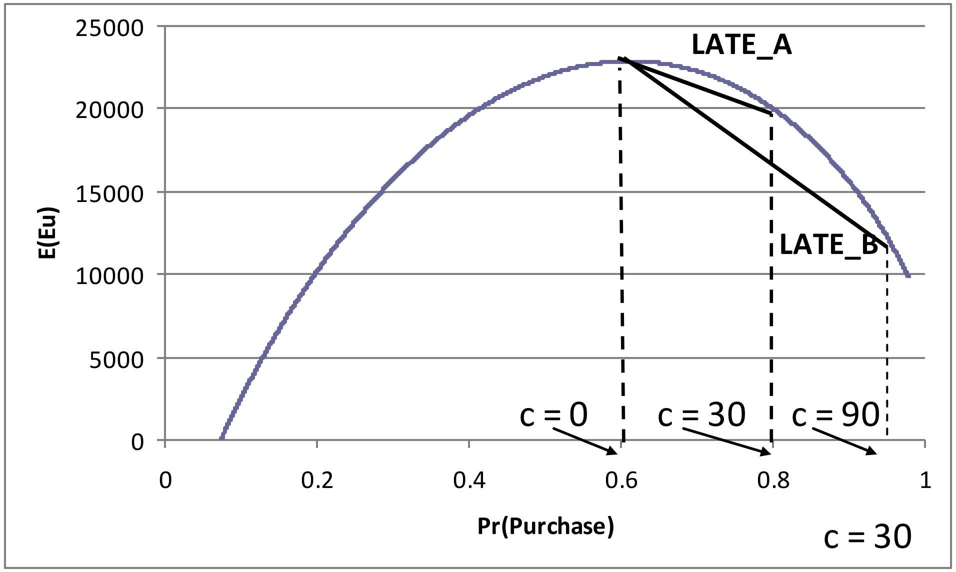
Multi-value Instruments are Important

- If we instead had all four of the coupon values, we could do a reasonably good job learning about the shape of the whole function.
- <u>Take-home point</u>: Non-linearity → Need at least 3 separate instrument values if we want to extrapolate beyond LATE's.



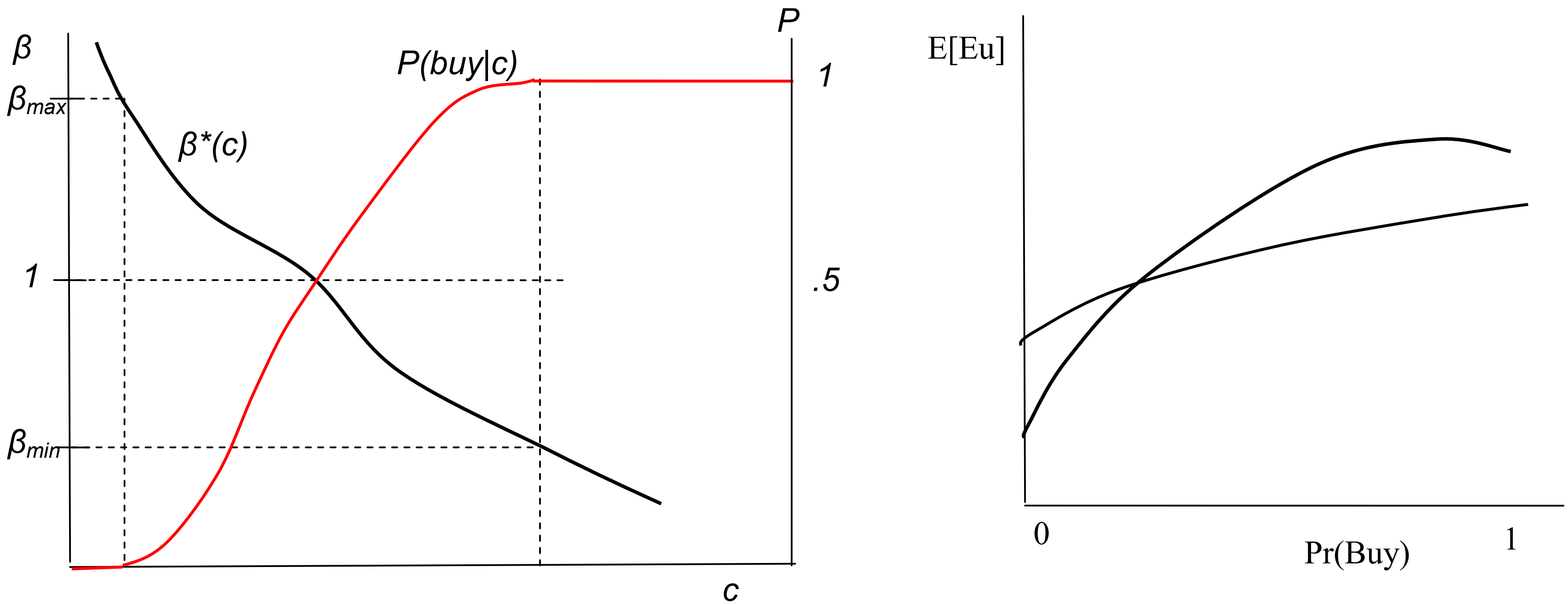
Should Consider Policy Relevance when Choosing Instrument Values

- Consider offering only two coupons: A) c = 0 & c = 30 or B) c = 0 & c = 90.
- Which would give you more policy relevant results?
- A. Because B requires huge subsidy that is unlikely to be sustainable – or desirable – because it costs a lot.
- And we’re learning about impacts of insurance on people who should not be insured!



Empirical Distribution β Affects What We Can Learn

- With disperse distribution…



- Can learn about most of Expected outcome curve
- With tighter distribution, could only trace out smaller section of EU curve

Summary

- Importance features of agricultural insurance
  - Heterogeneous impacts (non-linear *E*(*y*) function);
  - Partial Compliance
- Implications for research design
  - If goal is to trace out full E(y) curve, we need high density along the support
    - Need instrument(s) with multiple values and;
    - Instruments must be "strong" (really predict demand)
    - Sparse support requires Herculean assumptions
  - Full compliance probably not economically interesting
    - Includes folks with, on average, negative benefits.
    - Wouldn't buy insurance outside our research design (big subsidy)
  - External validity highly dependent on instruments
- Efficient design of distribution of instrument values can benefit greatly from appeal to theory and ex-ante research.