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The Impact of the 2005 CAP-First Pillar Reform (FPR) as a Multivalued Treatment Effect

Alternative Estimation Approaches

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OUTLINE

Objective: Is the increasingly complex TE econometrics toolkit suitable for "complex" policy treatments like the FPR? By the way: about 40 bil €/year (30% of EU budget)

1. **The FPR case: methodological challenges**
2. **MT-ATE alternative estimation approaches**
3. **Results**
4. **Concluding remarks**

1. FPR: methodological challenges (1/5)

What is needed to recreate such a quasi-experimental situation and identify/estimate the Avg. TE (ATE):

Requirements	Issues
A clear treatment (T)	- Multiple treatments - Multivalued treatments 2
A clear objective (Y)	- Unclear (undeclared) outcome/target variable 1 - Multiple objectives
2 A clear counterfactual (T = 0)	- No counterfactuals - Unsuitable counterfactuals
Observable confounding variables (X)	- Controlling for (un)observables - Proper matching

1. FPR: methodological challenges (2/5)

Objective – Estimate the TE of FPR

→ The treatment: the 2003/2005 Reform of the First Pillar of the CAP (FPR)

- Decoupling of support: the key of the reform
  - **Reorientation to market**:
    - Let farmers choose what (and if) to produce
    - Let farmers achieve an higher allocative efficiency

Objective/Expected outcome: change in the production mix of farmers receiving the treatment

1. FPR: methodological challenges (3/5)

Why don’t use powerful TE econometrics to assess the impact of the FPR?

– We have micro-data!

  - **The sample**: a balanced panel (constant sample) of **6542 farms** obs. over years 2003-2007 (*pre* and *post*-reform).

– But:

1. CAP is a multioutcome policy
2. CAP is a multitreatment policy
3. CAP is a multivalued treatment
4. No suitable counterfactuals for the FPR

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1. FPR: methodological challenges (4/5)

1 FPR as a multioutcome policy: How do we measure if and to what extent farms changed their output vector?

– Two different types of outcome (*i-th* farm):
  - **In a short-run perspective**: change in the composition of output (K is the of possible production activities; s_k the respective share on GPV). Measures of distance between *pre* (A) and *post (B)*

Alternative: y^2 simply counts the changes in the output vector

Output-distance index

$$y_i^1 = \sqrt{\sum_{k=1}^{K}\left(s_{ik,B} - s_{ik,A}\right)^2}$$

  - **In a long-run perspective**: investment decisions (I = investments; VA = Value Added)

Alternative: y^3 investments in absolute values

Investment rate

$$y_i^4 = \left(\frac{I_{i,B}}{VA_{i,B}} - \frac{I_{i,A}}{VA_{i,A}}\right)$$

Note: the outcome/target variable **is ALREADY a difference**. The TE is a difference in the difference

1. FPR: methodological challenges (5/5)

2 FPR as a Multivalued Treatment (MT) →Treatment Intensity (TI) = FPs/GPV

Distribution of the continuous treatment (*TI*), First Pillar support on farm's GPV (in %): Kernel density (**K**) and frequency histogram (avg. over 2003-2007 period)

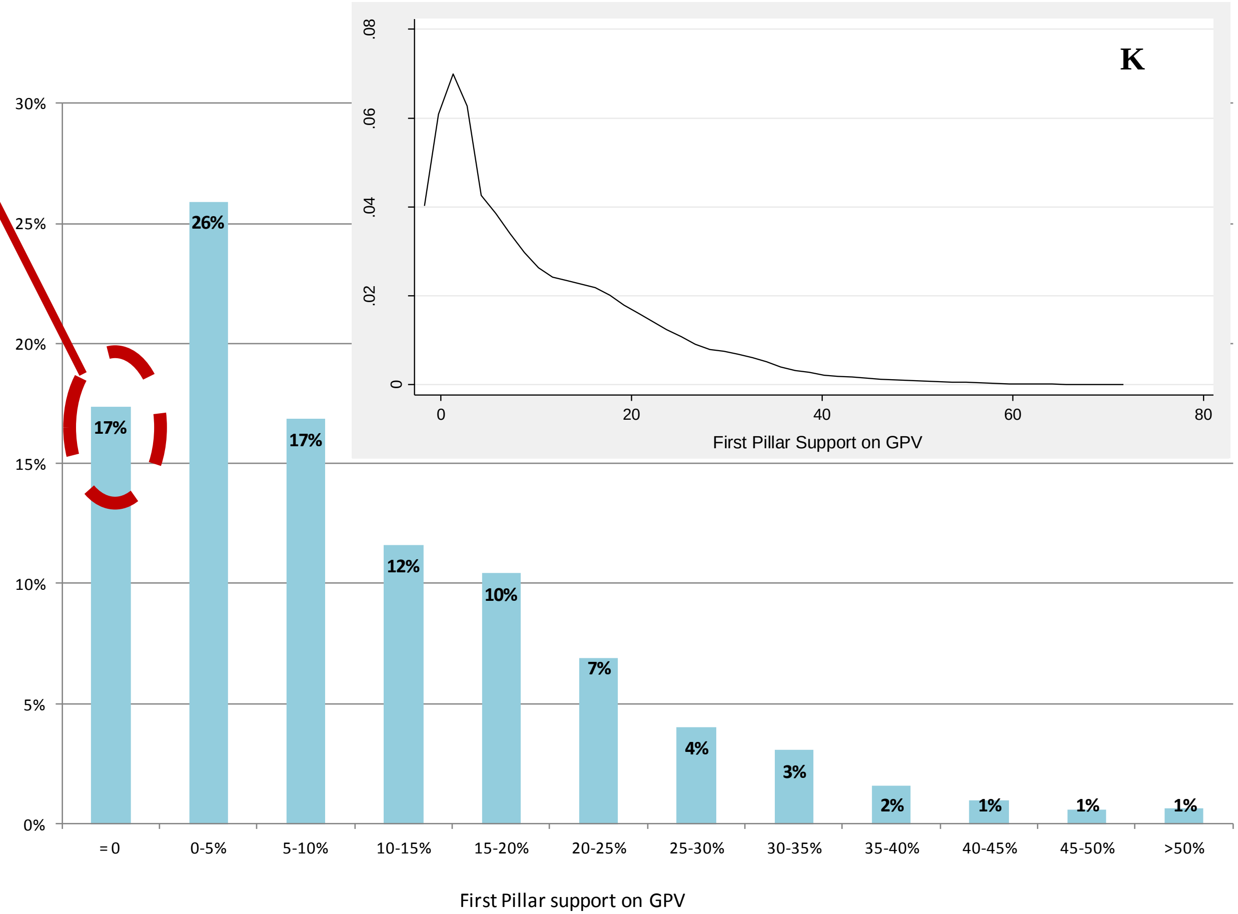
5430 treated farms

1112 non-treated farms

Can't they be suitable counterfactuals for the FPR?

Eligibility to FPR depends on production choices made in the 2000-2002 period. If they made very peculiar choices they must be peculiar

But with MT we do not need counterfactuals



2. MT-ATE estimation approaches (1/4)

3 POSSIBLE EMPIRICAL STRATEGIES:

- 1st strategy – PSM-ATT: binary treatment; counterfactuals found through matching conditional on a set of covariates
  - Selection-on-unobservables bias still a problem
- 2nd strategy – DID-ATT: binary treatment, counterfactuals are the treated observations themselves before the treatment, still non-treated are needed to get rid of the effects of time
  - Selecting the baseline and the follow-up obs. (years) is critical → CIIA and placebo testing
- **3rd strategy – MT-ATE: the treatment is a continuous/discrete variable, a relationship between the treatment level and the outcome variable can be estimated (the *DRF*); non-treated units (counterfactuals) are not needed→which is the effect for a treated unit of receiving an higher (lower) treatment level?**

2. MT-ATE estimation approaches (2/4)

Hirano-Imbens approach - Start with the Rubin (1974) intuition:

- Define a set of *potential outcomes* $\{Y_i(T)\}_{T \in \Xi}$ where Ξ is the set of potential treatment levels and $Y_i(T)$ is a random variable that maps, for the i-th unit, a particular potential treatment, T, to the potential outcome Y
- However, for any i-th only one Y_i is observed corresponding to the actual treatment level T_i
- The approach estimates the function linking $Y=f(T)$ on average: the *average Dose-Response Function* (*aDRF*)

❖ It is a 4-step parametric estimation approach

2. MT-ATE estimation approaches (3/4)

Hirano-Imbens approach - Estimation:

- 1st step: the GPS estimation: $GPS_i = r(T_i, \mathbf{X}_i) = T_i | \mathbf{X}_i \sim N\left(\boldsymbol{\beta}'\overline{\mathbf{X}}_i, \sigma^2\right)$
  - ✓ Probability of the i-th unit to receive the treatment level T_i
- 2nd and 3rd steps: the *uDRF* and *aDR*F estimation
  - ✓ Estimation of the conditional expectation of the potential outcome with respect to *T* and the estimated *GPS:* a fully interacted flexible function (K,H-th order polynomial) then averaged for any given *T*
- 4th step: the *ATE* estimation

$$ATE_j = \partial\left(aD\hat{R}F_j\right) / \partial T \quad \text{or} \quad ATE_j = \left(aD\hat{R}F_j - aD\hat{R}F_{j-1}\right)$$

2. MT-ATE estimation approaches (4/4)

The Cattaneo alternative (1):

- Hirano-Imbens approach: computationally complex and too arbitrary parametric assumptions
- Cattaneo (2010) approach: a semiparametric estimation
  - Discrete instead of continuous treatment
- A 3-step approach:
  - The first step is common: GPS estimation (but now is a MLM)
  - The second step is a semiparametric estimation: based on the estimated GPS, the potential outcome means for any treatment level (μ_j) are estimated imposing a set of moment restrictions
  - Two asymptotically equivalent alternatives (the latter is preferable in finite sample):
    - ✓ IPW (Inverse Probability Weighting) Estimation
    - ✓ EIF (Efficient Influence Function) Estimation
  - The third step consists in estimating the ATE

$$ATE_{IPW/EIF,j} = \left(\hat{\mu}_{IPW,j} - \hat{\mu}_{IPW,j-1}\right)$$

3. Results of the application (1/7)

Covariates - Three (+1) groups of confounding factors:

- ✓ ***Individual characteristics*** of the farmer (AGE) and of the farm (Altitude - ALT).
- ✓ Economic (ES, FC) and physical (AWU, HP, UAA and, at least partially, LU) ***size*** of the farm clearly matters.
- ✓ Variables directly expressing the ***production specialization*** of the farm(TF and, in part, LU) .
- ✓ A final confounding variable included in the analysis is the dummy expressing ***second pillar support*** (RDP) (1766 farms; 27%)

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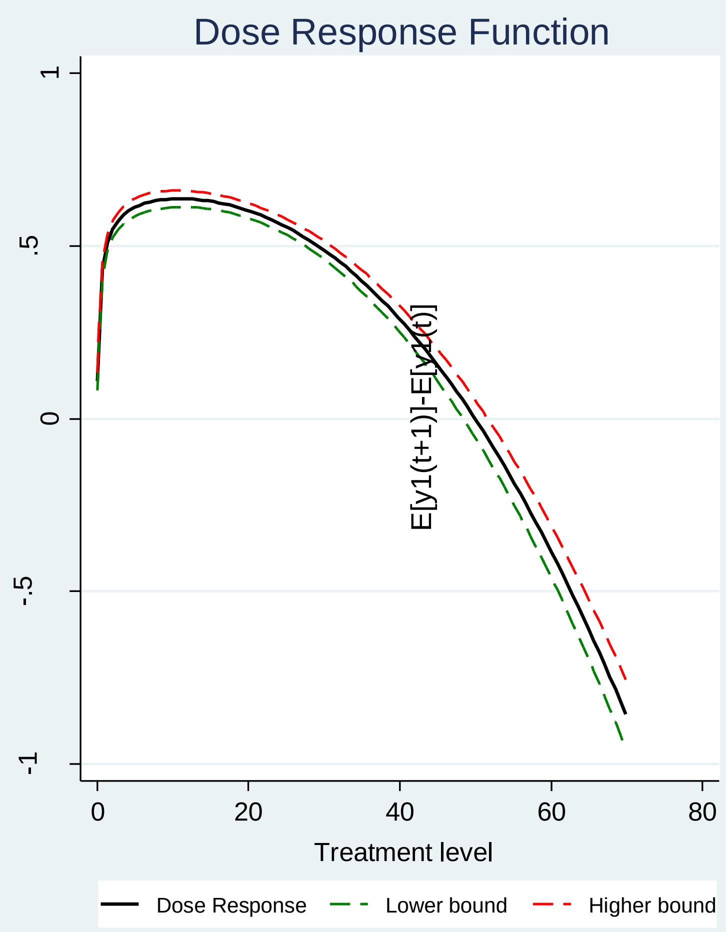
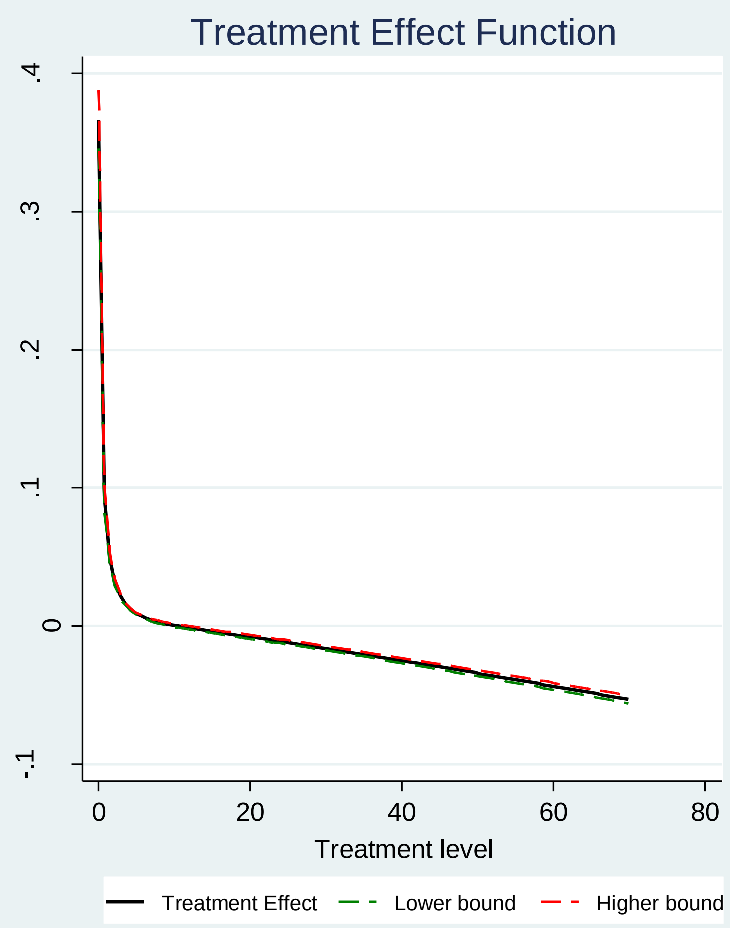
3. Results of the application (2/7)

❖ MT estimation - Hirano-Imbens: *aDRF* and *TE*

y¹

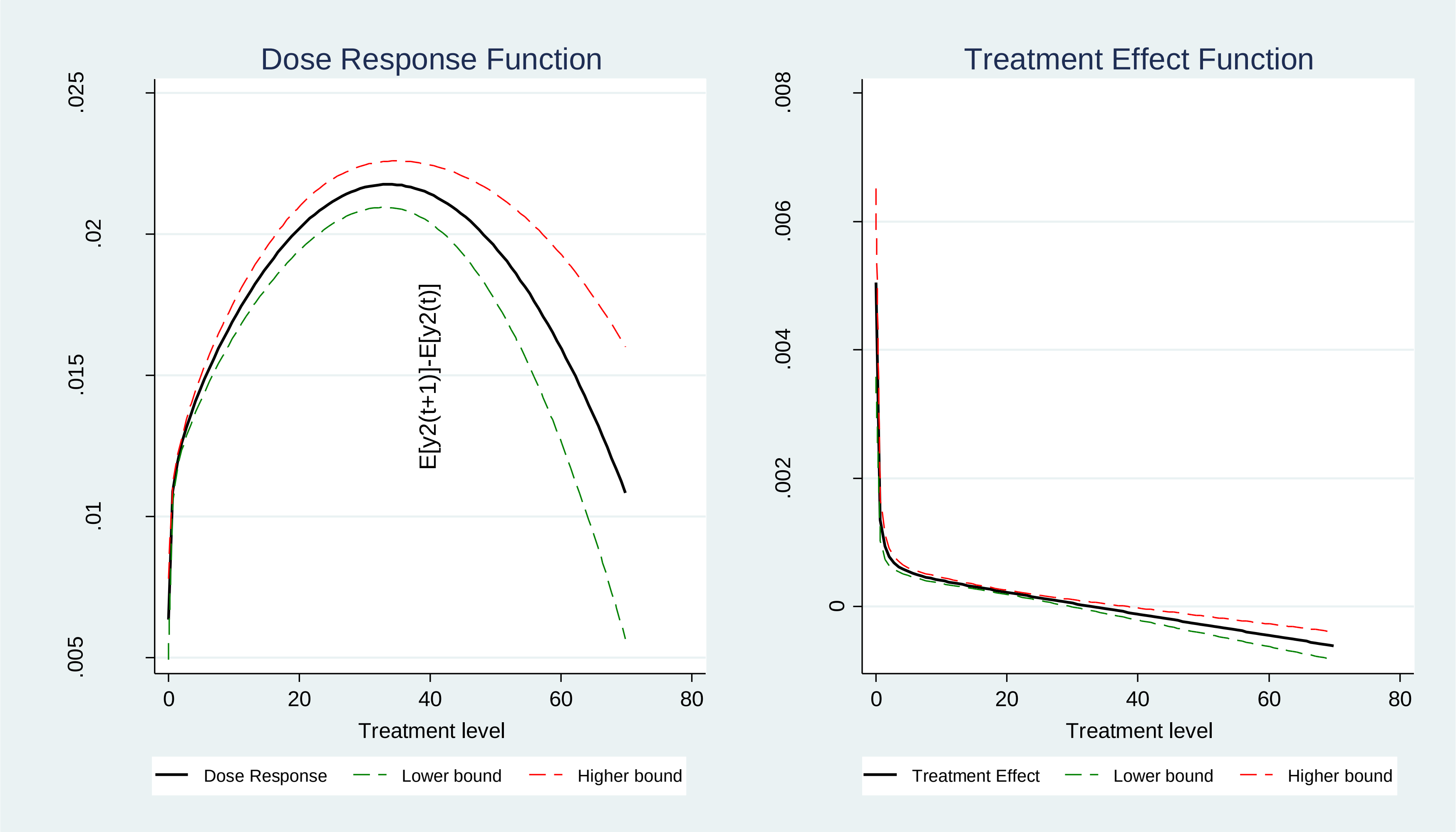




3. Results of the application (3/7)

MT estimation - Hirano-Imbens: *aDRF* and *TE*

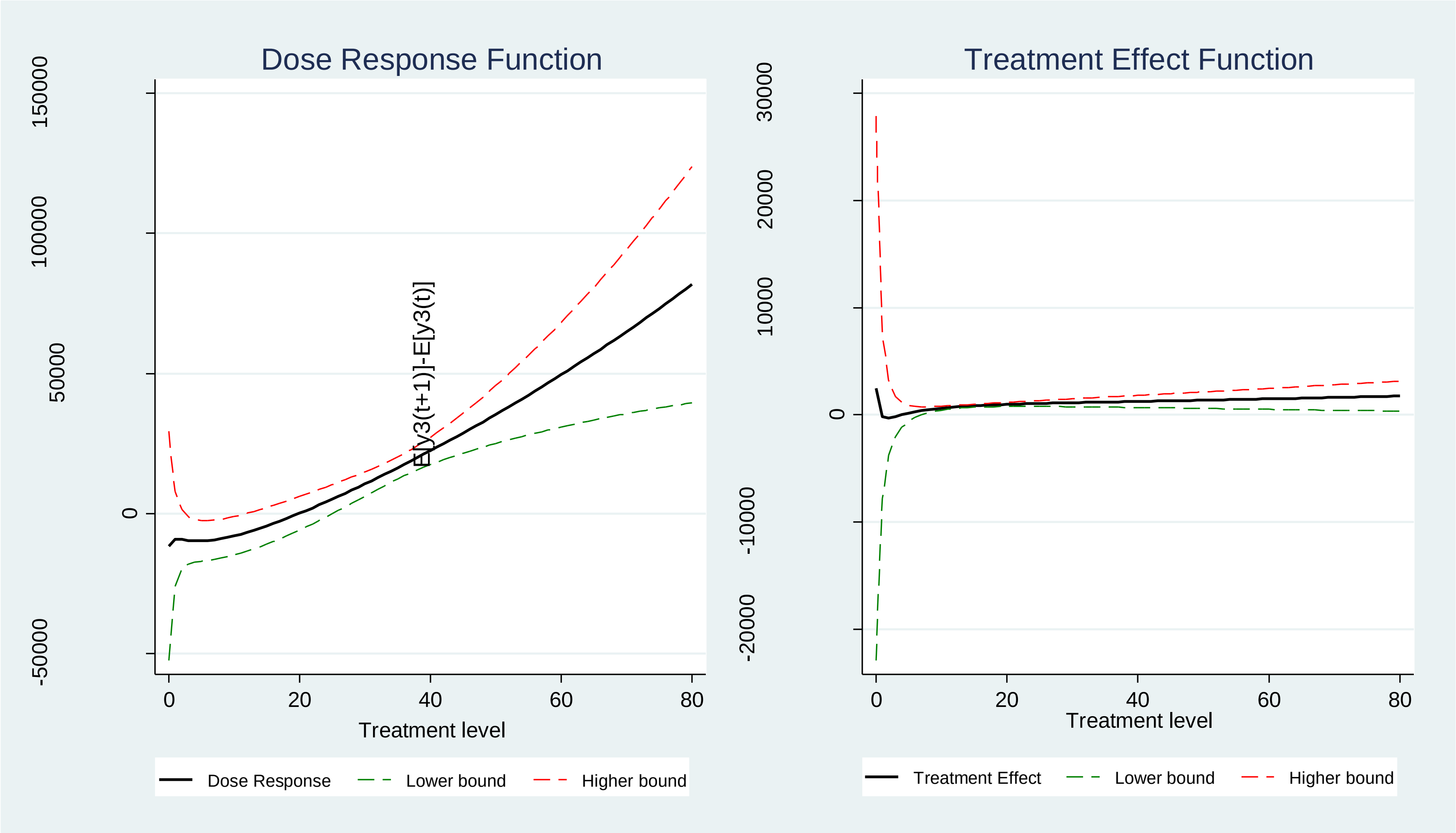
y^2



3. Results of the application (4/7)

❖ MT estimation - Hirano-Imbens: *aDRF* and *TE*

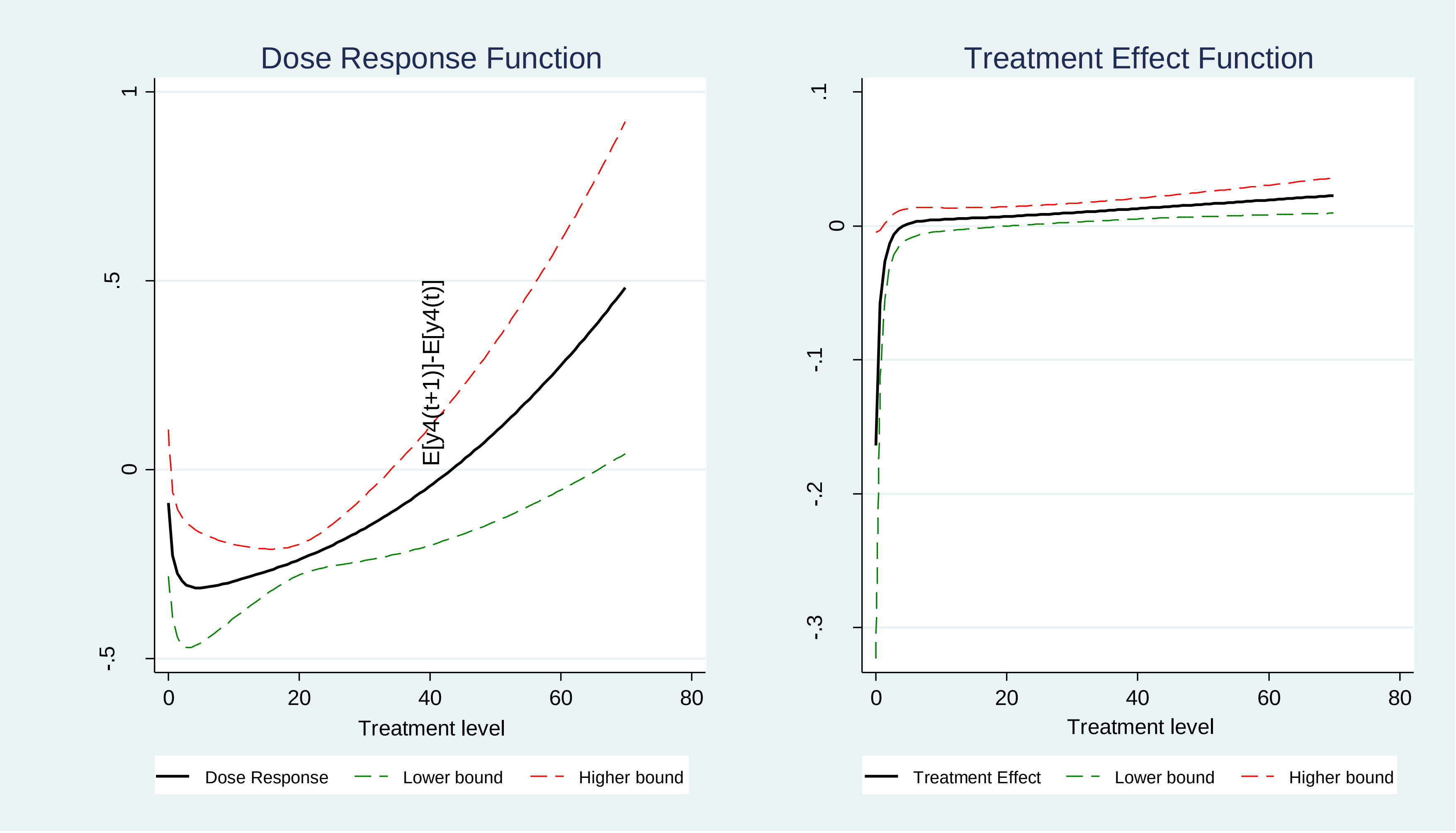
y^3



3. Results of the application (5/7)

MT estimation - Hirano-Imbens: *aDRF* and *TE*

y^4

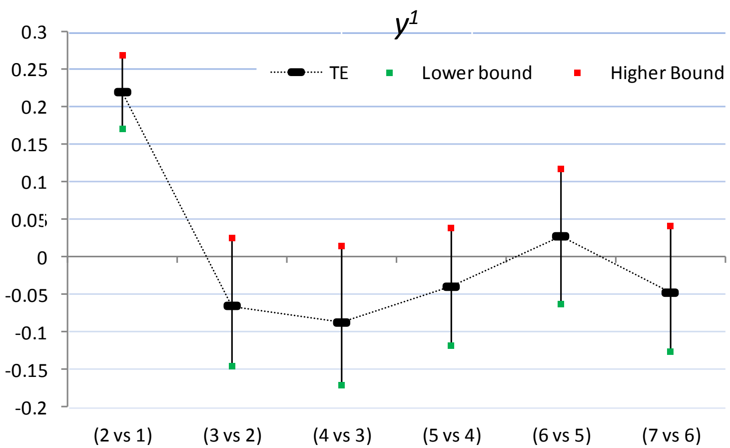


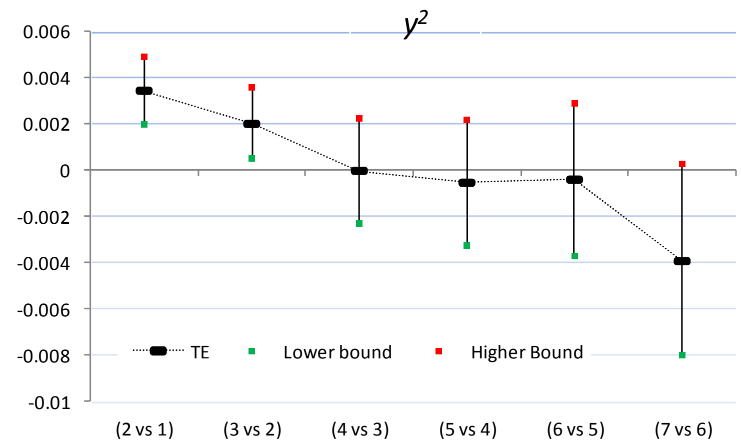
3. Results of the application (6/7)

MT estimation - Cattaneo (EIF, IPW)

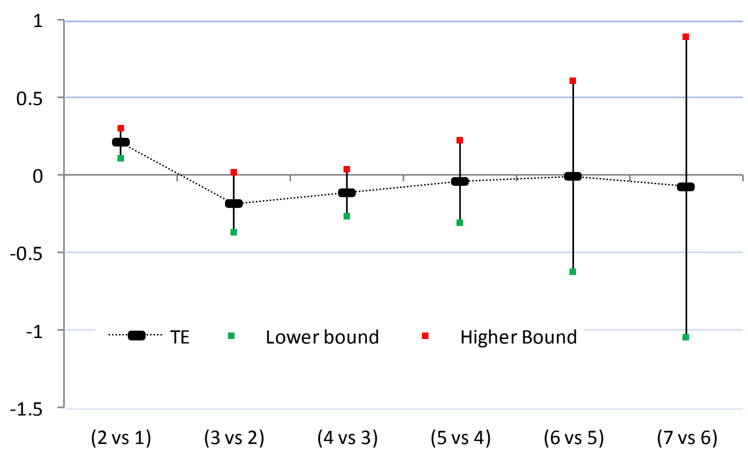
- TE (y^1,y^2)

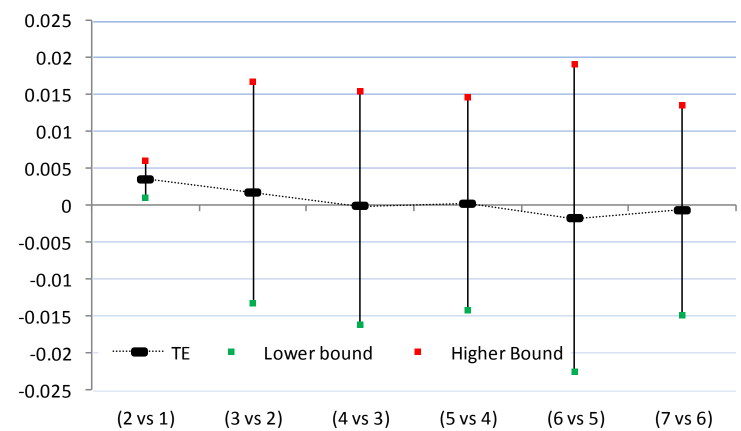
EIF





IPW

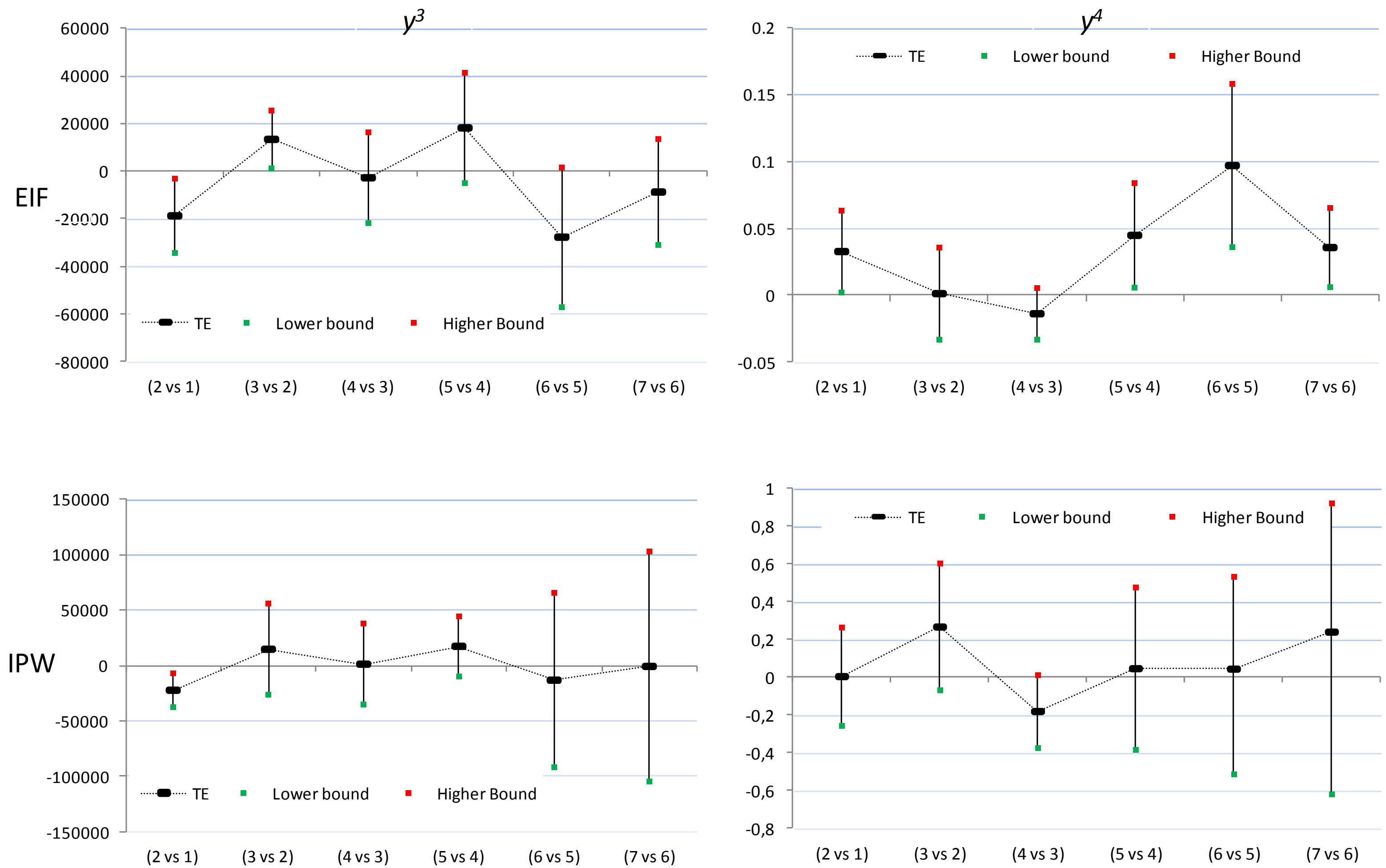




3. Results of the application (7/7)

MT estimation - Cattaneo (EIF, IPW)

- TE (y^3,y^4)



4. Concluding remarks

- Did the FPR reoriented production decisions? **YES**
- Short-run vs. Long-run production decisions
  - FPR affected SR production decisions
  - SR changes seem conservative: +in number of products, - in GPV shares
  - SR impact is lower (or null) for higher treatment levels: **lock-in effect**?
  - Impact on LR (inv.) decisions is questionable
  - LR impact (if any) is higher for higher treatment levels: **pure financial effect**?
  - LR impact may come from the complementarity of the two pillars
    - *Multitreatment effects?*
- Pros and cons of the MT estimation approaches
  - Advantages on PSM-ATT and DID-ATT estimation :
    - no need of counterfactuals (non-treated units)
    - take the continuous nature of the treatment into account
    - more robust
  - MT-ATT estimation complex and based on arbitrary assumptions
    - Results of good quality with the Hirano-Imbens approach
    - Cattaneo approach: poorer results (especially with IPW estimation)

pros

cons

Thanks for your attention