# The side effects on health of a Recovery plan in Italy
# A nonparametric bounding approach

Domenico Depalo

BANCA D'ITALIA

# Overview

The *Piani di Rientro* were implemented in some Italian regions.

**Target regions**: Those with large deficit on health care expenditure.

**Goals of the policy**:

1. restoring economic and financial sustainability ...
2. ... without jeopardizing the health condition of the population

I identify the **causal effect** of the recovery plan on health related outcomes.

# Summary

1. Motivation
2. Data
3. (Intuition of the) Identification strategy
4. Results
5. Conclusions

# Summary

# Motivation

Two (possible) contributions:

- **Specific to *Piani di Rientro***

  Although there is general consensus that the measures successfully contained costs, the consequences in terms of health outcomes are less clear.

  Central Government & Regions have opposite views

  With official documentation it is difficult to draw conclusions

- **More general**

  Different levels of Govt

  The approach might contribute to the debate regarding the health consequences for countries that cut their health expenditures during the Great Recession.

# In this paper . . .

We are interested in the causal effect of Piani di rientro

Different methods exist, **but** if the benchmark is not able to replicate what would have been the outcome in the treated regions there is a bias.

The main reason why Central and local Govts have different views is related to the **benchmark** (or counterfactual) against which to compare the outcomes.

I deal with the **fundamental ignorance** concerning the appropriate benchmark. To this aim, I estimate a set of admissible effects, or **bounds** (Manski, 1990).

# Reference model

Suggested directly by the policy it follows that:

Formal model

$$\max \quad -\Delta\text{Costs}, \Delta\text{Efficiency} \tag{1}$$

$$\text{such that} \quad \Delta\text{Health outcomes} \geq 0. \tag{2}$$

# Summary

# Data

**Administrative data** from NSI and MoH

**Outcomes of interest**:

- Health related indicators (Lorgelly et al., 2010):
  - **mortality rates**;
  - **hospitalization rates**.
- Cost containment:
  - **Current health care expenditure**;
- Efficiency:
  - **Inappropriate hospitalization**.

**Period**: 2003-2010 / 2003-2015.

Two **important strengths** for the following analysis:

1. Broad overlap with the indicators relevant for the ex-post monitoring
2. Administrative nature that prevents from systematic non-response.

# Summary

# The estimator

The goal of our evaluation is the comparison of an outcome $y(t)$ in two mutually exclusive states of the world, $t \in \{0, 1\}$.

The parameter of interest is the average treatment effect for regions undergoing the plan, i.e. treated (ATT):

$$E[y(1)|t = 1] - \underbrace{E[y(0)|t = 1]}_{y^*}$$

I cannot observe $E[y(0)|t = 1]$ (Manski, 1990)

The central problem of the analysis is recovering what would have been the outcome in the unobserved state of the world (i.e., a counterfactual).

# Standard approaches

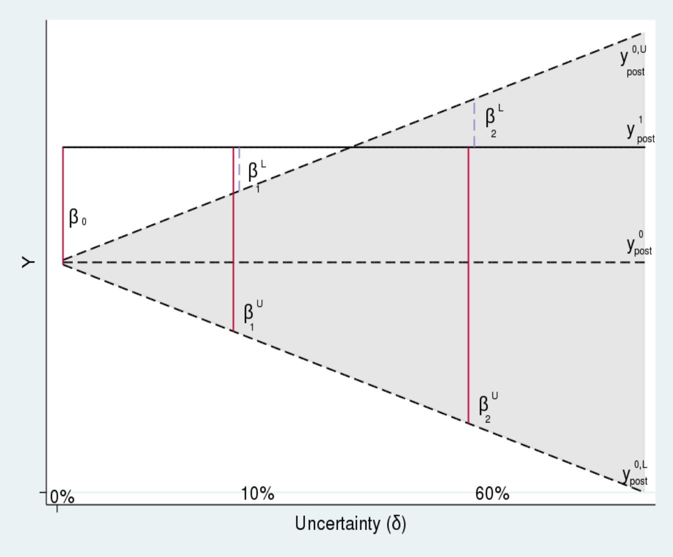
**Standard approaches** impose a set of assumptions, including some forms of invariance, that allow point identification of the effect of the treatment (Imbens and Wooldridge, 2009).

Standard alternatives to estimate the counterfactual $y^*$ are:

- a **state invariance** uses as benchmark the control unit after the treatment (i.e., $y^* = y^0_{j,post} = y^1_{\neq j,post}$, or state invariance),
- a **time invariance** uses the outcome after the treatment focusing only on the treated unit $j$ (i.e., $y^* = y^0_{j,post} = y^0_{j,pre}$, or time invariance)
- a **Difference-In-Differences** (DID) uses the evolution of the outcome in the control units to project the expected outcome in the treated unit (i.e., a common trend assumption; $y^1_{j,post} - y^1_{j,pre} = y^0_{j,post} - y^0_{j,pre}$)
- a **Synthetic control** (SC) may be seen as a flexible version of DID that also includes state invariance. Under the assumption $y_{SC,post} = w' \, y^1_{\neq j,post}$.

# The idea of the estimator by Manski and Pepper (2013, 2017)

▸ Detail



# Summary

# Results

**Method**: Synthetic Control & Time invariance ▸ Details on SC

**Conditioning variables**: ▸ Why not regional migration/taxation

based on the distribution of the population by age and gender & population

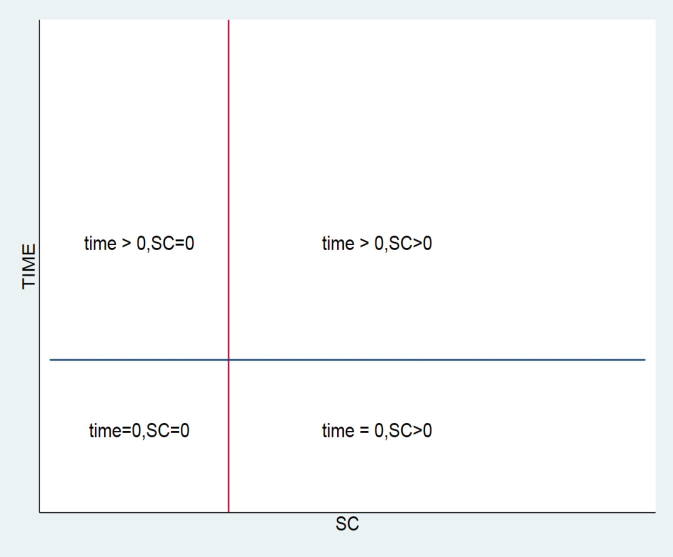
+ regional GDP (Michaud and van Soest, 2008), immigration rate (Giuntella and Mazzonna, 2015), poverty rate
+ FE (Ferman and Pinto, 2016)

Similar to SiVeAS (2014); Bordignon and Turati (2009); Caruso and Dirindin (2012).

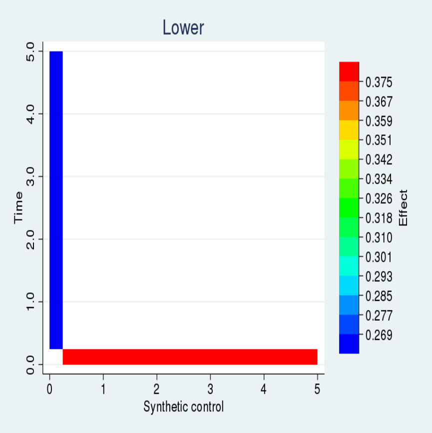
**Other issues**: ▸ Details

1. the appropriate values of $(\delta_{\text{State inv.}}, \delta_{\text{Time inv.}})$
2. the standard errors.

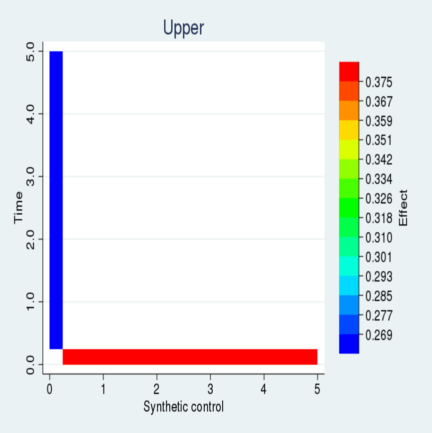
# The approach in a nutshell: 4 possible combinations of hps



# The example of mortality in Lazio




(a) Lower




(b) Upper

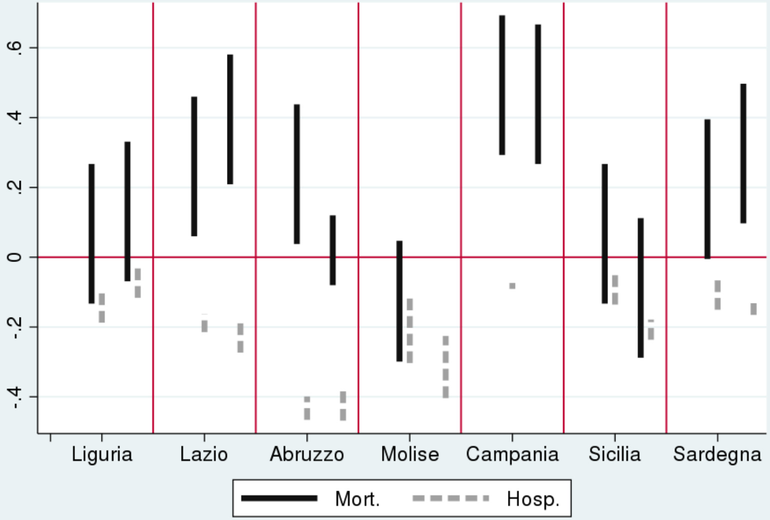
Table

# Results using optimal uncertainty parm

Example

| | Low. | Upp. | Low. | Upp. | Low. | Upp. | Low. | Upp. | Low. | Upp. | Low. | Upp. | Low. | Upp. |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| ‰ Mortality rates | | | | | | | | | | | | | | |
| | Liguria | | Lazio | | Abruzzo | | Molise | | Campania | | Sicilia | | Sardegna | |
| $(\delta_T, \delta_{SC})$ | 1.000 | 0.200 | 0.500 | 0.200 | 0.500 | 0.200 | 0.500 | 0.200 | 0.500 | 0.200 | 1.000 | 0.200 | 1.000 | 0.200 |
| Δ (2007 2010) | -0.133 | 0.267 | 0.060 | 0.460 | 0.038 | 0.438 | -0.299 | 0.047 | 0.293 | 0.693 | -0.133 | 0.267 | -0.005 | 0.395 |
| Δ (2007 2013) | -0.069 | 0.331 | 0.209 | 0.581 | -0.080 | 0.120 | 0.211 | 0.048 | 0.267 | 0.667 | -0.288 | 0.112 | 0.097 | 0.497 |
| % Hospitalization rates | | | | | | | | | | | | | | |
| | Liguria | | Lazio | | Abruzzo | | Molise | | Campania | | Sicilia | | Sardegna | |
| $(\delta_T, \delta_{SC})$ | 2.000 | 0.500 | 0.500 | 0.500 | 1.500 | 0.500 | 1.500 | 1.000 | 1.500 | 1.000 | 1.500 | 0.500 | 1.000 | 0.500 |
| Δ (2007 2010) | -1.875 | -0.875 | -2.145 | -1.635 | -4.659 | -3.989 | -3.031 | -1.160 | -0.906 | -0.738 | -1.356 | -0.356 | -1.504 | -0.551 |
| Δ (2007 2013) | -1.162 | -0.162 | -2.733 | -1.752 | -4.683 | -3.683 | -4.036 | -2.257 | -2.105 | -2.598 | -2.364 | -1.787 | -1.653 | -1.251 |

# Results using optimal uncertainty parm




Not plotted if Lower>Upper bound; Hospitalization rates are divided by 10 (to make the reading easier)

# Results using optimal uncertainty parm

| | Low. | Upp. | Low. | Upp. | Low. | Upp. | Low. | Upp. | Low. | Upp. | Low. | Upp. | Low. | Upp. |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Health care current exp. | | | | | | | | | | | | | | |
| | Liguria | | Lazio | | Abruzzo | | Molise | | Campania | | Sicilia | | Sardegna | |
| $(\delta_T, \delta_{SC})$ | 0.500 | 0.200 | 1.500 | 0.500 | 0.300 | 0.100 | 0.500 | 0.500 | 1.000 | 0.500 | 1.000 | 0.200 | 0.500 | 0.100 |
| $\Delta$ (2007 2010) | -0.357 | -0.050 | -1.035 | -0.035 | -0.295 | -0.108 | -0.496 | -0.157 | -0.698 | -0.428 | -0.816 | -0.626 | -0.032 | 0.168 |

| | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Avoidable/unavoidable access | | | | | | | | | | | | | | |
| | Liguria | | Lazio | | Abruzzo | | Molise | | Campania | | Sicilia | | Sardegna | |
| $(\delta_T, \delta_{SC})$ | 0.500 | 0.500 | 0.500 | 0.500 | 0.500 | 0.500 | 0.500 | 0.500 | 0.500 | 0.500 | 0.500 | 0.500 | 0.500 | 0.500 |
| $\Delta$ (2007 2010) | 1.091 | 0.123 | 1.315 | 0.425 | 0.596 | -0.608 | 1.929 | 0.694 | 1.574 | 0.844 | 0.483 | -0.485 | 1.747 | 0.854 |

# Summary

# Consequences of the Recovery plan

- The target in terms of **cost containment was achieved**.
- For all the regions that underwent a Recovery plan **hospitalization** drops; **mortality** rates increased in some of the regions
- No gain in terms of **efficiency**.

# Thank you for your attention

Questions, critiques, suggestions to: domenico.depalo@bancaditalia.it

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Bordignon, M. and G. Turati (2009). Bailing out expectations and public health expenditure. *Journal of Health Economics 28*(2), 305 – 321.

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Ferman, B. and C. Pinto (2016). Revisiting the synthetic control estimator. Mpra paper, University Library of Munich, Germany.

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Lorgelly, P., K. Lawson, E. Fenwick, and B. AH (2010). Outcome measurement in economic evaluations of public health interventions: a role for the capability approach? *International Journal of Environmental Research and Public Health 7*(5), 2274–2289.

Manski, C. F. (1990, May). Nonparametric Bounds on Treatment Effects. *American*

# The Recovery plans: Regions

Back

The first round of plans formally ended in 2009 with some funds and measures postponed to 2010; afterward, regions were allowed to sign new plans over the period 2010-2012.

To date, **ten regions** underwent *Piani di Rientro*: Lazio was the first region; in the same year, also Abruzzo, Campania, Liguria, Molise and Sardegna in March and Sicilia in July joined the plan.

# The idea of the estimator by Manski and Pepper (2013, 2017)

Bounded variations can be considered jointly or separately.

$$\begin{array}{rcl} \max(y_{\neq j,post} - \delta_{\text{State inv.}}, y_{j,pre} - \delta_{\text{Time inv.}}) & \equiv & y_{j,post,Lower}(0) \\ \leq & y_{j,post}(0) & \leq \\ \min(y_{\neq j,post} + \delta_{\text{State inv.}}, y_{j,pre} + \delta_{\text{Time inv.}}) & \equiv & y_{j,post,Upper}(0) \end{array} \tag{3}$$

The treatment effect can now be bounded as
$[\mathbf{y_{j,post}(1) - y_{j,post,Upper}(0); y_{j,post}(1) - y_{j,post,Lower}(0)}]$. Back

# Why not regional migration/taxation

- For the evaluation of Piani di Rientro, using regional migration is **potentially affected by the policy**, jeopardizing the exact identification of the treatment effects.
- Similar considerations apply to the regional taxation, due to the design of the policy.
- Interestingly, if one is not convinced by this justification, the effect of omitting these variables would be reflected in a larger uncertainty regarding the true benchmark, therefore the bounding approach of this paper would still be valid.

Back

# The construction of a counterfactual

**Under time invariance**: $y_{j,pre}$ as a counterfactual for $y_{j,post}$: No problem

**Under state invariance**: $y_{\neq j,post}$ as a counterfactual for $y_{j,post}$: what is the best set of units $\neq j$?

The outcomes in the regions that underwent Recovery plan to all the regions not in repayment plan (as done in the official report released by SiVeAS (2014)).

I exploit the synthetic cohort approach suggested in Abadie and Gardeazabal (2003) and Abadie et al. (2010).

Back

# The construction of a counterfactual : synthetic cohort

It is a weighted average of the control units (the synthetic counterfactual), such that

1. only regions with positive weights (the pool of donors) are used to build the counterfactual
2. the share of weights attached to each control unit makes explicit the relative contribution of each control unit to the counterfactual of interest.

Back

# Setting ($\delta_{\text{State inv.}}, \delta_{\text{Time inv.}}$) - 1

Abadie et al. (2010) emphasize that “the analyst can decide if the characteristics of the treated unit are sufficiently matched by the synthetic control. In some instances, the fit may be poor and then I would not recommend using a synthetic control. Even if there is a synthetic control that provides a good fit for the treated units, interpolation biases may be large if the simple linear model [. . . ] does not hold over the entire set of regions in any particular sample. Researchers trying to minimize biases caused by interpolating across regions with very different characteristics may restrict the donor pool to regions with similar characteristics to the region exposed to the event or intervention of interest.” (p. 495) Back

## Setting ($\delta_{\text{State inv.}}, \delta_{\text{Time inv.}}$) - 2

Hence:

- In general, some bias cannot be avoided and here is where bounds solves the issue.
- If the treated unit and the pool of donors are far apart for reasons independent on the Recovery plan by an unknown amount (otherwise the counterfactual would be known without uncertainty), one should set the dissimilarity parameter $\delta_{\text{State inv.}} >> 0$.

**But how large should $\delta$ be?**

Manski and Pepper (2017) propose to set $\delta_{\text{State inv.}}$ and $\delta_{\text{Time inv.}}$ based on the dissimilarity between treated and untreated units before the treatment takes place.

Back

# Standard errors

Making the same arguments in Manski and Pepper (2013) and Manski and Pepper (2017), this paper does not provide confidence intervals for the estimated average treatment effects, since I focus on the population of interest instead of on a realization from some sampling process. Also notice that "measurement of statistical precision requires specification of a sampling process that generates the data, but I are unsure what type of sampling process would be reasonable to assume" (Manski and Pepper, 2013, p. 6). This allows to focus exclusively on identification issues arising from the unobservability of counterfactual outcomes (Horowitz and Manski (2000) elaborate further on this point).

Back

# Setting ($\delta_{\text{State inv.}}, \delta_{\text{Time inv.}}$ for hospitalization) Back

| Year | Liguria | | Lazio | | Abruzzo | | Molise | | Campania | | Sicilia | | Sardegna | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | T | S | T | S | T | S | T | S | T | S | T | S | T | S |
| 2002 | | -0.0 | | 1.5 | | -0.2 | | -0.2 | | -0.8 | | 0.2 | | -0.5 |
| 2003 | -1.0 | -0.1 | -0.4 | -0.7 | -1.1 | -0.3 | -1.4 | -0.7 | -0.7 | -0.5 | -1.3 | 0.1 | -0.3 | 0.1 |
| 2004 | -0.7 | -0.2 | -0.2 | -0.4 | -0.1 | 0.2 | 0.1 | 0.1 | -0.3 | 0.2 | -0.9 | 0.1 | -0.3 | 0.5 |
| 2005 | 1.2 | 0.4 | -0.2 | -0.2 | 0.1 | 0.5 | 0.2 | 0.7 | -1.4 | 0.1 | -1.5 | -0.4 | -0.9 | 0.1 |
| 2006 | -1.9 | -0.1 | -0.4 | -0.2 | -1.4 | -0.2 | -1.1 | 0.2 | 0.9 | 1.0 | 0.1 | 0.0 | -0.7 | -0.2 |

Table: Mortality - Treatment effects ▸ Back

| Region | $\delta_S$ | 0 | | 0.5 | | 1.0 | | 2.0 | |
|---|---|---|---|---|---|---|---|---|---|
| | $\delta_T$ | Lower | Upper | Lower | Upper | Lower | Upper | Lower | U |
| Liguria | 0.0 | 0.24 | 0.07 | 0.24 | 0.24 | 0.24 | 0.24 | 0.24 | 0 |
| Liguria | 0.5 | 0.07 | 0.07 | -0.26 | 0.57 | -0.26 | 0.74 | -0.26 | 0 |
| Liguria | 1.0 | 0.07 | 0.07 | -0.43 | 0.57 | -0.76 | 1.07 | -0.76 | 1 |
| Liguria | 2.0 | 0.07 | 0.07 | -0.43 | 0.57 | -0.93 | 1.07 | -1.76 | 2 |
| Liguria | 3.0 | 0.07 | 0.07 | -0.43 | 0.57 | -0.93 | 1.07 | -1.93 | 2 |
| Liguria | 4.0 | 0.07 | 0.07 | -0.43 | 0.57 | -0.93 | 1.07 | -1.93 | 2 |
| Liguria | 5.0 | 0.07 | 0.07 | -0.43 | 0.57 | -0.93 | 1.07 | -1.93 | 2 |
| Lazio | 0.0 | 0.38 | 0.26 | 0.38 | 0.38 | 0.38 | 0.38 | 0.38 | 0 |
| Lazio | 0.5 | 0.26 | 0.26 | -0.12 | 0.76 | -0.12 | 0.88 | -0.12 | 0 |
| Lazio | 1.0 | 0.26 | 0.26 | -0.24 | 0.76 | -0.62 | 1.26 | -0.62 | 1 |
| Lazio | 2.0 | 0.26 | 0.26 | -0.24 | 0.76 | -0.74 | 1.26 | -1.62 | 2 |
| Lazio | 3.0 | 0.26 | 0.26 | -0.24 | 0.76 | -0.74 | 1.26 | -1.74 | 2 |
| Lazio | 4.0 | 0.26 | 0.26 | -0.24 | 0.76 | -0.74 | 1.26 | -1.74 | 2 |
| Lazio | 5.0 | 0.26 | 0.26 | -0.24 | 0.76 | -0.74 | 1.26 | -1.74 | 2 |
| Abruzzo | 0.0 | 0.24 | 0.19 | 0.19 | 0.19 | 0.19 | 0.19 | 0.19 | 0 |
| Abruzzo | 0.5 | 0.24 | 0.24 | -0.26 | 0.69 | -0.31 | 0.69 | -0.31 | 0 |

Table: Distribution of funds ▸ Back

| Region | Deficit | Debt | Loan | Add. | Targets |
|---|---|---|---|---|---|
| Liguria | 0.1 | – | ◇ | ◇ | Redefinition of the health care provided and better cooperation within RHA<br>Reduction of expenditure<br>Spending review |
| Lazio | 2.0 | 9.9 | 5.0 | 2.1 | Redefinition of the health care provided<br>Reorganization of the territorial assistance<br>Cost Containment |
| Abruzzo | 0.2 | ? | ◇ | 0.1 | Redefinition/Reorganization of the health care<br>Redefinition of agreements w/ private providers<br>Spending review |
| Molise | 0.1 | 0.1 | 0.1 | 0.2 | Redefinition/Reorganization of services/structure<br>Reorganization of the territorial assistance |
| Campania | 0.7 | 0.7 +2.8? | 1.2 | 0.4 | Deficit reduction<br>Reorganization of services/structure |
| Sardegna | 0.1 | – | ◇ | ◇ | Reorganization of the health care provided<br>Innovation of sercives provided |
| Sicilia | 1.1 | 2.8 | 2.8 | 0.2 | Cost Containment<br>Redefinition of the health care provided and better cooperation within RHA |

Consider

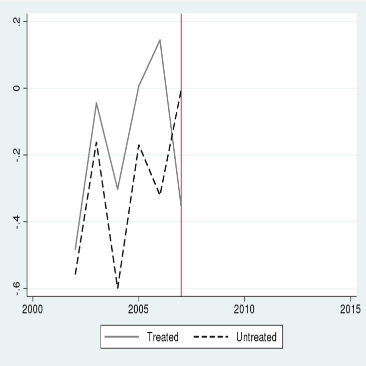
$$H = f(X_1, X_2)$$

subject to the budget constraint

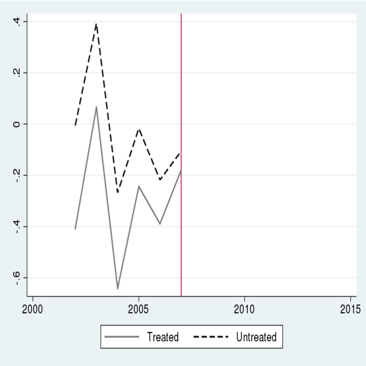
$$c = p_{X_1} X_1 + p_{X_2} X_2$$

As the aim of the policy is to decrease $c$ and keep $H$ at least constant, the only solution is to change $f(\cdot)$, making the production function (more) efficient, so as to obtain the same output with less inputs.
In principle, also $p_{X_i}$ can be reduced, so as to use the same inputs for less expenditure, and indeed was explicitly mentioned in the agreements. However, no unique purchase agency was established in any region until 2012, and therefore it is appropriate to consider $p_{X_i}$ as given during the period of this analysis. Back

# DID doesn't work!




(c) MOLISE




(d) SARDEGNA

# Setting the uncertainty: a practical example ▸ Back

| Year | y | $y^*$ | $\Delta$ |
|---|---|---|---|
| 2003 | 4 | 4 | 0 |
| 2004 | 4 | 5 | 1 |
| 2005 | 1 | 7 | -6 |
| 2006 | 9 | 8 | 1 |