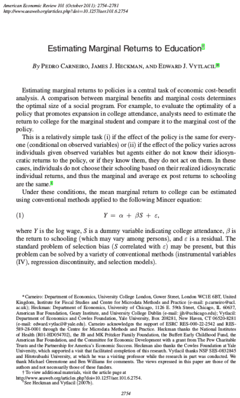
Economics of Human Capital

Static model of educational choice

Philipp Eisenhauer

Introduction

Figure: Motivation



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Estimating Marginal Returns to Education†

By Pedro Carneiro, James J. Heckman, and Edward J. Vytlacil*

Estimating marginal returns to policies is a central task of economic cost-benefit analysis. A comparison between marginal benefits and marginal costs determines the optimal size of a social program. For example, to evaluate the optimality of a policy that promotes expansion in college attendance, analysts need to estimate the return to college for the marginal student and compare it to the marginal cost of the policy.

This is a relatively simple task (i) if the effect of the policy is the same for everyone (conditional on observed variables) or (ii) if the effect of the policy varies across individuals given observed variables but agents either do not know their idiosyncratic returns to the policy, or if they know them, they do not act on them. In these cases, individuals do not choose their schooling based on their realized idiosyncratic individual returns, and thus the marginal and average ex post returns to schooling are the same.[1]

Under these conditions, the mean marginal return to college can be estimated using conventional methods applied to the following Mincer equation:

$$Y = \alpha + \beta S + \varepsilon, \quad (1)$$

where Y is the log wage, S is a dummy variable indicating college attendance, β is the return to schooling (which may vary among persons), and ε is a residual. The standard problem of selection bias (S correlated with ε) may be present, but this problem can be solved by a variety of conventional methods (instrumental variables (IV), regression discontinuity, and selection models).

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† To view additional materials, visit the article page at http://www.aeaweb.org/articles.php?doi=10.1257/aer.101.6.2754.

[1] See Heckman and Vytlacil (2007b).

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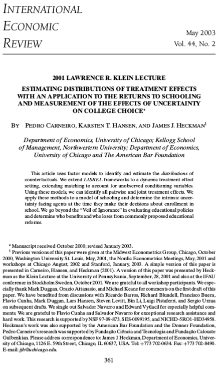
Carneiro & al. (2011)



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2001 LAWRENCE R. KLEIN LECTURE

ESTIMATING DISTRIBUTIONS OF TREATMENT EFFECTS WITH AN APPLICATION TO THE RETURNS TO SCHOOLING AND MEASUREMENT OF THE EFFECTS OF UNCERTAINTY ON COLLEGE CHOICE*

By Pedro Carneiro, Karsten T. Hansen, and James J. Heckman[1]

Department of Economics, University of Chicago; Kellogg School of Management, Northwestern University; Department of Economics, University of Chicago and The American Bar Foundation

This article uses factor models to identify and estimate the *distributions* of counterfactuals. We extend *LISREL* frameworks to a dynamic treatment effect setting, extending matching to account for unobserved conditioning variables. Using these models, we can identify all pairwise and joint treatment effects. We apply these methods to a model of schooling and determine the intrinsic uncertainty facing agents at the time they make their decisions about enrollment in school. We go beyond the "Veil of Ignorance" in evaluating educational policies and determine who benefits and who loses from commonly proposed educational reforms.

* Manuscript received October 2000; revised January 2003.

[1] Previous versions of this paper were given at the Midwest Econometrics Group, Chicago, October 2000, Washington University St. Louis, May, 2001, the Nordic Econometrics Meetings, May, 2001 and workshops at Chicago August, 2002 and Stanford, January, 2003. A simple version of this paper is presented in Carneiro, Hansen, and Heckman (2001). A version of this paper was presented by Heckman as the Klein Lecture at the University of Pennsylvania, September, 28, 2001 and also at the IFAU conference in Stockholm Sweden, October 2001. We are grateful to all workshop participants. We especially thank Mark Duggan, Orazio Attanasio, and Michael Keane for comments on the first draft of this paper. We have benefited from discussions with Ricardo Barros, Richard Blundell, Francisco Buera, Flavio Cunha, Mark Duggan, Lars Hansen, Steven Levitt, Bin Li, Luigi Pistaferri, and Sergio Urzua on subsequent drafts. We single out Salvador Navarro and Edward Vytlacil for especially helpful comments. We are grateful to Flavio Cunha and Salvador Navarro for exceptional research assistance and hard work. This research is supported by NSF 97-09-873, SES-0099195, and NICHD-5RO1-HD34958. Heckman's work was also supported by the American Bar Foundation and the Donner Foundation, Pedro Carneiro's research was supported by Fundação Ciência and Tecnologia and Fundação Calouste Gulbenkian. Please address correspondence to: James J. Heckman, Department of Economics, University of Chicago, 1126 E. 59th Street, Chicago, IL 60637, USA. Tel: +773 702-0634. Fax: +773 702-8490. E-mail: *jjh@uchicago.edu*.

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Carneiro & al. (2003)

Heckman (2008) defines three policy evaluation tasks:

- Evaluating the impact of historical interventions on outcomes including their impact in terms of well-being of the treated and the society at large.

- Forecasting the impact of historical interventions implemented in one environment in other environments, including their impact in terms of well-being.

- Forecasting the impacts of interventions never historically experienced to various environments, including their impact on well-being.

Econometrics of policy evaluation

- is important
- is complicated
- is multifaceted

Numerous applications

- labor economics
- development economics
- industrial economics
- health economics

Numerous effects

- conventional average effects
- policy-relevant average effects
- marginal effects
- distributional effects
- effects on distributions

Numerous estimation strategies

- instrumental variables
- (quasi-)experimental methods
- matching

Model

Generalized Roy model

Potential Outcomes

$$Y_1 = \mu_1(X) + U_1$$

$$Y_0 = \mu_0(X) + U_0$$

Observed Outcome

$$Y = DY_1 + (1 - D)Y_0$$

Choice

$$D = \mathrm{I}[\mu_D(X, Z) - V > 0]$$

Individual Heterogeneity

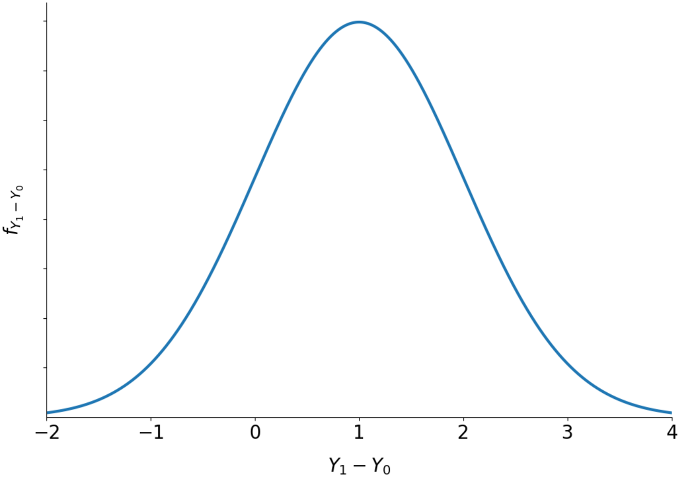
Individual-specific Benefit of Treatment

$$Y_1 - Y_0 = (\mu_1(X) - \mu_0(X)) + (U_1 - U_0)$$

Sources of Heterogeneity

- Difference in observables
- Difference in unobservables
  - Uncertainty
  - Private information

Figure: Distribution of benefits



Econometric problems

- **Evaluation problem**, we only observe an individual in either the treated or untreated state.
- **Selection problem**, individuals that select into treatment differ from those that do not.

Essential Heterogeneity

Definition: Individuals select their treatment status based on gains unobservable by the econometrician. More formally,

$$Y_1 - Y_0 \not\perp\!\!\!\perp D \quad | X = x.$$

$\Rightarrow$ consequences for the choice of the estimation strategy

Objects of interest

Useful Notation

$$P(X, Z) = \Pr(D = 1 \mid X, Z) = F_V(\mu_D(X, Z))$$

$$U_D = F_V(V)$$

Figure: First-stage unobservable

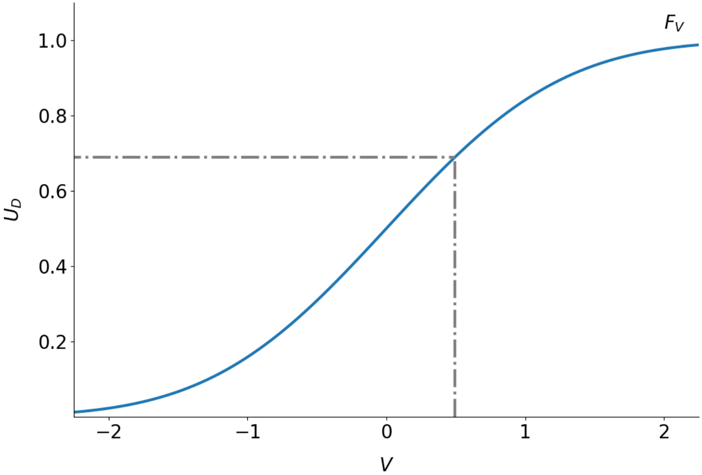


Figure: Support

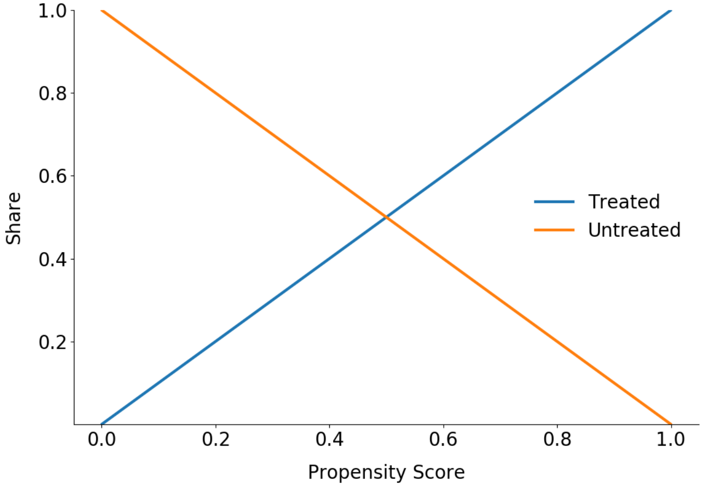


Figure: Distribution of benefits

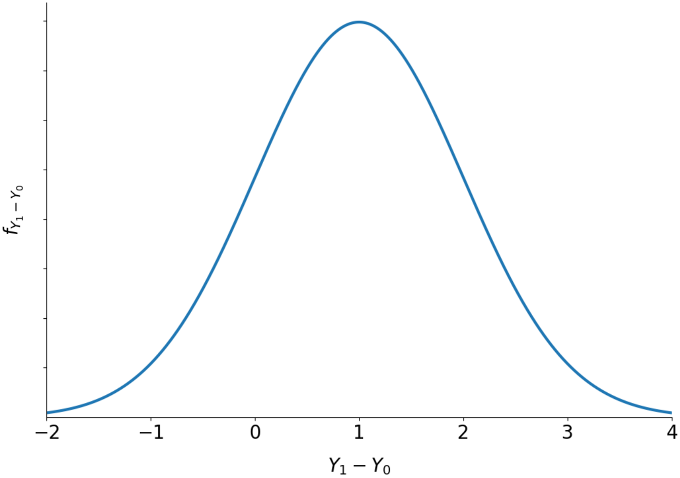
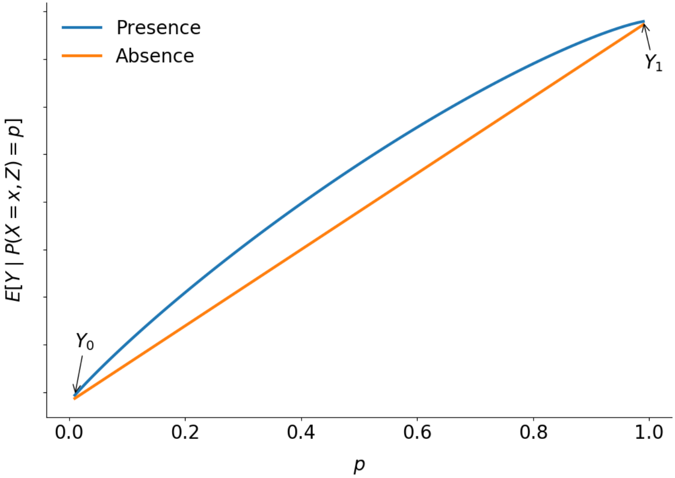


Figure: Conditional expectation and essential heterogeneity



Conventional Average Treatment Effects

Conventional Average Treatment Effects

$$\begin{aligned} B^{ATE} &= E[Y_1 - Y_0] \\ B^{TT} &= E[Y_1 - Y_0 \mid D = 1] \\ B^{TUT} &= E[Y_1 - Y_0 \mid D = 0] \end{aligned}$$

$\Rightarrow$ correspond to *extreme* policy alternatives

Selection Problem

$$
\begin{aligned}
E[Y \mid D=1]-E[Y \mid D=0] &= \underbrace{E[Y_1-Y_0]}_{B^{ATE}} \\
&+ \underbrace{E[Y_1-Y_0 \mid D=1]-E[Y_1-Y_0]}_{\text{Sorting Gain}} \\
&+ \underbrace{E[Y_0 \mid D=1]-E[Y_0 \mid D=0]}_{\text{Selection Bias}}
\end{aligned}
$$

$$E[Y \mid D=1] - E[Y \mid D=0] = \underbrace{E[Y_1 - Y_0 \mid D=1]}_{B^{TT}} + \underbrace{E[Y_0 \mid D=1] - E[Y_0 \mid D=0]}_{\text{Selection Bias}}$$

$\Rightarrow$ the bias depends on the parameter of interest

Figure: Distribution of effects with essential heterogeneity

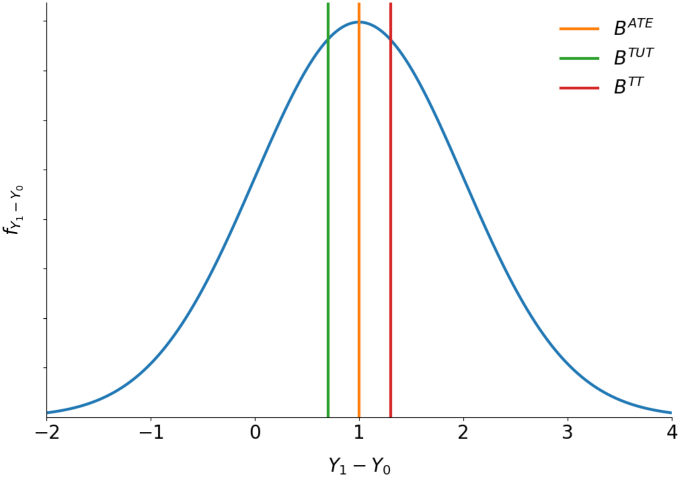
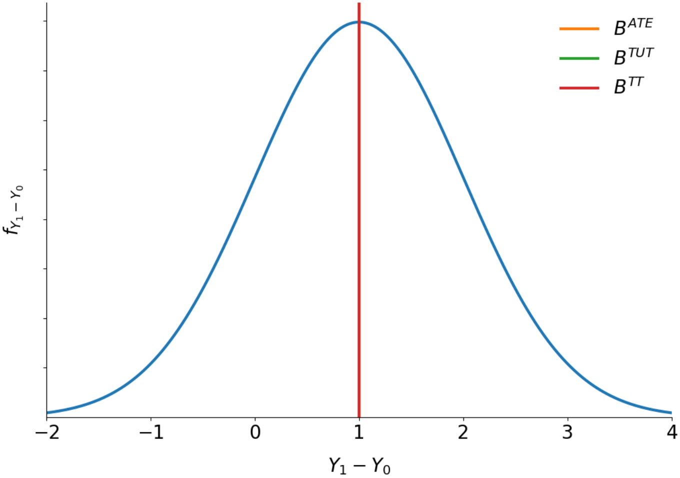


Figure: Distribution of effects without essential heterogeneity



Policy-Relevant Average Treatment Effects

Observed Outcomes

$$Y_B = D_B Y_1 + (1 - D_B) Y_0$$
$$Y_A = D_A Y_1 + (1 - D_A) Y_0$$

Effect of Policy

$$B^{PRTE} = \frac{1}{E[D_A] - E[D_B]} (E[Y_A] - E[Y_B])$$

Marginal Effect of Treatment

Marginal Benefit of Treatment

$$B^{MTE}(x, u_D) = E[Y_1 - Y_0 \mid X = x, U_D = u_D]$$

Intuition: Mean gross return to treatment for persons at quantile u_D of the first-stage unobservable V or a willingness to pay for individuals at the margin of indifference.

Figure: Margin of indifference

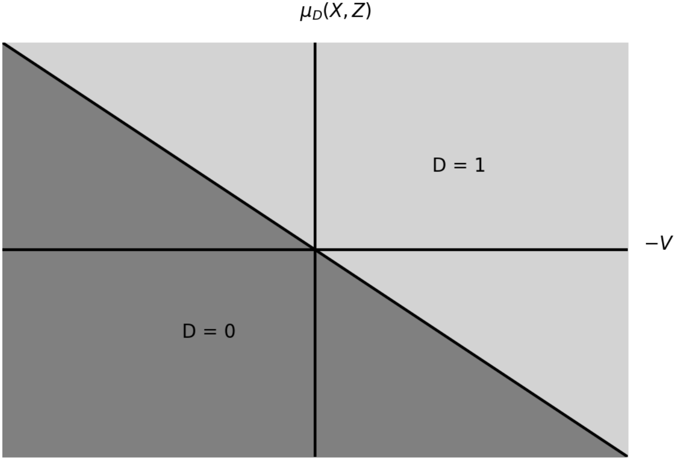
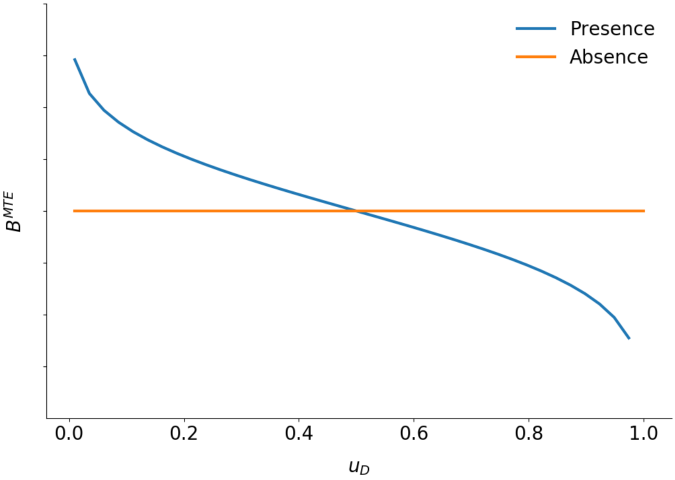


Figure: B^{MTE} and essential heterogeneity



Effects of treatment as weighted averages Parameter Δ_j, can be written as a weighted average of the $B^{MTE}(x, u_D)$.

$$\Delta_j(x) = \int_0^1 B^{MTE}(x, u_D)\omega^j(x, u_D)du_D,$$

where the weights $\omega^j(x, u_D)$ are specific to parameter j and integrate to one.

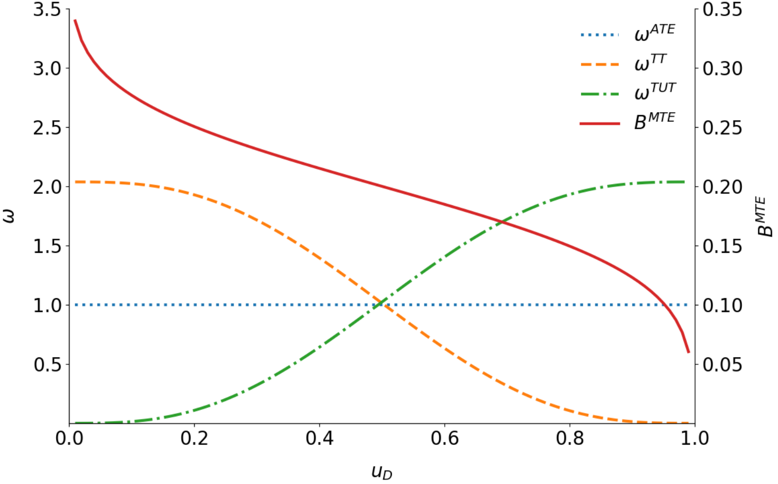
Weights

$$\omega^{ATE}(x, u_D) = 1$$

$$\omega^{TT}(x, u_D) = \frac{1 - F_{P|X=x}(u_D)}{E[P \mid X = x]}$$

$$\omega^{TUT}(x, u_D) = \frac{F_{P|X=x}(u_D)}{E[1 - P \mid X = x]}$$

Figure: Effects of treatment as weighted averages



Local Average Treatment Effect

Local Average Treatment Effect

- **Local Average Treatment Effect:** Average effect for those induced to change treatment because of a change in the instrument.

  $\Rightarrow$ instrument-dependent parameter

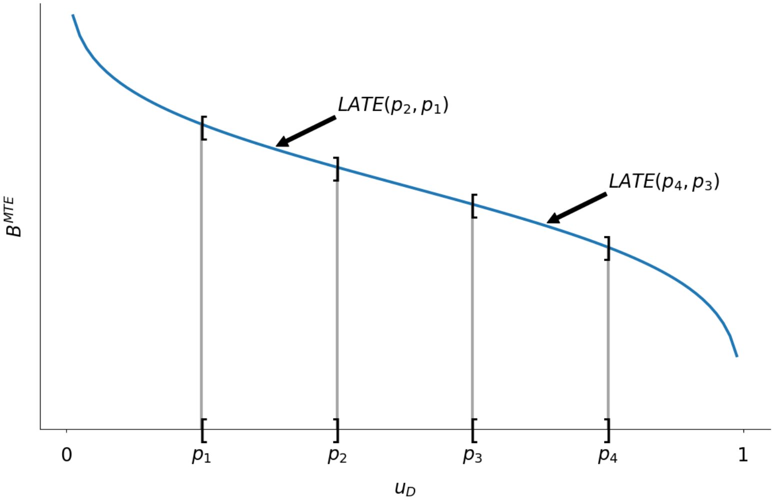
- **Marginal Treatment Effect:** Average effect for those individuals with a given unobserved desire to receive treatment.

  $\Rightarrow$ deep economic parameter

$$B^{LATE} = \frac{E[Y \mid Z = z] - E[Y \mid Z = z']}{P(z) - P(z')}$$

$$B^{LATE}(x, u_D, u_{D'}) = \frac{1}{u_D - u_{D'}} \int_{u_D}^{u_{D'}} B^{MTE}(x, u) du,$$

Figure: Local average treatment effect



Distributions of Effects

Distrbutions of Effects

- marginal distribution of benefits
- joint distribution of potential outcomes
- joint distribution of benefits and surplus

Figure: Distribution of benefits

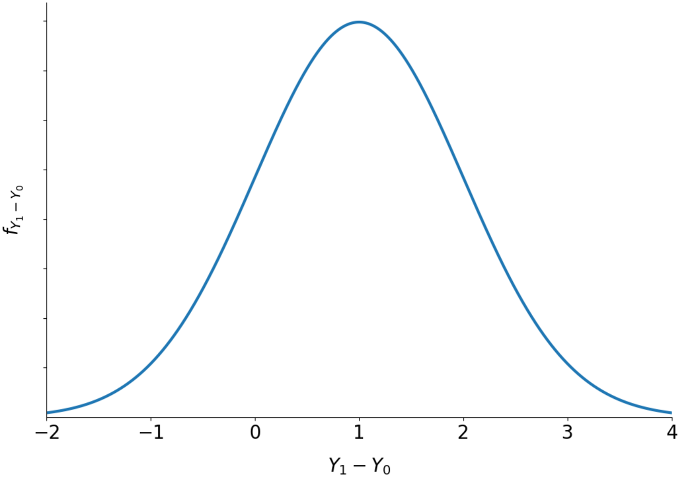


Figure: Distribution of potential outcomes

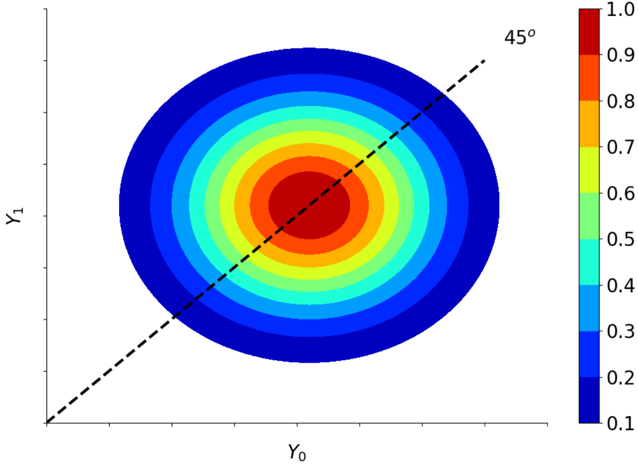
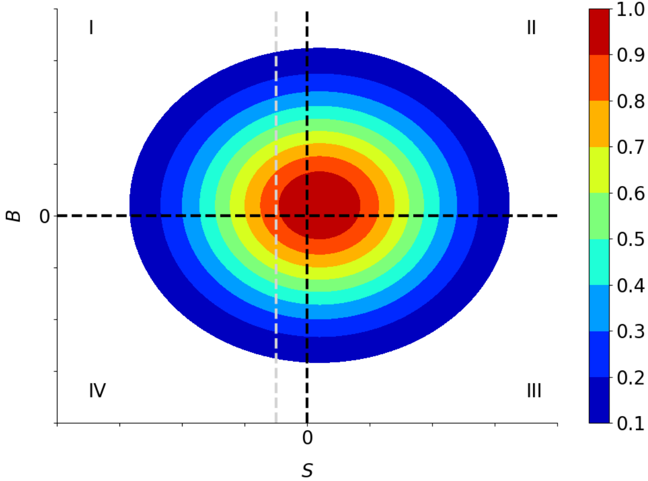


Figure: Distribution of benefits and surplus



Conclusion

Appendix

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