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The Impact of Integrated Management for Salt Tolerant Forage Production on Small Farmers Poverty Egypt Case Study (Sahl El-Tina)

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ABSTRACT

This study examines the impact of New Integrated Management Package (IMP) adoption on income and poverty among fodder farming household in Sahl El-Tina. The IMP such as Rate, time, and methods of nitrogen fertilization and other fertilization, Leaching requirements for some crops, Intercropping system, Use of suitable crop genotype/variety, Use of modern irrigation systems or modified systems to save water, date, rate and method of planting. The study aims mainly to improve the lives of small farmers through the level of dissemination and application of cultivation techniques forage crops tolerant to salinity through develop and disseminate technologies packages of forage production. And reducing their probability of falling below the poverty line. Therefore suggest that intensification of the investment on IMP dissemination is a reasonable policy instrument to raise incomes and reduce poverty among fodder farming household. It used instrumental variables (IV)-based estimator to estimate the Local Average Treatment Effect (LATE) of adoption of IMP on income and poverty reduction, using cross-sectional data of 200 farmers from Shal El-Tina. The findings reveal a robust positive and significant impact of IMP adoption on farm household income and welfare measured by per capita expenditure and poverty reduction. Specifically, the empirical results suggest that adoption of IMP raises household per capita expenditure and income by an average of 529.27$ and 1371$ in Shal El-Tina per cropping season respectively, thereby reducing their probability of falling below the poverty line. Therefore suggest that intensification of the investment on IMP dissemination is a reasonable policy instrument to raise incomes and reduce poverty among fodder farming household, although complementary measures are also needed. The incidence of poverty was higher among non-IMP adopters (55.2%) than IMP adopters (49.5%). In addition, both the depth and severity of poverty were also higher (20.85% and 15.42%) among non-adopters than the adopters (18.48% and 9.88%). All three poverty measures indicate that poverty was more prevalent and severe among non-adopters compared to adopters.

Introduction

On the basis of the strategic, economic and social importance, Sinai Peninsula, is considered one of the main development pillars on national level. The ecosystem of Sinai is considered fragile where water resources are slightly poor (saline ground water or mixed water) in addition of the low productivity of soils due to the low fertility with high level of salinity. In view of scarcity of water resources and possible negative impact of climatic changes, the utilization of such fragile resources (saline soils and brackish water) in growing salt tolerant fodder crops, cereals and oil plants may contribute to the development of the areas and hence improve the standard of living of local inhabitants (local Bedouins and new settled farmers moved from Nile Valley).

The study was implemented in El Tina plain (so-called Sahl El Tina) area, North Sinai region, representing the most severe marginal environmental system of the Egyptian deserts, in addition to the economic and social problems that affecting the population of this area. It is located at Al Salaam Canal, on the eastern side of Suez Canal in North Sinai region. It lies in the north-western Mediterranean coast of Sinai, between 32 350 and 32 450 E and 31 000 and 31 250 N. It has a triangular shape, surrounded by the Suez Canal to the west, the Mediterranean Sea to the north and the northern Sinai sand sea to the south. The north-western corner of the El-Tina plain, south of Port-Fouad and directly east of the Suez Canal, is covered by the El-Malha Lake. It occupies a large triangle area of about 56 km^2 with a 14-km base and up to an 8 km maximum width. It is filled with hyper saline water all year. It has a concave shoreline configuration that is about 39 km long and 818 km^2 in area.

Sahl El-Tina area can be divided into two zones; a northern strand plain and a southern delta plain. The strand plain's width increases from 1 km in the east to 12.5 km in the west and most of this area is covered by the El-Malha Lake. The southern part of the El-Tina plain is part of the Nile flood plain and is composed of silty clay intercalated with salts and evaporates in the western part. Moving eastward, sediment composition shifts to silty clay and clayey silt covered with a salt crust (El Shaer, 2010). The southern delta plain is composed of muddy deltaic sediments and is 1–2 m above sea level.

The irrigation water is obtained from mixed water (Nile water + drainage waters) of El Salam Canal. The soil is characterized by severe salt affected, differs in depth and stratified profile layers. The soil salinity and salinity of irrigation water vary between 12.5–15.6 dS/m and 1.6–2.3 dS/m, respectively. In addition, the poverty and inappropriate agriculture management practices beside the marginal soil and water resources are the constraints of agriculture development in this area (Anon, 2014).

It was important to identify progressive farmers in the selected benchmark sites to be fully trained on seed production processing. Therefore, four sites were chosen for sorghum and pearl millet seed production; improved management practice package was applied. The selected farmers grew the grasses for seed production and green forage as well to feed their livestock. The main salt tolerant tested plant species were namely: pearl millet, sorghum, barley, fodder beet, safflower and triticale genotypes. A full package of the improved management practices (IMP) was applied for growing all plant species for seed production which included soil levelling, proper water irrigation and drainage systems and fertilizers, harvesting techniques, etc.

The adoption and diffusion of the innovation process has been characterized as the acceptance over time of some specific item by individuals (or adopting units) linked to specific channels of communication, typically, innovations diffuse over time in a pattern that resembles an s-shaped curve. That is, the adoption rate of an innovation goes through a period of slow, gradual growth before experiencing a period of relatively dramatic and rapid growth (FAO, 2001). A technological innovation usually has two components: a hardware aspect "the tool, product" and a software aspect "how to use the hardware", Time is a main factor in the decision-making process, innovativeness and an innovation's rate of adoption. Potential adopters are uncertain what an innovation may offer. Over time information from different sources and from the farmer's own experience reduces this uncertainty. A better base is established for adoption/rejection and intensity of use decisions. The adoption reasons are mainly focused on the characteristics of the innovation and the perceived demand of such innovation.

Objective of the Study

The study aims mainly to improve the lives of small farmers through the level of dissemination and application of cultivation techniques forage crops tolerant to salinity through develop and disseminate technologies packages of forage production and reducing their probability of falling below the poverty line. Therefore suggest that intensification of the investment on IMP dissemination is a reasonable policy instrument to raise incomes and reduce poverty among fodder farming household.

Analytical Framework

The Local Average Treatment Effect (LATE)

The average treatment effect (ATE) is a measure used to compare treatments (or interventions) in randomized experiments, evaluation of policy interventions, and medical trials. The ATE measures the difference in mean (average) outcomes between units assigned to the treatment and units assigned to the control. In a randomized trial (i.e., an experimental study), the average treatment effect can be estimated from a sample using a comparison in mean outcomes for treated and untreated units. However, the ATE is generally understood as a causal parameter (i.e., was estimated or property of a population) that a researcher desires to know, defined without reference to the study design or estimation procedure. Both observational and experimental study designs may enable one to estimate an ATE in a variety of ways. **(**Heckman and Vytlacil, 2007a; 2007b).

The expression "treatment effect" refers to the causal effect of a given treatment or intervention (for example, the administering of a drug) on an outcome variable of interest (for example, the health of the patient). In the Neyman – Rubin "Potential Outcomes Framework" of causality a treatment effect is defined for each individual unit in terms of two "potential outcomes." Each unit has one outcome that would manifest if the unit were exposed to the treatment and another outcome that would manifest if the unit were exposed to the control. The "treatment effect" is the difference between these two potential outcomes. However, this individual-level treatment effect is unobservable because individual units can only receive the treatment or the control, but not both. Random assignment to treatment ensures that units assigned to the treatment and units assigned to the control are identical (over a large number of iterations of the experiment). Indeed, units in both groups have identical distributions of covariates and potential outcomes. Thus the average outcome among the treatment units serves as a counterfactual for the average outcome among the control units. The differences between these two averages are the ATE, which is an estimate of the central tendency of the distribution of unobservable individual-level treatment effects (Holland, 1986). If a sample is randomly constituted from a population, the ATE from the sample (the SATE) is also an estimate of the population ATE (or PATE) (Imai et al., 2008).

While an experiment ensures, in expectation, that potential outcomes (and all covariates) are equivalently distributed in the treatment and control groups, this is not the case in an observational study. In an observational study, units are not assigned to treatment and control randomly, so their assignment to treatment may depend on unobserved or unobservable factors. Observed factors can be statistically controlled (e.g., through regression or matching), but any estimate of the ATE could be confounded by unobservable factors that influenced which units received the treatment versus the control (Imbens and Wooldridge, 2009). It was important to identify progressive farmers in the selected benchmark sites to be fully trained on seed production processing. Therefore, four sites were chosen for sorghum and pearl millet seed production; improved management practice package was applied. The selected farmers grew the grasses for seed production and green forage as well to feed their livestock. The main salt tolerant tested plant species were namely: pearl millet, sorghum, barley, fodder beet, safflower and triticale genotypes. A full package of the improved management practices (IMP) was applied for growing all plant species for seed production which included soil levelling, proper water irrigation and drainage systems and fertilizers, harvesting techniques, etc.

The Methodology of the Study

In order to define formally the ATE, we define two potential outcomes: Y_{0i} is the value of the outcome variable for individual *i* if he is not treated, Y_{1i} is the value of the outcome variable for individual i if he is treated. For example, Y_{0i} is the health status of the individual if he is not administered the drug under study and Y_{1i} is the health status if he is administered the drug.

The treatment effect for individual i is given by $Y_{1i}-Y_{0i}=\beta_i$. In the general case, there is no reason to expect this effect to be constant across individuals.

Let $E[.]$ denote the expectation operator for any given variable (that is, the average value of the variable across the whole population of interest). The Average treatment effects is given by: $E[Y_{1i} - Y_{0i}]$.

If we could observe, for each individual, Y_{1i} and Y_{0i} among a large representative sample of the population, we could estimate the ATE simply by taking the average value of $Y_{1i} - Y_{0i}$ for the sample:

$$\frac{1}{N}\sum_{i=1}^{N}(Y_{1i} - Y_{0i})$$ (Where N is the size of the sample).

The problem is that we cannot observe both Y_{1i} and Y_{0i} for each individual. For example, in the drug example, we can only observe Y_{1i} for individuals who have received the drug and Y_{0i} for those who did not receive it; we do not observe Y_{0i} for treated individuals and Y_{1i} for untreated ones. This fact is the main problem faced by scientists in the evaluation of treatment effects and has triggered a large body of estimation techniques (Abadie, 2003; Abadie and Gardeazabal, 2003; Abadie and Imbens, 2006).

Once a policy change occurs on a population, a regression can be run controlling for the treatment. The resulting equation would be

$$y = B_0 + \delta_0 d2 + B_1 dT + \delta_1 d2 \cdot dT$$

Where y is the response variable and δ_1 measures the effects of the policy change on the population.

The difference in differences equation would be

$$\widehat{\delta_1} = (\bar{Y}_{2,T} - \bar{Y}_{1,T}) - (\bar{Y}_{2,C} - \bar{Y}_{1,C})$$

Where T is the treatment group and C is the control group. In this case the δ_1 measures the effects of the treatment on the average outcome and is the average treatment effect.

From the diffs-in-diffs example we can see the main problems of estimating treatment effects. As we cannot observe the same individual as treated and non-treated at the same time, we have to come up with a measure of counterfactuals to estimate the average treatment effect (Imbens and Wooldridge, 2009).

So each farm household has ex-ante two potential outcomes: an outcome when adopting an IMP method that we denote by y_1 and an outcome when not adopting an IMP method that we denote by y_0. If we let the binary outcome variable d stand for IMP adoption status, with $d=1$ meaning adoption and $d=0$ non adoption, we can write the observed outcome y of any farm household as a function of the two potential outcomes:

$$y = dy_1 + (1 - d)y_0$$

For any household, the causal effect of the adoption on its observed outcome y is simply, the difference between its two potential outcomes $(y_1 - y_0)$. But- because the realizations of the two potential outcomes are mutually exclusive for any household (i.e. only one of the two can be observed ex-post), it is impossible to measure the individual effect of adoption on any given household. However, one can estimate the mean effect of adoption on a population of households. Such a population parameter is called the average treatment effect (ATE) in the literature (Imbens and Wooldridge, 2009). One can also estimate the mean effect of adoption on the sub-population of adopters – $E(y_1 - y_0/d = 1)$ – which is called the average treatment effect on the treated and is usually denoted by ATE1 (or ATT). The average treatment effect on the untreated – $E(y1\text{-}y0 \mid d=0)$ – denoted by ATE0 is also another population parameter that can be defined and estimated. Several methods have been proposed in the statistics and econometric literature to remove (or at least minimize) the effects of overt and hidden biases and deal with the problem of non-compliance or endogenous treatment variable. The methods can be classified under two broad categories based on the types of assumptions they require to arrive at consistent estimators of causal effects (see Imbens, 2004; Imbens and Wooldridge, 2009).

The Poverty Decomposition Model

There are two time periods, $t = 1, 2$ (or $\tau = 1, 2;\ t \neq \tau$), and in each period there are it $= 1t, \ldots, n\,t$ individuals who are non-decreasingly ranked by their income, χ_{i_1}, where a_{i_1} is income share, $m\,t$ is average income, and Xt is total income.

In both periods, z is the poverty line and a person is poor if $\chi_{i_1} < z$. An individual's population share is b_{i_1}. The additively decomposable class of poverty measures by FGT can be represented in a general form as:

$$P_{a_1} = \sum_{i_1=1}^{n_1} b_{i_1} \left(\frac{z-\chi_{i_1}}{z}\right)^{\alpha} ; \alpha \geq 0.$$

In equation, *α=0, 1, 2,* denotes head count ratio (incidence), poverty gap (depth), and squared poverty gap (severity), respectively (Foster et al., 1984).

Where $\alpha \geq 0$ and takes the values of 0, 1 and 2 for poverty incidence, depth and severity respectively. *q*=the number of people with an income below the poverty line, *Yi*=income of the household, *n*=total population and *Z*=poverty line.

When *α=0, P0* gives the Incidence of Poverty (Headcount Index,); *α=1, P1* gives the Depth of Poverty (Poverty Gap,) and *α=2, P2* gives the Poverty Severity (Squared Poverty Gap) (Abadie and Javier, 2003).

Data and Descriptive Statistics

This study was based on survey data collected in 2013/2014 from Sahl El-Tina where IMP dissemination activities were being conducted. A multistage sampling technique was used for the collection of the data. We stratified the sampling frame into two strata according to the main IMP farming system practice. We selected farmers where IMP had been introduced and those where they were not yet introduced. A total of 200 farmers were selected, farmers were randomly selected. Interviewed (85.8%) of the total number of farmers in the sample were selected. Frequencies and percentages were utilized for data presentation and analysis.

Results and Discussion

Showed from Table 1 that the majority of respondents (95%) and 90% of the adopters of IMP practices were male. At the time of the survey, the average age of the farmers was 45 years. The average household size of respondents (both adopters and non-adopters) was 15 people per family; about 85.2% of respondents were native of their respective farmers and have spent an average of about 40 years in Sahl El-Tina village.

The educational level of the household's head was significantly different between adopters and non-adopters. Whereas 11.5% of the adopters had at least primary school level of education 45% of non-adopters had a similar level of education. In addition, there was a significant difference in the attendance of vocational training as well as in the type of experience in farming between adopters and non-adopters IMP practices.

Table 2 presents the mean difference analysis of the impact of IMP adoption in terms of area cultivated, crop output, yield, household expenditures, annual per capita expenditures, annual income and poverty status between adopters and non-adopters of IMP practices.

Table 1 Household socio-economic characteristics adoption

Characteristic	Non-adopters	Adopters	Total	Difference test
Socio-demographic factors				
Proportion of male farmers (%)	95.8%	90%	95%	0.02
Proportion of female farmers (%)	74	12.4	7.8	0.03
Age (average)	43	48	45	3.5
Household size (average)	15	15	15	0
Number of years of residence in Sahl ElTina (average)	40	41	40	0.09
Education and experience in crop farming				
% of no formal education	55.6	7.51	63.11	0.35
% of primary school	18.2	8.9	27.1	0.11
% of secondary school	11.2	5.9	17.1	0.24
% of post-secondary school	5.5	0.4	5.9	0.03

Source: IMP impact study survey 2013/2014,

Table 2 Descriptive analysis of impact of IMP adoption.

Characteristic	Non-adopters	Adopters	Total	Difference test
Area cultivated(Feddan)	3.16 (0.15)	1.93 (1.2)	3.20 (0.11)	0.66 (0.42)
Yield (ton/Feddan)	2055.59 (150.4)	2775.87 (188.3)	2271.2 (122.8)	-540.8 (300.4)
Crop output (ton)	2008.5 (122.9)	1170.11 (88.7)	1977.8 (100.34)	569.5 (215.9)
Annual household expenditure (LE)	7544.8 (348.07)	7255.8 (477.9)	7224.11 (583.0)	-224.8 (687.3)
Poverty measure %				
Headcount ratio (incidence) %	55.2 (4.2)	49.5 (3.9)	50.22 (2.88)	
Poverty gap (depth) %	20.85 (2.15)	15.42 (1.95)	17.97 (2.11)	
Poverty severity %	18.84 (1.9)	9.88 (2.50)	8.34 (1.80)	

Source: IMP impact study survey 2013/2014, by Stata program

The result shows that while there is a significant difference between the gross incomes of adopters and non-adopters, there was no significant difference in the amount spent per head by both groups. As is evident from the Table 2, the incidence of poverty was higher among non-IMP adopters (55.2%) than IMP adopters (49.5%). In addition, both the depth and severity of poverty were also higher (20.85% and 15.42%) among non-adopters than the adopters (18.48% and 9.88%). All three poverty measures indicate that poverty was more prevalent and severe among no adopters compared to adopters.

Table 3 shows that the adoption of improved crop varieties exerts a positive and significant impact on the per capita expenditure in Sahl El-Tina.

Specifically, LATE estimates suggest that IMP adoption significantly increased the household per capita expenditure by about 529.27$. This is the average change in per capita expenditure of households that belong to a change in technological status. The results further reveal that the impact was much higher among male farmers than their female counterparts. Comparison ecologies also shows that the highest impact of IMP adoption was observed in agri-process, that order of increased in per capita expenditure. These results suggest that the causal effect of IMP adoption on poverty reduction was greater for farmers falling in the poverty depth followed by those in poverty headcount and poverty severity, respectively.

The determinants of household per capita expenditure as given by their local average response functions (LARF) are presented in Table 4 & 5. These estimates provides evidence that, apart from a change in technology (IMP adoption), other household socio demographic variables significantly explain the change in per capita expenditure.

These variables include gender, age of the household head, household size, farm size and year of experience on farming. Similarly, a number of coefficients for the interacted terms were statistically significant, thus confirming the heterogeneity of the impact of IMP adoption on expenditure.

The F statistics of 147.36 for the joint significance of the interacted terms as well as the non-interacted terms indicate that they are jointly statistically significantly different from zero. Here as the coefficient for gender of the household head is positively significant indicating male-headed households have higher per capita expenditure than female-headed households, the coefficient for household size and age were negatively significant, suggesting that larger households and elderly people spend less per person than smaller households (Table 4).

Table 3 The impact of IMP adoption on per capita expenditure

Parameters	LATE	LATE Wald	LATE-ps	ATE-ipsw	ATE-exp
ATE	4700	1289.98**	3259.8	4700	2505.5
ATE1			-890.5	4182.7**	1298.5*
ATE0			4250.75	4066.7	2189.1
psB			4055.8	131.9	-755.4
Impact by gender					
Male	1839.85** (0.00)				
Female	1495.65**(0.00)				
Impact by Poverty					
Headcount ratio (incidence)	1994.55**				
Poverty gap (depth)	1887.67**				
Poverty severity	699.14**				

Source: IMP impact study survey 2013/2014, Stata program. ATE average treatment effect, LATE local average treatment effect, LATE-ps local average treatment effect, where the conditional probability of treatment P(d = 1| x) ≡ P(x) (called the propensity score), ATE-ipsw average treatment effect independence-based estimators used inverse propensity score weighing estimators (IPSW), ATE-exp average treatment effect per expenditure, ATE1 The average treatment effect on the untreated , ATE0 another population parameter, that can be defined and estimated, PSB propensity score matching method.

Table 4 Estimated coefficient of the exponential local average response function (LARF) for per capital expenditure

Per Capita Expenditure	Coef.	St.Err.	T-statistics
IMP adoption	18	0.88	15.99**
Age	-0.09	0.01	9.77**
Gender	14.95	0.55	42.53**
No formal education dummy	-0.06	0.22	-0.33
Primary education dummy	0.02	0.23	0.13
Secondary education dummy	-0.25	0.44	-0.59
Household size	0.19	0.05	-3.77**
Farm size	0.33	0.05	6.88**
Age_adoption	0.09	0.01	4.22**
Gender_adoption	-15.66	0.77	-25.9**
Household size - adoption	-0.15	0.09	-1.78*
Farm size - adoption	0.11	0.19	1.95*
R^2	0.69		
$R^{/2}$	0.62		
F	147.36**		

Source: IMP impact study survey 2013/2014, Stata program.

Table 5 The impact of IMP adoption on household crops income

Parameters	LATE	LATE Wald	LATE-ps	ATE-ipsw	ATE-exp
ATE	12175**	6950**	12175**	-8189.1	-8800.9
ATE1			9000.5	-6050.11	-6017.2
ATE0			1622.8	8188.6	-7211.9
psB			-7771.8	-311.2	1008.5*
Impact by gender					
Male	6002.5** (115.5)				
Female	2880.6** (155.5)				
Impact by Poverty					
Headcount ratio (incidence)	6970.9**				
Poverty gap (depth)	5550.11**				
Poverty severity	2750.3**				

Source: IMP impact study survey 2013/2014, Stata program

The impact of improved technology adoption on household income of farmers was estimated through the local average treatment effect (LATE). Results presented in Table 5 show that IMP adoption had a positive and significant effect on household income. Adoption of IMP increased the income of adopters. Which show a positive impact of the adoption of agricultural technologies? The interaction term for gender and household size is negative and significant, suggesting that the impact of IMP adoption on per capita household expenditure will be smaller among female farmers and larger households. However, the interaction terms of age and farm size are positive and significant, suggesting that the impact of IMP adoption will be high for elderly farmers and those with large farm sizes.

Conclusions and Recommendations

This study examined the impact of different IMP practices adoption on household income and poverty status proxy by per capita expenditure in Sahl El-Tina. Given the non-experimental nature of the data used in the analysis, associated with the biases and non-compliance behaviour of some farmers, a local average treatment effect (LATE) model was used. Also, the local average response function (LARF) was used to account for other factors that could have affected our outcomes. The results did suggest the presence of bias in the distribution of covariates between groups of adopters and non-adopters, indicating that accounting for selection bias is a significant issue.

Overall, the findings in this study indicate that adoption of improved practices helped raise farmers' income and per capita expenditures, thereby increasing their probability of escaping poverty. So we must be developing agricultural production systems to be more resilient in an integrated comprehensive approach that help the participant farmers in marginal environments achieving better management of their farm resources along the value chain and attain high production and income. This confirms the widely held view that productivity-enhancing agricultural innovations can contribute to raising incomes of farm households, poverty alleviation, and food security in developing countries. It should, however, be noted that the implementation of such a set of pro-poor agri-processing interventions requires detailed assessment of the poverty situation of the targeted farmers and assessment of alternative measures in order to define pragmatic actions to bring about the desired results. Along with changes in policy and institutional framework to ensure an enabling environment, such actions need to include specific interventions e.g., managerial reforms in agricultural organizations, administration of water rights and water pricing, regulatory and supervisory measures, and supportive incentives/mechanisms to improve both system performance and equity.

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References

Abadie A. 2003. Semi-parametric Instrumental Variable Estimation of Treatment Response Models. Journal of Econometrics 113: 231-263.

Abadie A, Imbens GW. 2006. “Large Sample Properties of Matching Estimators for Average Treatment Effects.” Econometrica, 74(1): 235–67.

Abadie A, Gardeazabal J. 2003. “The Economic Costs of Conflict: A case Study of the Basque Country.” American Economic Review, 93(1): 113–32.

Anon 2014. Project “Adaptation to Climate Change in Wana Marginal Environments through Sustainable Crop and Livestock Diversification. Annual Report, 2014, DRC, Cairo, Egypt

El Shaer HM. 2010. Halophytes and salt-tolerant plants as potential forage for ruminants in the Near East region. Small Ruminant Research, 91(1): 3-12.

FAO. 2001. The Economics of Conservation Agriculture. Natural Resources Management and Environment Department. Rome.

Foster JE, Greer J, Thorbecke E. 1984. A Class of Decomposable Poverty Measures, Econometrica, 52(3), pp.761-776.

Holland PW. 1986. "Statistics and Causal Inference". J. Amer . Statist. Assoc. 81 (396): 945– 60. doi:10.1080/01621459. 1986.10478354. JSTOR 2289064.

Heckman JJ, Vytlacil E. 2007a. "Econometric Evaluation of Social Programs, Part I: Causal Models, Structural Models and Econometric Policy Evaluation." In Handbook of Econometrics, Volume 6B, ed. James J. Heckman and Edward E. Leamer, 4779–4874. Amsterdam and Oxford: Elsevier, North-Holland.

Heckman JJ, Vytlacil E. 2007b."Econometric Evaluation of Social Programs, Part II: Using the Marginal Treatment Effect to Organize Alternative Econometric Estimators to Evaluate Social Programs, and to Forecast Their Effects in New Environments." In Handbook of Econometrics, Volume 6B, ed. James J. Heckman and Edward E. Leamer, 4875–5143. Amsterdam and Oxford: Elsevier, NorthHolland.

Imai K, King G, Stuart EA. 2008. "Misunderstandings between Experimentalists and Observationalists About Causal Inference".J.R. Stat. soc. Series A 171 (2): 481–502. doi:10. 1111/j.1467-985X.2007.00527.x.

Imbens G. 2004. Nonparametric estimation of average treatment effects under exogeneity: A review, Review of Economics and Statistics. 86: 4-29.

Imbens G, Wooldridge JM. 2009. "Recent Developments in the Econometrics of Program Evaluation," Journal of Economic Literature, 47:1, 5–86.