Poverty and Landownership

Quasi-experimental Evidence from South Africa

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Introduction

- Resurgent academic interest in the relationship between inequality and economic performance.
- Key finding is that (non-market) transfers of assets from the wealthy to the poor can enhance efficiency and reduce poverty by changing underlying incentives (Bardhan, Bowles and Gintis (2000), Legros and Newman (1997), Moene (1992), Mookherjee (1997), Shetty (1987), Banerjee, Gertler and Ghatak (2002), and many others).
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Land Redistribution for Agricultural Development (LRAD): introduced in 2001; targeted at the individual level; awarded to beneficiaries on a sliding scale, depending on own contributions.

Settlement Land Acquisition Grant (SLAG): targeted to entire families; slowly being phased out at the time the survey; no matched contribution.

Extension of Security of Tenure Act (ESTA): farm workers

Labour Tenants Act (LTA): protection to labour tenants

Restitution of Land Rights Act: dispossession under Apartheid

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- So in the absence of random assignment to treatment group, we need to make sure our control group is comparable.
- Many factors, unrelated to producer characteristics, can influence the types of comparisons we make.
- Key identification problem: can we figure out some way of holding these factors constant (because they are hard to measure in a survey) thereby removing the confound induced by this category of unobservables?
- Design of the study:
  - Ex-ante Identification
    - Quasi-experimental survey design (control/treatment type structure)
    - Qualitative work on approval process
    - Re-sample
  - Ex-post evaluation methods:
    - Matching on the (generalized) propensity score, IV
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  1. Project Registration
  2. Approval of Planning Grant
  3. Preparation of Project Identification Report
  4. Approval of District Screening Committee
  5. Approval of Provincial Government
- At each milestone, projects are either approved to pass on to subsequent stages, referred back to the the government appointed planner for further development, or rejected altogether.
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Treatment Group: households to whom land has already been transferred. Three main programs: restitution (rights-based), redistribution (out-right transfer), security of tenure (prevention of evictions).

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   - Formally, we can define the set of potential control group matches (based on the propensity score) for the ith household in the treatment group with characteristics $\mathbf{x}_i$ as $A_i(p(\mathbf{x})) = \{p_j | \min_j |p_i - p_j|\}$
   - The average treatment effect is then:

$$\text{ATT} = (N_1)^{-1} \sum_{i \in \{T=1\}} (y_{1i} - \Sigma_j \omega(i,j) y_{0j})$$

   where j is an element of $A_i(p(\mathbf{x}))$ and $\omega(i,j)$ is the weight given to j.
   - When the weight function is $\omega(i,j) = \dfrac{K(p_i(\mathbf{x}) - p_j(\mathbf{x}))}{\sum_{j=1}^{N_{0j}} K(p_i(\mathbf{x}) - p_j(\mathbf{x}))}$ and where $K = \dfrac{1}{\sigma\sqrt{2\pi}} e^{-\frac{p(\mathbf{x})^2}{2\sigma^2}}$, we have a Kernel estimator of ATT
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1. Matching on generalized propensity score (Hirano and Imbens, 2004)
   - Now define continuous dose, $D_i \in [d_0, d_1]$
   - Potential outcome: $Y_i = Y_i(D_i)$
   - Goal is to estimate:

$$\theta(d) = E[Y(d)] - E[Y(\tilde{d})] \qquad \tilde{d}, d \in \mathcal{D}$$

   , where $\tilde{d}$ is a fixed level of treatment against which we compare all “doses"
   - Confront same fundamental identification problem as in binary case
   - Assume weak unconfoundedness, once conditioning on GPS
   - Next define expected outcome conditional on treatment dose and GPS:

$$\beta(d, r) = E[Y|D = d, R = r]$$

   - Average treatment effect is expectation of conditional treatment over R:

$$\mu(d) = E[\beta(d, r(d, X))]$$

   - Write final estimate of interest as:

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   , where $\tilde{d}$ is a fixed level of treatment against which we compare all “doses"
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Table: Mean Per Capita Consumption

Program	Total	Treatment	Control	N	p-val	Δ
All	461.85	456.97	465.50	2979	0.73	0
LRAD	494.97	557.43	471.96	1761	0.03	$+$
SLAG	335.25	318.02	386.93	268	0.14	0
Restitution	459.70	428.25	550.18	469	0.02	$-$
Tenure Reform	346.18	328.40	365.12	320	0.57	0

Jump to GPS Adjusted ATT

Table: Test of Difference in Means for Covariates

Variables	Total	Treatment	Control	N	p-val
Number employed in agriculture	0.54	0.77	0.44	1725	0.00
Log days in pipeline	6.74	5.94	7.08	1725	0.00
Days in pipeline (DoseIV)	1423.26	844.27	1666.97	1725	0.00
Days since treatment (Doserec)	352.01	1188.30	0.00	1725	0.00
Household head is male	0.69	0.76	0.67	1725	0.00
Education of household head (yrs)	5.98	6.31	5.85	1725	0.06
Mean farming experience (yrs)	1.51	1.62	1.46	1725	0.40
Number plots accessed pre-95	1.15	0.65	1.34	1663	0.00
Distance to DLRO (100 km)	0.93	0.94	0.92	1718	0.54
Area plots accessed pre-95 (hectares)	51.55	31.60	59.18	1663	0.26
Land allocated by municipality (post-94)	0.13	0.03	0.21	916	0.00
Land allocated by other farmer (post-94)	0.09	0.00	0.15	916	0.00
Land allocated by tribal authority (post-94)	0.06	0.00	0.09	916	0.00

Table: Propensity Score Regressions

Variable	(1)	(2)
No. employed in agric	.381 (.061)***	.703 (.120)***
Log days in pipeline	-.838 (.072)***	-.892 (.117)***
Household head is male	.404 (.152)***	.871 (.236)***
Education of household head (yrs)	.008 (.014)	-.064 (.022)***
Mean farming experience (yrs)	-.002 (.018)	-.011 (.025)
No: all plots accessed pre-95		.875 (.203)***
Distance to DLA divided by 100		-.053 (.174)
Hectares: all plots accessed pre-95		.003 (.003)
ever been allocated land by the municipality (post-94)?		-2.935 (.540)***
Const.	3.869 (.510)***	4.993 (.856)***
Obs.	1586	677

Table: Propensity Score Balance

Block	$\min \hat{p}(\mathbf{x})$	N_0	N_1	$\bar{p}_0(\mathbf{x}) - \bar{p}_1(\mathbf{x})$	SE	t	t_{cv}
1.00	0.03	133.00	11.00	-0.01	0.16	-0.66	2.58
2.00	0.20	64.00	23.00	-0.02	0.01	-2.50	2.64
3.00	0.30	48.00	29.00	-0.01	0.01	-1.81	2.64
4.00	0.40	80.00	73.00	-0.01	0.01	-1.55	2.58
5.00	0.60	38.00	119.00	0.00	0.01	-0.32	2.58
6.00	0.80	19.00	139.00	-0.03	0.02	-2.19	2.58

“Block” refers to an interval placeholder from among 6 mutually exclusive intervals of the propensity score distribution. These intervals are defined by the cut-off points given by $\min \hat{p}(\mathbf{x})$. The fifth column in the table reports on the magnitude of the difference in means for the propensity score between treatment and control for each block. t refers to the t-statistic for testing that the reported difference in column 5 is significant.

Table: Covariate Balance

Variable	1	2	3	4	5	6
$onfarmemp$	-0.01	0.88	-0.30	-0.42	-0.05	-0.90
$ldoseIV$	1.81	2.55	-0.55	-0.40	-0.63	1.79
$sexhhead$	-0.46	0.68	1.41	-0.59	0.12	-0.40
$hheadeduc$	-1.01	0.92	0.98	0.11	-0.80	0.40
$farmexper$	-1.53	0.44	1.88	-0.89	0.67	-0.19
$pre95sum$	0.75	-0.70	0.53	-1.40	-1.02	-0.07
$dist100$	-0.90	-1.53	0.87	-0.19	0.74	0.53
$pre95size$	0.29	1.05	0.77	-1.83	-0.72	-0.60
$MUNpl$	0.21	-1.81	1.37	0.96	1.78	-0.37

The entries report the t-statistic for an equality of means test of each regressor by treatment status within the 6 intervals of the balanced propensity score distribution.

Table: Summary of Treatment Effects

Method	Definition	$T = 1$	$T = 0$	ATT	SE	t
Single Difference	Per capita	474	1287	85.47	38.67	2.21
Stratification Method	Per capita	286	673	174.80	65.08	2.69
Kernel	Per capita	286	312	180.52	63.88	2.83
Bootstrapped Kernel	Per capita	286	391	188.38	61.79	3.05

Differences in sample sizes are the result of the combined effect of matching and trimming. Stratification matching is based directly on the blocking used in the tests for balance.

- Impact of LRAD on per capita consumption is positive, and remains positive and significant even once we have controlled for selection bias.
- Poverty line is R555.55 per capita.
- Average PCE for our control group is R471.96.
- Our estimated impact of the land transfer is R188.38.
- Several caveats to these calculations: see paper for more details.

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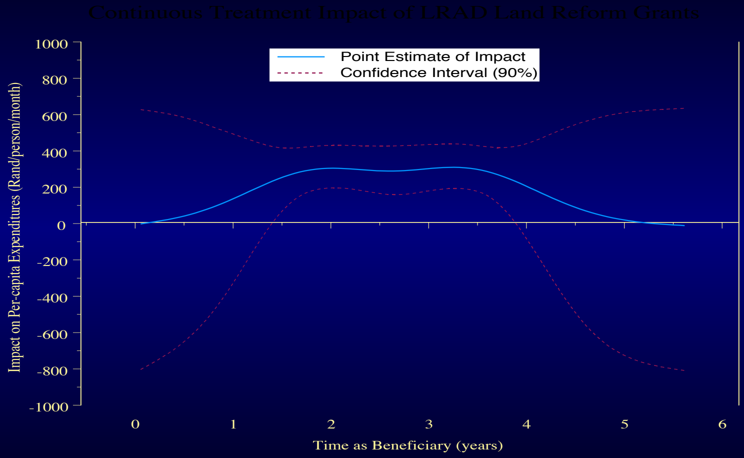
Table: Descriptive Statistics

	Control	Treatment Terciles (yrs)		
		$<$ 2.1 yrs	2.1–3 yrs	$>$ 3 yrs
Dose (days)	0	621	892	1344
Days in Pipeline	1662	876	883	686
Days Since Application	1662	1497	1775	2030
Application Delay (days)	–	–	–	–
Farm Experience	1.49	1.21	1.46	2.10
Education	5.88	6.57	6.61	7.04



Jump to Single-Difference Estimates

- Weak Unconfoundedness: $Y(d) \perp D | X \qquad \forall d \in \mathcal{D}$
- Hirano and Imbens lottery example of weak unconfoundedness
- More formally:
  - Generalized Propensity Score: Let $r(d,x)$ be the conditional density of the treatment given the covariates:

$$r(d,x) = f_{D|X}(d,x)$$

    Then the generalized propensity score is $R = r(D,X)$.
  - Weak unconfoundedness then implies $f_D(d|r(d,x), Y(d)) = f_D(t|r(d,X))$

Jump back to GPS Method

1. First estimate the GPS: $D_i|X_i \sim N(\psi' X_i, \sigma^2)$

$$\hat{R}_i = \frac{1}{\sqrt{2\pi\hat{\sigma}^2}}\left(-\frac{1}{2\hat{\sigma}^2}(D_i - \hat{\psi}' X_i)\right)$$

2. Then compute the DRF:

$$\beta(D_i, R_i) = E[Y_i|D_i, R_i] = \alpha_0 + \alpha_1 D_i + \alpha_2 D_i^2 + \alpha_3 R_i + \alpha_4 R_i^2 + \alpha_5 D_i R_i$$

Treatment effect estimator becomes:

$$\hat{\mu}(d) = \widehat{E[Y(d)]} = \frac{1}{N}\sum_{i=1}^{N}(\hat{\alpha}_0 + \hat{\alpha}_1 \cdot d + \hat{\alpha}_2 \cdot d^2 + \hat{\alpha}_3 \cdot \hat{r}(t, X_i) + \hat{\alpha}_4 \cdot \hat{r}(t, X_i)^2 + \hat{\alpha}_5 \cdot d \cdot \hat{r}(t, X_i))$$

3. Finally, Effect of Treatment on Treated:

$$\hat{\theta}(d) = \hat{\mu}(d) - \hat{\mu}(\tilde{d}) \qquad \forall d \in \mathcal{D}$$