Closing the Tap

How School Enrollment is Affected when Conditional Cash Transfer Payments Break Off

Martin Wiegand

PhD Candidate at Vrije Universiteit Amsterdam and Tinbergen Institute

Research Question

Conditional cash transfer (CCT) programs for education are successful at getting children into school. But often payments stop before end of school career. Aftereffects of CCTs on school enrollment have not been studied yet.
Necessary to fully understand impact of CCTs on education distribution, and important for policy makers who want to be aware of unintended consequences.

- Look at data from Progresa in Mexico. Covered middle school (which usually ends at age 15), but not high school.
- Question: Would a student who never received Progresa payments be more or less likely to go to high school if she had received such payments?
- Look at effects on Prob(high school) and Prob(high school | finished middle school).

Program and Data

Experimental setup of Progresa: rural localities randomized into two groups.

- Treatment group: program started in May 1998.
- Control group: program started in December 1999.

Three main student outcome variables:

1. Enrolled in high school in school year 2000/01.
2. Done some high school by winter 2003.
3. Completed high school by 2004.

I consider the cohort of students who were expected to start high school in the academic year of 2000/01. Study treatment effects for two samples:

- Unconditional: completed primary school in 1997.
- Conditional: completed middle school in 2000.

Identification Strategy

Want ATE $:= \mathrm{E}[Y(1) - Y(0)]$. Two issues:

1. For conditional probability: treatment likely has had effect on group composition. Progresa may have led children to finish middle school who otherwise wouldn't have done so.
   → Assume conditional independence.
2. There is some attrition from the panel, leading to missing outcomes for some students.
   → Assume missingness at random.

Both assumptions are based on large set of pre-treatment covariates (student and household characteristics, parents' assessments and opinions, actual and desired household expenditures, location characteristics).

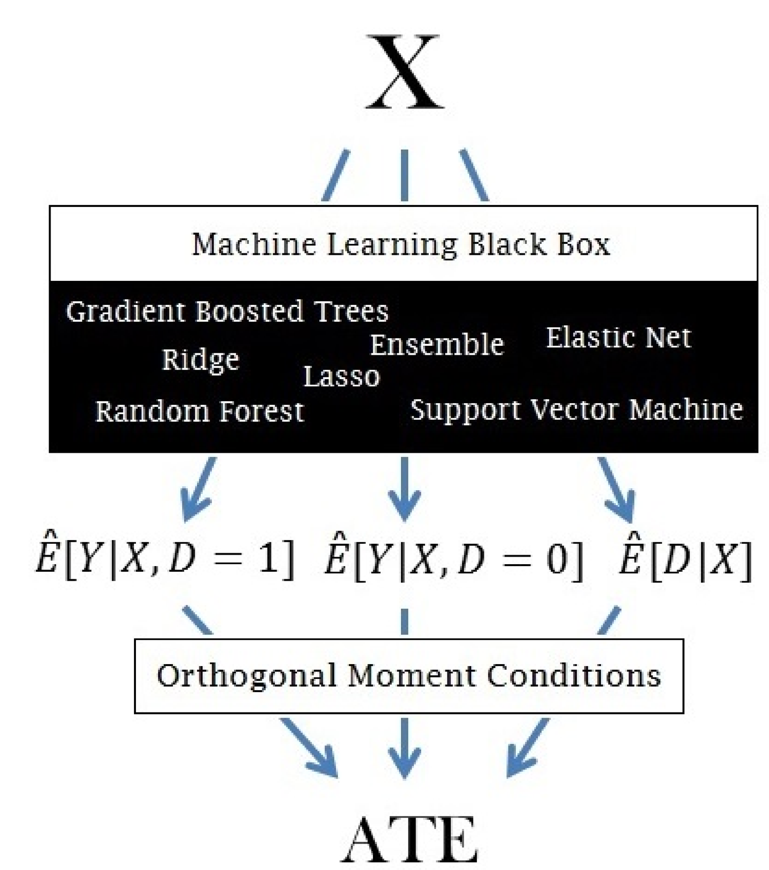
Results

Dependent variable	unconditional	conditional
Started high school in 2000	-0.032	-0.084*
	(0.024)	(0.051)
Some high school by 2003	-0.079**	-0.100**
	(0.034)	(0.047)
Completed high school by 2004	-0.045	-0.076*
	(0.029)	(0.045)
Observations	1,507	566

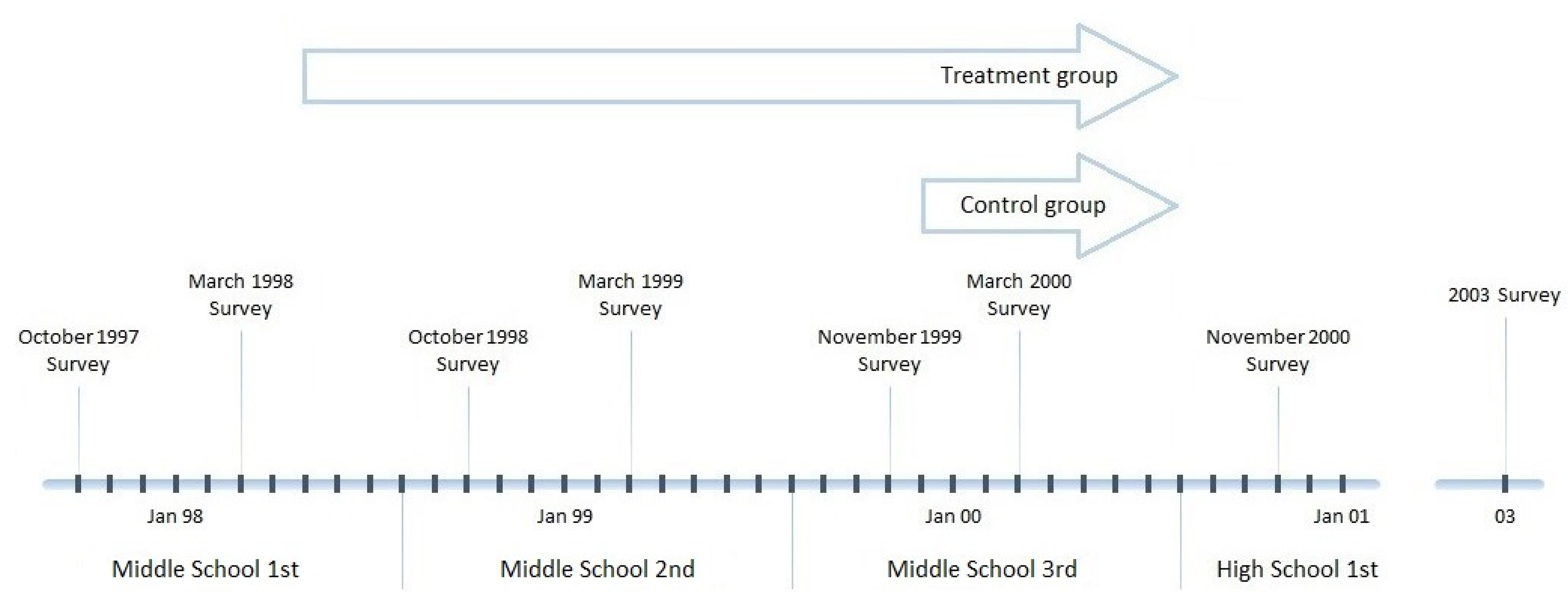
*: 10% level, **: 5% level.

Double Machine Learning

The imbalance between the treatment and control group is an inherent property of conditional aftereffects estimation. There is no ideal experiment serving as benchmark. This makes it important to make best use of available pre-treatment characteristics.
Problem: Possibly many potential confounders—perhaps even more than observations. Don't know a priori which ones matter, and how.
→ Use method by Chernozhukov et al. (2018) called double machine learning. Essentially extension of doubly-robust estimation to high-dimensional case:



The resulting estimator of the ATE is approximately unbiased and asymptotically normally distributed.



Summary of Findings

- Main result: Progresa has large negative effect on school continuation once the program stops. → Puzzling!
- Even the unconditional treatment effect is significantly non-positive.
- Positive effect on middle school attendance (confirmation of earlier studies), which is however partly offset by implicit incentive to repeat a year of middle school.

Reasons for Negative Aftereffects

1. Motivation crowding: Monetary incentives replace intrinsic motivations. Once the payments stop, no reason left to continue school.
2. Anchoring: Progresa payments anchor perceived value of school. Reducing payments later (to zero) may signal that further education is not worth the time.
3. Loss aversion: Progresa may shift reference point for consumption: beneficiaries view end of program as financial loss which needs to be offset by child wage. (But program has no significant effect on p.c. consumption, and reported reasons for not going to school are not money-related.)
4. Classroom peer effects: CCT may change composition of students. New ones are perhaps worse on average, more bad students may negatively affect good ones. (But middle school graduates in the treatment group are, if anything, better at school than those in control group.)

Reference

Chernozhukov, Victor, Denis Chetverikov, Mert Demirer, Esther Duflo, Christian Hansen, Whitney Newey, and James Robins (2018). Double/debiased machine learning for treatment and structural parameters. *The Econometrics Journal 21* (1), 1–68.

2nd International Conference on Globalization and Development, May 3-4 2018, University of Göttingen