# About Causal Inference and How It Can Improve Impact Evaluation of Takaful and Karama

by Scott Cunningham (Baylor University)

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# Roadmap

What is causal inference?

- Core questions in causal inference
- Treatment Assignment Mechanisms

Takaful and Karama Impact Evaluation

- Description of program and methodology
- Authors' findings
- Comments and suggestions

# Overview of Today's Talk

- Firstly, we'll explore *causal inference*:
  - → What is it? Why is it important? What is at stake?
  - → Importance of *controlled randomization* and options when we can't.
- Secondly, we'll delve into a 2018 evaluation by IFPRI:
  - → Focusing on the Takaful (Solidarity) and Karama (Dignity) programs.
  - → Understanding the evaluation's findings and implications.

# Advances in causal inference

- Causal inference is having its day in the sun
- Explosion in advances in causal inference recently awarded with several major awards:
  - → Josh Angrist, David Card and Guido Imbens (2021 Nobel Prize in Economics)
  - → Judea Pearl (2011 Turing Award in computer science)
  - → James Robins, Miguel Hernán, Thomas Richardson, Andrea Rotnitzky, and Eric Tchetgen Tchetgen (2022 Rousseeuw Prize for Statistics)
- Widespread adoption of causal inference for data driven decision making, both in government and commerce, has replaced simpler correlational methods
- Exciting time!

# Examples of causal decisions

Causal inference helps us know whether things work and by how much

- Will mandatory vaccination laws reduce the spread of COVID?
- How will a early reading curriculum impact youth literacy?
- How much, if any, will cash transfers impact poor family's overall well-being?

# Counterfactuals and causal inference

Ladder of causation: observe relationships, intervene, and counterfactual

Fundamental problem of causal inference: We don't have anyone's counterfactuals because *by definition* they never happened

Causal inference *estimate* counterfactuals to understand intervention's impact but as counterfactuals don't exist, estimation require *assumptions*, data and appropriate methods

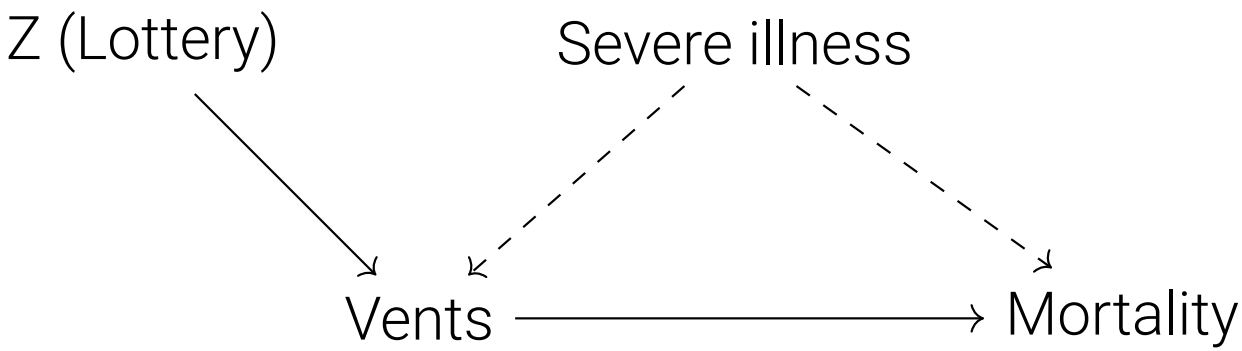
# Correlations, Causal Effects, and Selection Bias

- Imagine we find patients on ventilators have higher mortality than patients who aren't; two problems we face
  1. **Average causal effect**: Can we find the average effect of ventilators on mortality? If so how?
  2. **Selection bias**: How much of the observed differences between people on and off vents is because these the ventilator group always would've had higher mortality?
- Our goal: find situations where we can credibly delete the second term so all that is left is the first term when comparing program participants to non-participants
- Requires understanding the *behavioral reason* people were selected, but some behavioral reasons for program participation make this a very difficult problem disentangle

# Spectrum of Treatment Assignment

- Ironically, the better run a program is, the more difficult it is to infer the effect
- Voluntary participation in well run programs can make it impossible because the selection bias can be extreme
- Overcoming this, researchers typically need something that put them into the program other than their own voluntary participation, but what?

# Randomization




- Randomized experiments are valuable for causal inference because program participation is *not* based on voluntary participation, and therefore selection bias is minimized almost to nothing
- But for some questions, the *controlled* randomization may not be possible
- Randomized assignment rural regions to good and bad schools would definitively measure the impact of schools on female children, but this might be too expensive, infeasible or unethical to knowingly deprive some areas of crucial educational improvements

# Running Variables and Regression Discontinuity

- But sometimes people don't choose to participate and aren't even randomized but are assigned to treatment based on a *test*
- When their *grade* on a test is used to put them in a program, we call the test a *running variable* and the eligibility a *cutoff*
- Impact study by IFPRI published in 2018 used this method (also called *regression discontinuity* to study the impact of Takaful and Karama on a variety of health and life outcomes

# Methodology commentary

- RDD is a design that can under certain assumptions identify the average effect of the program on well being for those people right at the cutoff
- Method has a variety of techniques but at their core, they compare program participants who just barely got in because of some score they received on a running variable to those who just barely missed the cutoff
- Not the “most scientific” – all causal inference is equally scientific and valid so long as the assumptions hold; for RDD is a truly randomized experiment at the threshold

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# Proxy Means Test

- PMT formula is based on a statistical model measuring log per capita spending and the PMT score used for eligibility into Takaful and Karama was originally 5.003 and lowered to 4.5 for Takaful in Nov 2015
  - → "*PMT [is] an index of well-being based on household demographics, income, housing quality, assets and other characteristics. In poor districts, potentially eligible households were registered and interviewed to collect information for the PMT. Households with a PMT score below a preset threshold were considered eligible for the program and would begin receiving transfers*" – authors
  - → "The PMT has been used to identify the poor within the selected districts, based on selection criteria and a set cutoff score, based on the poverty line derived from Egypt's Household Income, Expenditure and Consumption Survey (HIECS) for 2012/13" – authors
- When this rule is followed perfectly, there is no selection bias when we compare program participants with non-participants, but *only* for the people who just *barely missed* because their score was too low (compared to those who just barely got in)

# Changing thresholds

**Table 3.2.1 *Takaful* proxy means test score thresholds**

| Registration period | Dates | Takaful threshold |
|---|---|---|
| 1 | March to November 2015 | 5003 |
| 2 | November 2015 to September 2016 | 4296 |
| 3 | September 2016 to April 2017 | 4500 |
| 4 | April 2017 to present | 4500 for male-headed households; 6500 for female-headed households |

**Table 3.2.2 *Karama* proxy means test score thresholds**

| Registration period | Dates | Karama threshold |
|---|---|---|
| 1 | March to November 2015 | 5003 |
| 2 | November 2015 to May 2016 | 5063 |
| 3 | May 2016 to April 2017 | 7203 |
| 4 | April 2017 to present | 8500 |

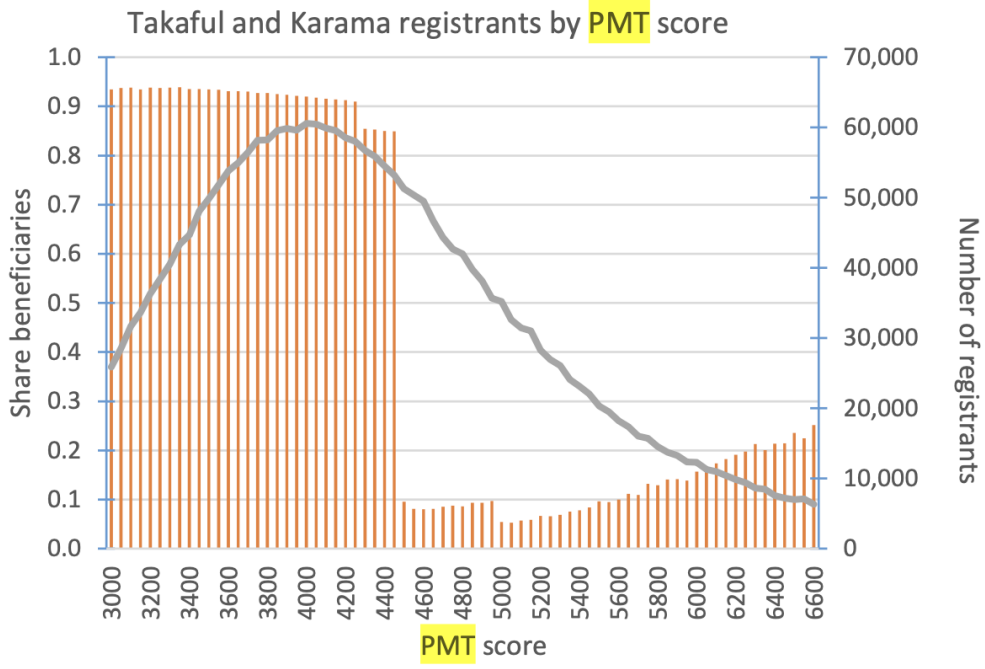
*Figure:* PMT thresholds over time for both programs

# Fuzzy participation

- Does not work, though, if administrators sometimes break the rules (i.e., it isn't followed perfectly)
- Authors note that sometimes people who are eligible still won't participate (sometimes called "non-compliance")
- Authors augment their study to account for this type of *voluntary compliance* using "fuzzy RDD"
- But pretty sharp as you'll see, at least for one of the cutoffs (4.5)

# Outcomes

**Figure 3.2.1 Beneficiary status in the proxy means test score distribution**

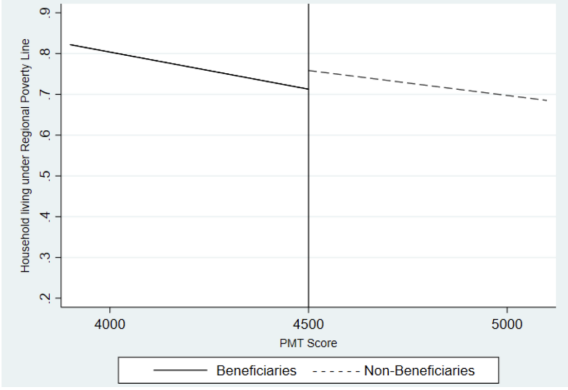



Source: Administrative data from MoSS, received June 2017. Includes only registrants up to April 2017 due to time required to update the database after receiving registration forms.

*Figure:* Participation by score

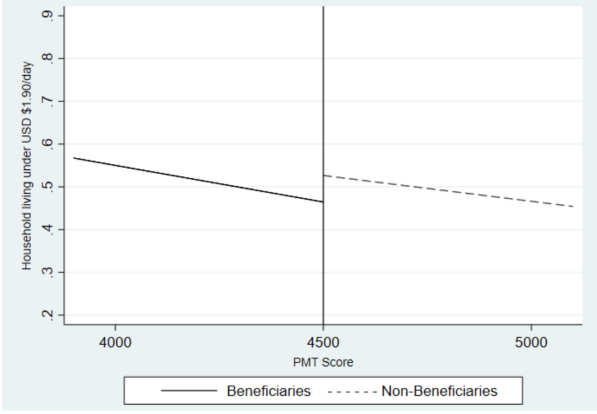
# Poverty (top), food and total spending (bottom)

**Figure 6.1.4 Regression discontinuity model impact estimates of *Takaful* program on poverty (regional poverty line)**



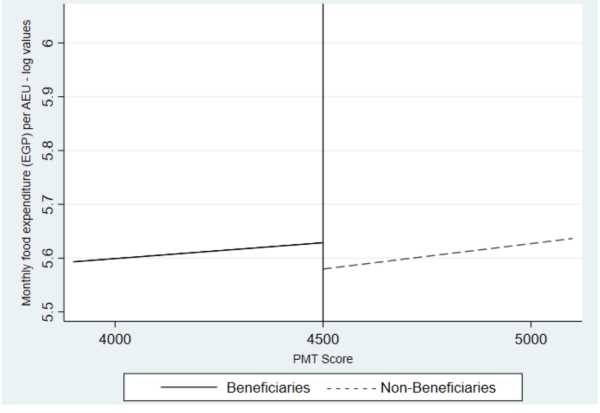

**Note:** PMT = proxy means test.

**Figure 6.1.3 Regression discontinuity model impact estimates of *Takaful* program on poverty (US$1.90/day)**



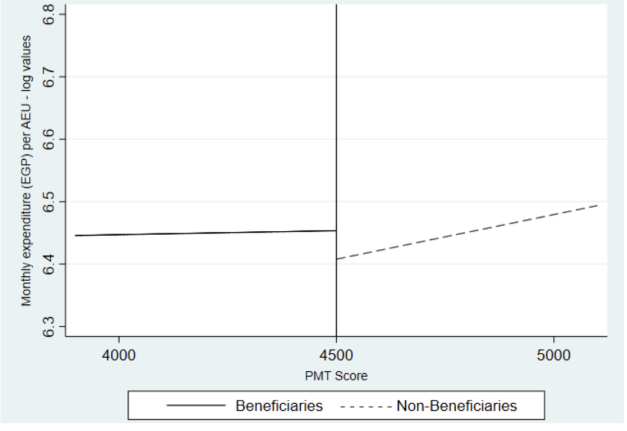

Note: PMT = proxy means test.

**Figure 6.1.2 Regression discontinuity model impact estimates of *Takaful* program on log monthly food expenditure per adult equivalent unit**




Note: AEU = adult equivalent unit; EGP = Egyptian pounds; PMT = proxy means test.

**Figure 6.1.1 Regression discontinuity model impact estimate of the *Takaful* program on log monthly expenditure per adult equivalent unit**




Note: AEU = adult equivalent unit; EGP = Egyptian pounds; PMT = proxy means test.

# Summary

- Some effects are clearer than others
  - → Large effects on food spending (around 8%) and total spending (around 9%)
  - → Large reductions in poverty (around 12% reduction in living under poverty line)
  - → Huge effects on child “weight-for-length/height” (30-40% SD) and reduced malnourishment (3-4%)
- Some effects, particularly on food and clothes spending are unclear
  - → Increased consumption of fruit (around 25%) but this is a little noisy and only shows up for one model
  - → Large increases in meat consumption (around 30-40%)
  - → Some evidence for increased spending on clothes but also noisy
- Inconsistent evidence for optimism about future, spending on schooling, but some paradoxes like weakened female bargaining power over children schooling and healthcare

# Comments

- Very thorough, very contemporary in many ways, very interesting, very valuable – highly encourage people to study it carefully, and re-evaluations done to confirm, as many good news and somewhat bad news (lots of null results)
- RDD and the fuzzy method helps paint a picture that particularly around 4.5 there seems to be some improvements due to the program
- Some things are strange too – like worsened female bargaining power around child welfare, which I think makes this a somewhat intriguing finding meriting more research later
- Much stronger evidence for Takaful than Karama, which is also puzzling

# More pictures needed

- To really communicate the findings, I think the authors need to find a way to communicate these results without so many tables
- They may want to consider presenting the results using a boxplot of coefficients after normalizing scores into $z$-scores everywhere (see the following example)
- This could help summarize the results as 150 pages is being chewed up by tons and tons of tables
- RDD plots are hard to evaluate without scatter plot means along the bandwidth – is this noise? Is this linear like they show?

# Example of $z$-score box plots from another paper

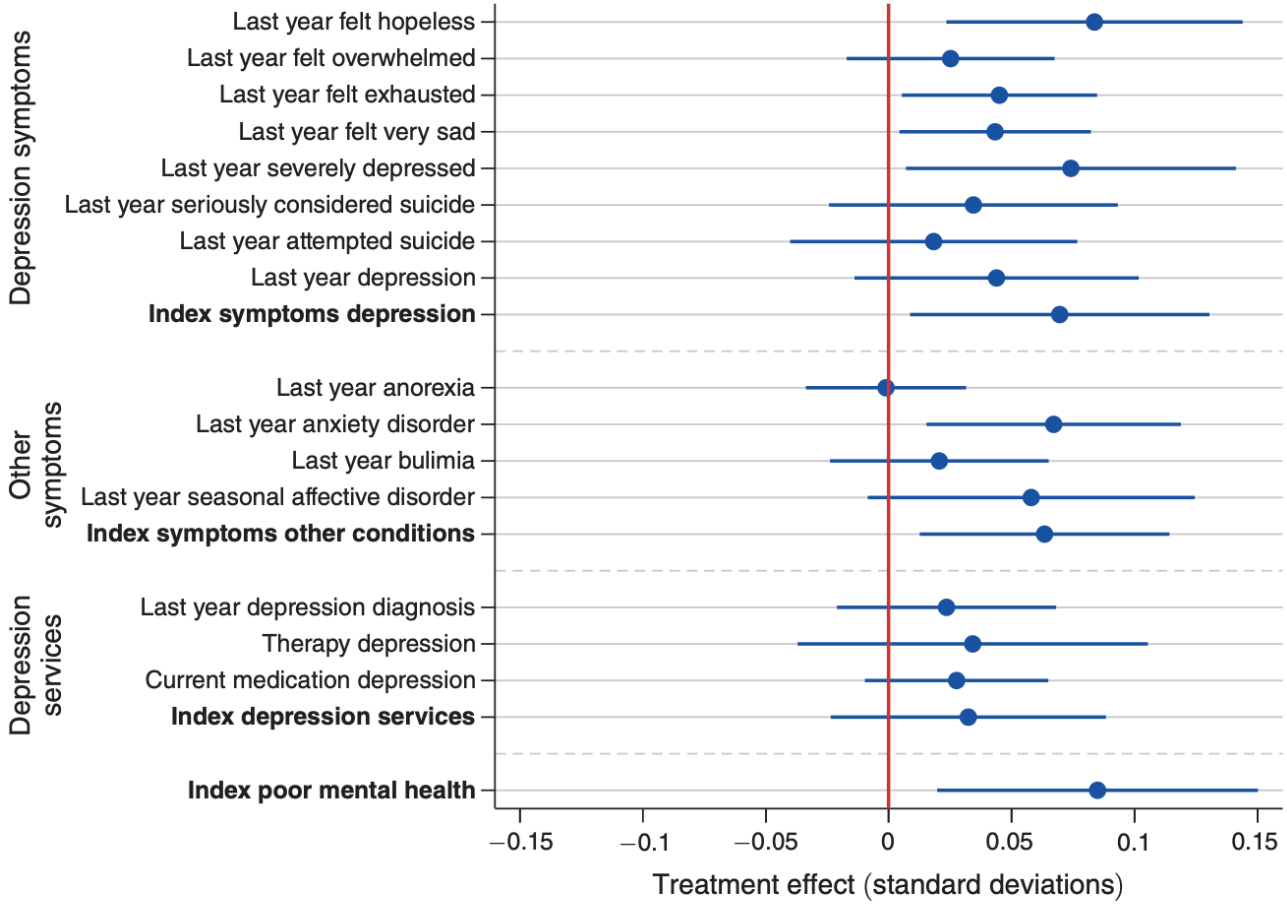



FIGURE 1. EFFECTS OF THE INTRODUCTION OF FACEBOOK ON STUDENT MENTAL HEALTH

*Figure:* Example of alternative data visualization

# Comments on fuzzy model

- Note, it is inappropriate to use either the conventional or heteroskedasticity robust F-test for evaluating first stage strength
- Strongest instrument seems to be the 4.5 threshold, but authors are using multiple thresholds; would prefer to see a single eligibility threshold with a re-centered running PMT score so they can interact eligibility with score, plus this is then just identified which makes first stage tests easier
- Doing so will give a *single instrument* which will minimize biases due to weak instruments (unclear strength of first stage beyond 4.5 PMT)

# Comments on fuzzy model

- First and second stage of instrumental variables should have same controls, but authors only control for strata in second stage according to their equation
- Highly encourage the authors to use IV models like `ivregress 2sls` in Stata (or equivalent in R) so that this is guaranteed
- Consider controlling for score and a quadratic in score to model nonlinearities because ultimately RDD “extrapolates” based on the functional form and they may have underfitting

# Conclusion

- Paper's strengths are its rigor and focus on strong methods for overcoming selection bias
- Some findings stronger than others
- Causal inference methodologies have advanced in the non-randomized setting, but have not replaced the controlled randomization and never will
- Policymakers can consider studying programs using these methods, and should, but keep in mind limitations and challenges in inference

# Credible Causal Inference

- Validity in causal inference is based on methods that reflect the reality of why people entered a program (i.e., all methods are equally scientific)
- Fuzzy RDD *only* estimates the ”local average treatment effect” which is only the average effect for people at 4.5 (internal but not external validity unless effects are the same for everyone)
- Future avenues need to examine the average effect for *all participants* as treatment effect heterogeneity could strengthen or weaken results found at 4.5 participants
- Machine learning methods, such as causal forests and double debiased machine learning, can do this, but require a lot of information on observable confounders related to participation and outcomes
- Thank you!!