Eliciting and Utilizing Willingness to Pay: Evidence from Water Filters in Ghana

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Growth Week 2012

Why measure willingness-to-pay for health goods (e.g., mosquito nets, water treatment products, etc.)?

- Directly estimate demand
- Inform pricing policy:
  - Who does an organization want to target
  - Guide magnitude and targeting of subsidies
  - Carefully understand role of prices in take-up & usage
- Intermediate step to address other questions:
  - Demand formation
  - Role of credit constraints
  - Determinants of technology adoption, social learning, health spillovers, etc.

It is challenging to estimate willingness to pay

The problem is a lack of incentive compatibility

You may want to:

- Make a low offer in order to negotiate a lower price
- Make a high offer to convince me to enter the market

Common approaches to estimating WTP have important limitations

- Structural demand estimation
  - Computationally intense and often requires strong assumptions
- Contingent valuation
  - Remains subject to strategic responses
- Take-it-or-leave it
  - "Do you want to buy at price *p*, yes or no?"
  - Only give a bound
- Auction mechanisms
  - Potential for intra-community conflict & collusion
  - Only those with high values can get good
- The Becker-Degroot-Marschak Mechanism is an alternative with attractive properties

The BDM Mechanism looks much like a second-price auction against a random draw

- Consumer makes bid
- Random price drawn
- If the customer's bid is less than the price drawn, the customer cannot purchase
- If the customer's bid is at least as large, then the customer can buy at the price drawn
- Breaks the link between price stated and price paid

Makes it optimal to tell the truth

Benefits of BDM

- Truth telling is optimal
- Precise measure
- Random variation in allocation
  - There is a randomized control trial of the product in question for every bid
- Random variation in price paid
  - For those with a given valuation who buy the product, some will pay more, some less
  - Can investigate causal effect of price paid on use

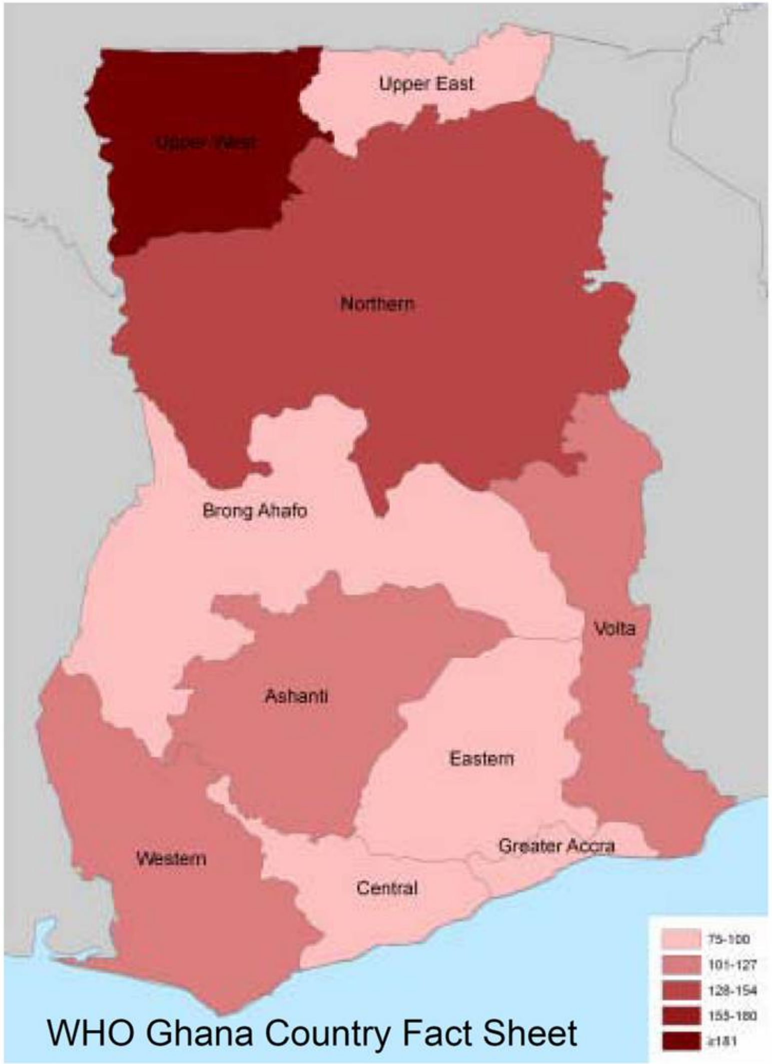
But BDM also faces several challenges

- Novel mechanism
- Limited experience outside the lab
- Non-standard beliefs about randomness or value

What do we do?

- Implement BDM to estimate willingness to pay for point-of-use (household) clean drinking water technology in rural Northern Ghana: the *Kosim* filter
- Compare BDM to take-it-or-leave-it
- Directly estimate demand
- Estimate the effect of filters
- Estimate heterogenous treatment effects conditional on our measure of willingness-to-pay
- Utilize clean analytical framework to study usage, screening, and sunk costs

Pure Home Water distributed water filters in rural Northern Ghana via BDM



A typical local water source

The *Kosim* water filter

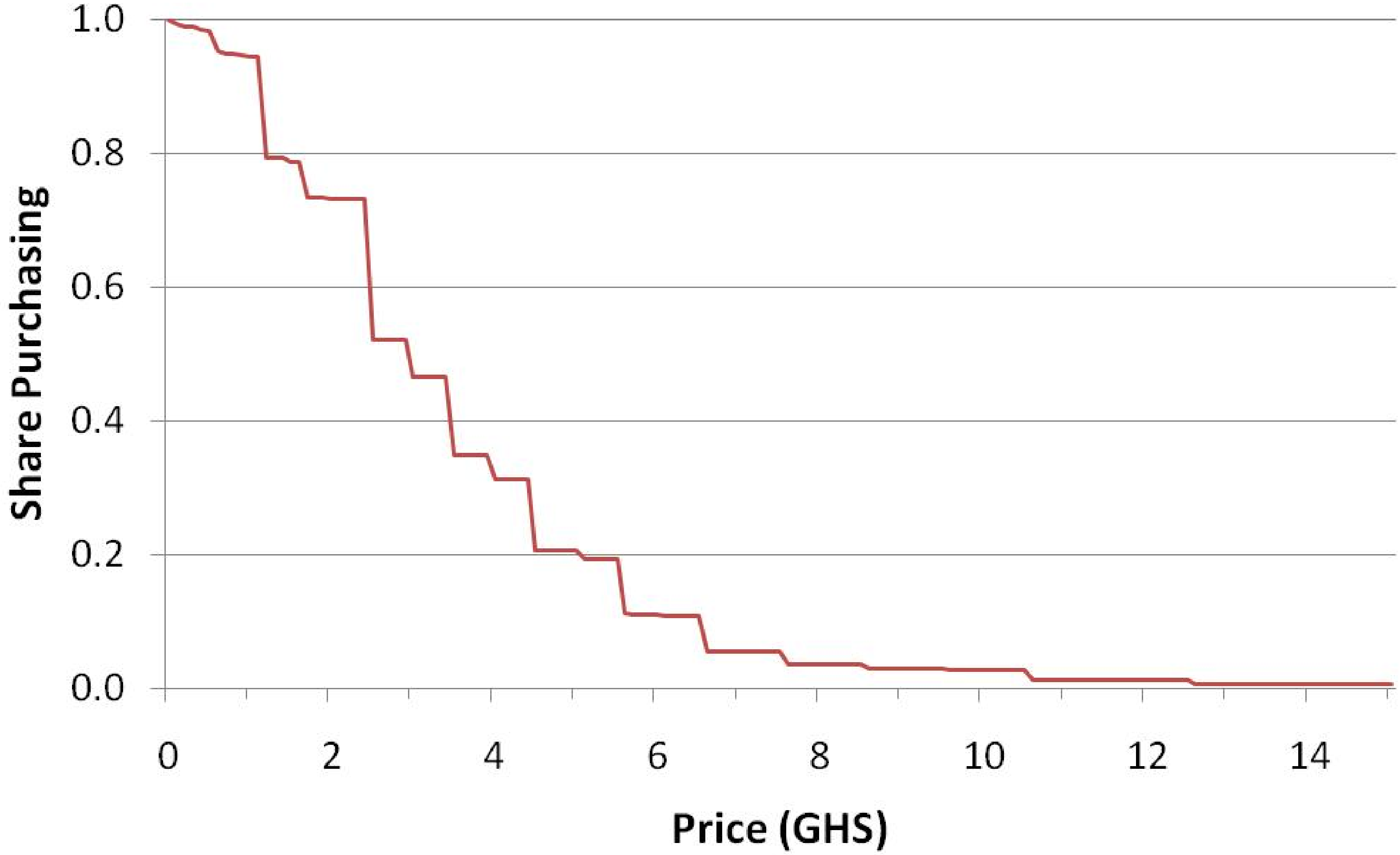
Functioning of the filter: before & after

First step: Implementing the mechanism successfully

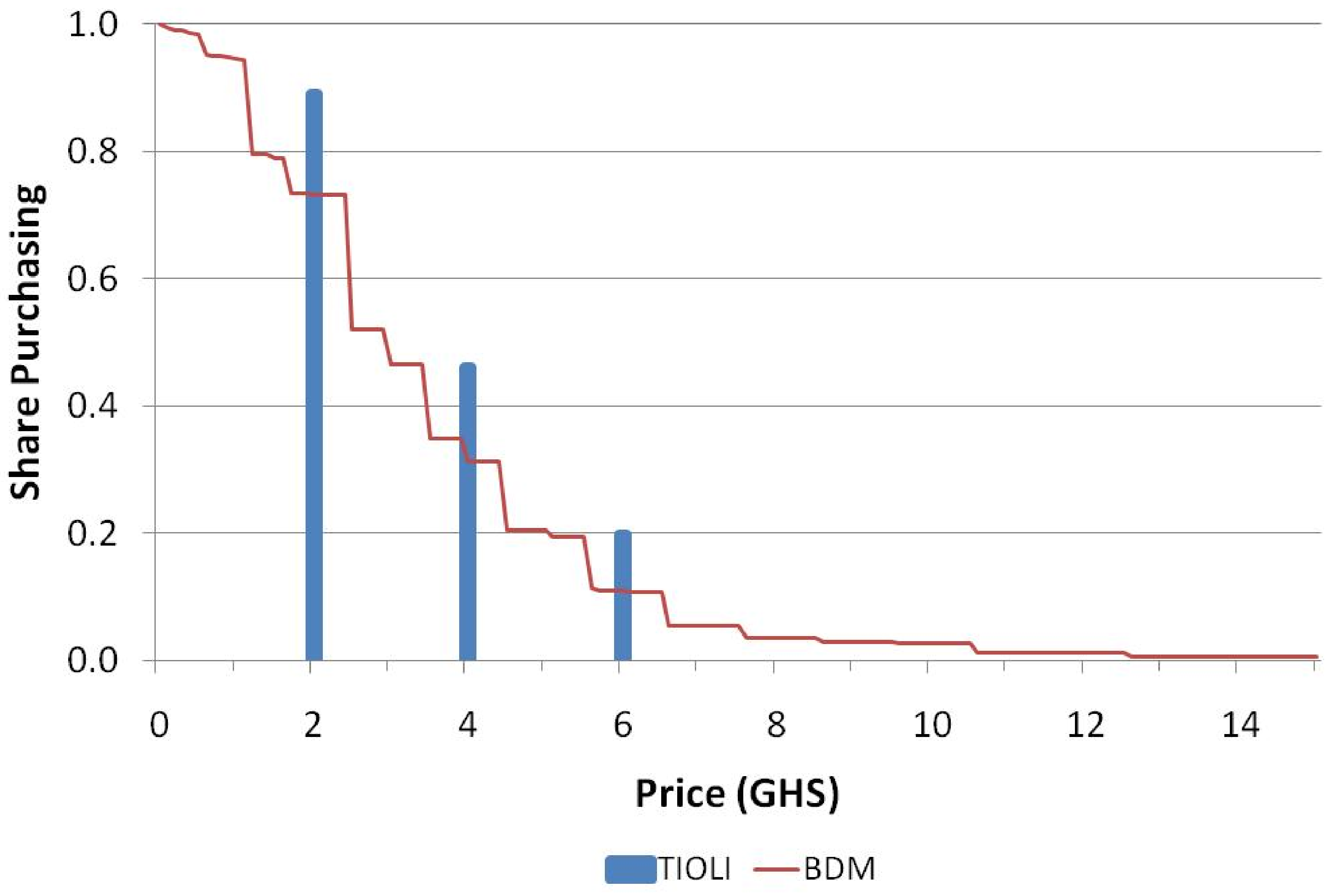
- Move from lab to “real world”
  - True field setting
  - Low-income country
  - Non-trivial good
- We tailored BDM implementation towards feasibility and ease of understanding
- Compare BDM to take-it-or-leave-it in same setting

They actual implementation was physical, transparent, and (relatively) easy to understand

BDM directly estimates the demand curve



We compare BDM bids to TIOLI responses



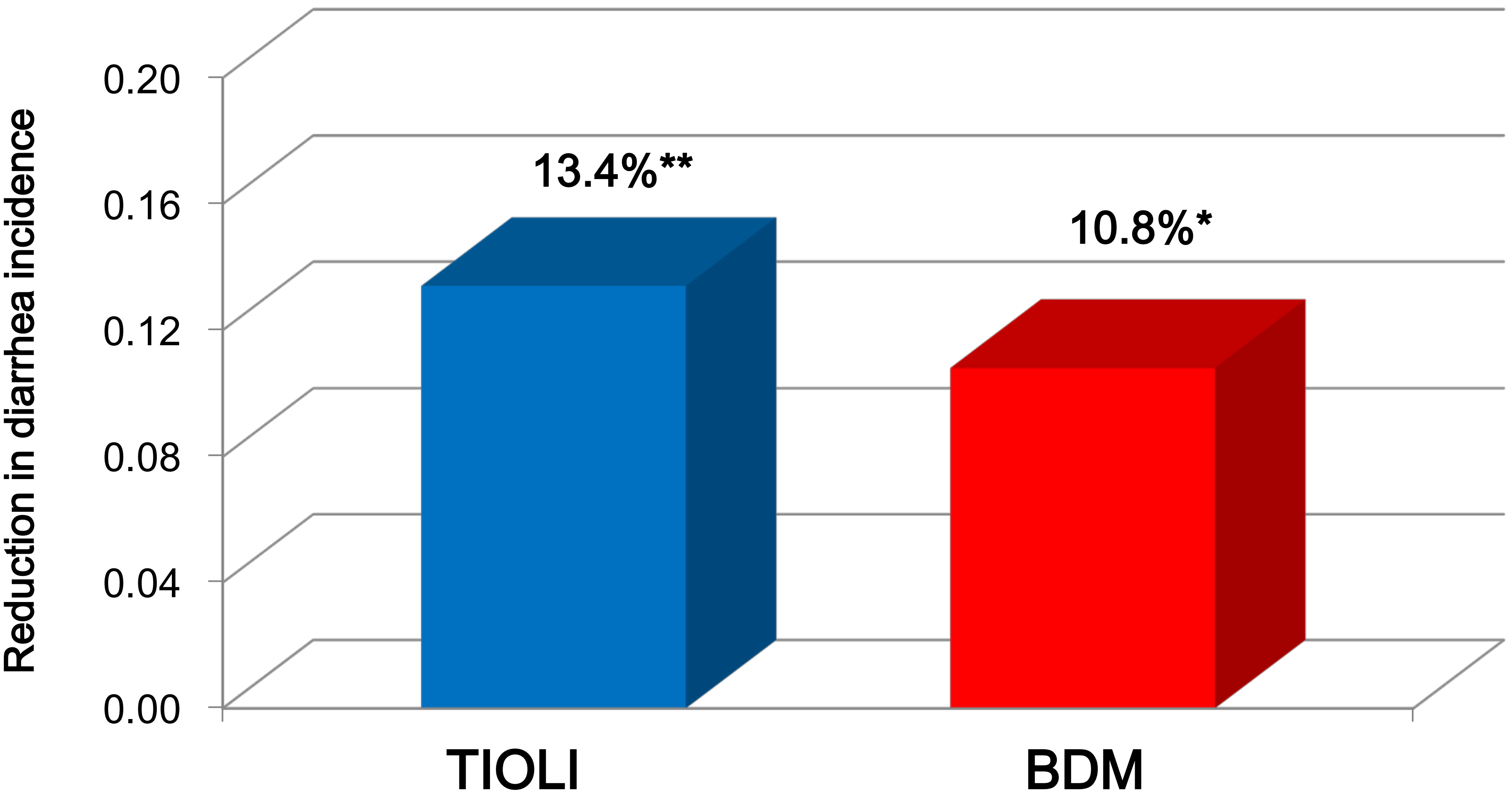
Next we estimate the effect of access to filtered drinking water

- This is normally complicated
- Consider the problem of comparing those who bought a filter for GHS 6 and those who did not
  - These two groups are inherently different (healthier, wealthier, value water more, etc.)
  - They may have different health outcomes for many reasons other than the filter
- Randomized distribution of the filter is one option
- But organizations may have reasons not to distribute their products for free

Both BDM and TIOLI provide instruments to estimate the causal effect of filters

- TIOLI: some people offered a price of 2, some 4 and some 6
  - Example: Consider 30 people who each would have been willing to pay GHS 3 for the filter
  - ~10 offered price of 2, 10 price of 4, and 10 price of 6
  - The randomly assigned price creates variation in who buys the filter that one can use to estimate its effect
- BDM: variation is generated by random draw
  - Example: Consider two individuals who valued the filter at GHS 3
  - One may draw a price less than 3 and buy the filter
  - The other may draw a price greater than 3 and not

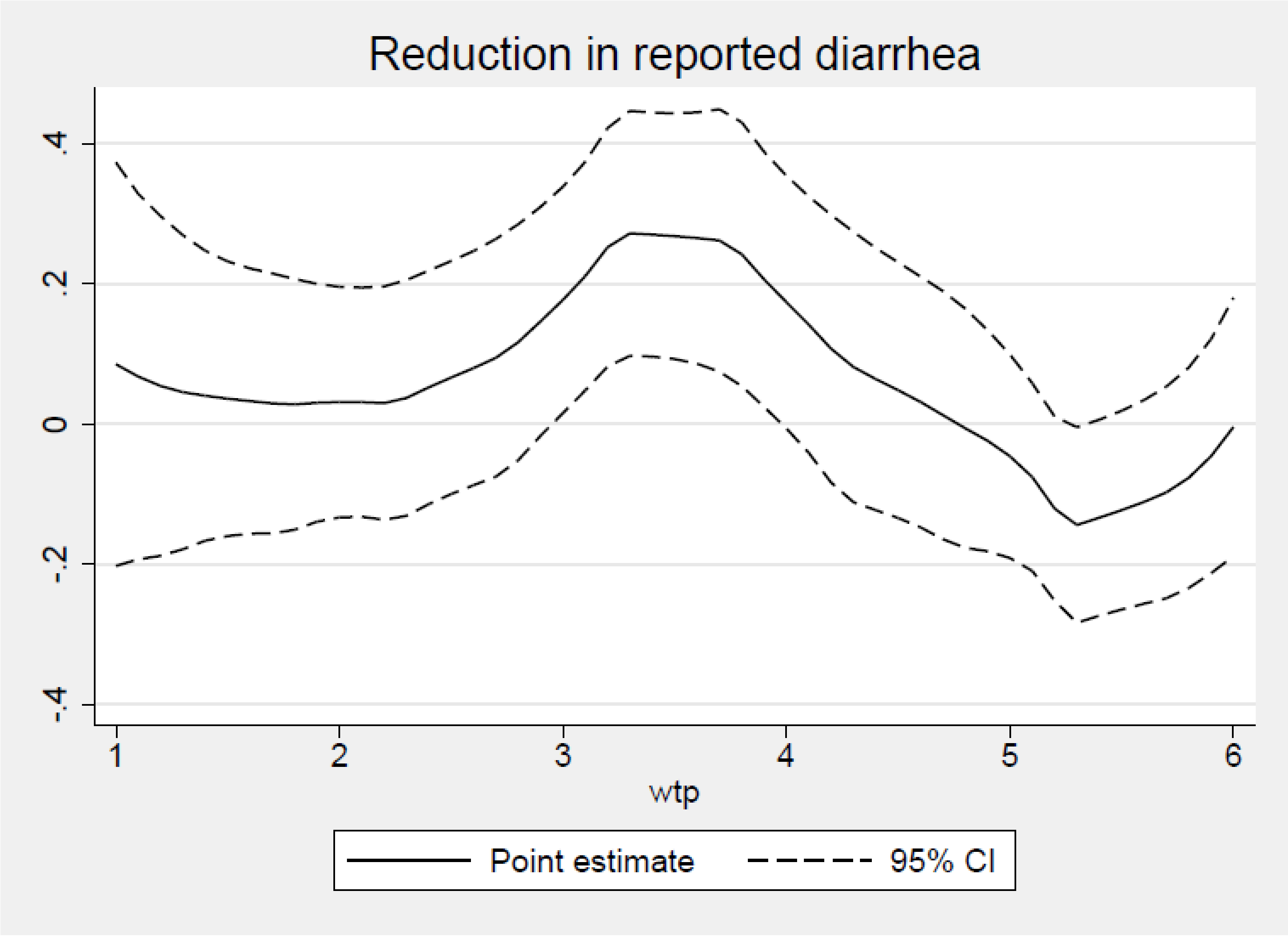
Both TIOLI and BDM detect short-term treatment effects from having a filter



So why should we bother with BDM?

- It provides much more precise information
- We may want to know how much different individuals benefit from the filter
- In general, that's hard because we don't get to see the same individual with and without a filter
- The standard approach with take-it-or-leave-it prices would only give us the effect for a very particular subset of the population
  - We recover a "local average treatment effect"
  - E.g., the effect on individuals with a value between 2 and 4
- BDM allows us to recover the entire distribution of effects conditional on each individual's valuation

We calculate local local average treatment effect for the entire value distribution



Why is this useful

- One complaint about RCTs is that they only tell us about the mean effect or for a well-defined subgroup (e.g., women)
- BDM allows us to recover the entire distribution conditional on each individual's willingness to pay
- This allows us to make precise welfare calculations for different pricing policies
  - E.g., consider the common conjecture that those least able to pay for health products are those who benefit most
- Can also help inform targeted subsidies

The method also lets us estimate the causal effect of prices

- On-going debate: do individuals only value something (e.g. a water filter) if they pay for it?
- Your ideal experiment to test this:
  - Take two individuals who are willing to pay GHS 6
  - Sell it to one for 6 and give it to the other for free
  - Compare usage and outcomes
- BDM implements exactly this experiment
- We find modest evidence of screening but no “sunk cost” effect from prices

The results are encouraging but there is more work to be done

- BDM can be feasibly implemented in the field
- Estimated demand is consistent with that from TIOLI but systematically lower
- Chief advantages:
  - Precise estimate of the full demand curve
  - Directly estimate heterogeneous treatment effects
  - Built in study for the direct effect of prices
- In the context of Pure Home Water's *Kosim* filter
  - Demand remains high through GHS 2
  - Strong evidence for heterogeneous treatment effects
  - Muted evidence on the causal effect of prices

Thank you!

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