Closing experimental-observational crop response gaps: Bayesian approach

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(a) Plot 1

(b) Plot 2

Figure: Which one is an experimental plot?

Motivation

- Stylized fact: Experimental crop responses to fertilizer application are higher than observational crop responses
- Why?: Key differences in confounders (Coe et al., 2016; Snapp et al.,2014)
  1. Experiments-potentially causal but not representative.
  2. Biased site selection and 'standardized' management tend to over-ride or control the factors that determine crop response (Vanlauwe, 2016)
  3. Observational studies-behavioural aspects and representative but not causal
- Long standing debates among agronomists leading to variations in farmer participation in agronomic experiments
  1. Agronomists: Coe et al (2017) vs Sileshi and Akinnifesi (2017)-Experimental Agriculture.

Why should we care?

- Crop response estimates are key ingredients in policy choices e.g. fertilizer subsidy, price stabilization. If we get them wrong, we make suboptimal policy choices.

- Letter to editor (Agricultural Economics) debates
  - Jayne et al (2015 ,Agricultural Economics) basing on observational evidence of crop responses (3.32 across 5 years) concludes the subsidy program may not be as beneficial ($BCR < 1$)

  - Dorward and Chirwa (2015, Agricultural Economics) basing on experimental crop response evidence of 16-18 claim the $BCR > 1$.

- Crop response rates-determining parameter for benefit cost ratios even in general equilibrium models (Arndt,2016 AJAE). Used 11.8-18.5 and find $BCR > 1$.

This paper

- What can we do about it? Explore the possibility of combining experimental and observational crop responses thereby closing the gaps using a Bayesian approach (more details to come!)
- Research questions:
  - What have the previous debates missed in closing of the gaps?
  - Are recommendations on the basis of Bayesian (combined) estimates the most profitable?
- Contribution: Closing the gaps
- Main findings:
  - Debates have focused on mean responses, inconclusive if variances are not included.
  - Even after combining estimates at different prior means and precision, crop responses are very low.

Roadmap

- Examples of similar ideas in economics
- A primer to Bayesian approach with an example
- Priors and data
- Empirical model (1)
  1. Baseline results
  2. Results on prior simulations
- Empirical model (2):Adding heterogeneity
- Conclusions and next steps

Examples of similar ideas in economics

- Economics of education: teacher valued added measures
  - Chetty and Hendren (2018)-QJE and Angrist et al (2017)-QJE combine lottery based teacher value added estimates (experimental) and traditional value added measures (quasi-experimental) using empirical Bayes.
- Macroeconomics: DSGE priors in the New Keynesian Macroeconomics and Minnesota prior! (Del Negro & Schorfheide,2004,International Economic Review)
- Economic Theory: Shrinking to various economic theories (Kasy, 2016) and duality (Rosas-Perez,2014)
- Market forecasting: Whether farmers should follow recommendations of market advisory services-Cabrini, Irwin and Good (2010)-AJAE
- Consumer preference heterogeneity: Allenby and Rossi (1999)-JoE.

Primer to Bayesian Approach

Based on Carlin and Louis (2009) and Zhang (2016)
Prior, $p(\theta)$ × Data, $L(X|\theta)$ → posterior, $p(\theta|X)$

- Let μ: prior mean and y likelihood/data mean. τ^2 be variance of prior and σ^2 variance of likelihood. $\sigma^{2*} = \frac{\sigma^2}{n}$ where n is sample size
- The posterior distribution (Normal-Normal conjugate) is:

$$p(\theta|y) = N(\theta|\frac{\sigma^{2*}\mu + \tau^2 y}{\sigma^{2*} + \tau^2}, \frac{\sigma^{2*}\tau^2}{\sigma^{2*} + \tau^2})$$

- Let $B = \frac{\sigma^{2*}}{\sigma^{2*}+\tau^2} \in [0,1]$. Then the posterior mean is a weighted average: $B\mu + (1-B)y$
- Posterior variance is: $Var(\theta|y) = B\tau^2 \equiv (1-B)\sigma^{2*}$ smaller than τ^2 and σ^2.
- Precision like information is additive: $var(\theta|y)^{-1} = var(y|\theta)^{-1} + var(\theta)^{-1}$

Bayes Example

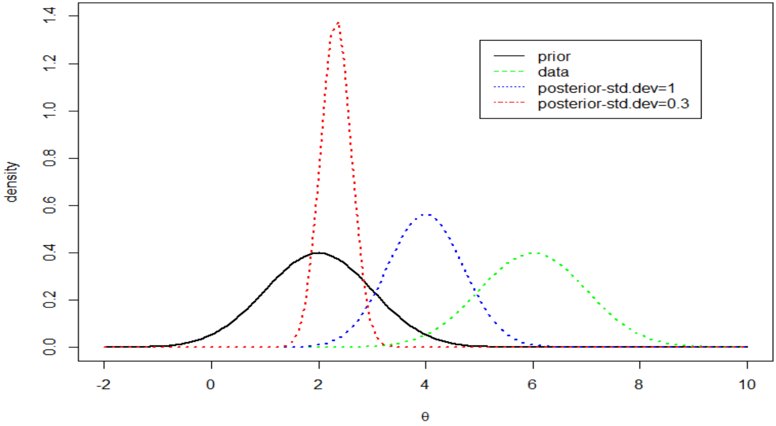


Figure: Bayes Example

Priors: Experimental and observational evidence

- Experimental maize responses to fertilizer from 1960 to 1998 range from 23.1 to 34 kg of maize per kg of nitrogen applied (Benson, 1998).
- Jayne et al (2013) estimate 3.32 from survey data.

Table: Maize responses to nitrogen fertilizer (Arndt et al 2016)

	Dorward et al. (2008) (Survey of literature)	Harou et al. (2014) (Malawi trials)	Chibwana et al. (2010) (Malawi FISP)	Ricker-Gilbert et al. (2011) (Malawi FISP)	Ricker-Gilbert and Jayne (2012) (Malawi FISP)
Local varieties	10-12		12.0		
Composites	15				
Hybrids	18-20				
All improved varieties			9.6		
All maize seed	15	24-32			
Contemporaneous effect				6.1	
Enduring effect				11.7	
Measured at the 10th percentile					2.8
Measured at the median					7.6
Measured at the mean					9.0
Measured at the 90th percentile					9.7

Data

- Using Malawi Integrated Household Survey 2010/11(NSO, World Bank). About 10,000 farm households.
- Data analyzed at plot-crop level with 19,692 observations
- Crops: Maize and legumes (Groundnuts, Beans, Soyabeans and Pigeonpeas)
- Focus: On maize responses grown in 89% of the plots.
- Average maize yields are very low: 763 kg per ha
- Average fertilizer applied is about 162kg per ha (about 55kg of nitrogen per ha). In US, $>$152kg of nitrogen per ha.

Empirical Model

- Selection on observables partial identification strategy
- **Estimating equation (1): Bayes Linear Model**:

$$y_i = \beta_0 + \beta_1 x_i + \beta_2 x_i^2 + \alpha z_i + \epsilon_i \tag{1}$$

where:

  - y_i: Maize yields (Kg/ha)
  - x_i: Fertilizer amount applied (Kg/ha)
  - z_i: Plot and household level controls including labor, slope, rainfall, elevation, soil type, soil quality, district dummies, seed rate,organic fertilizer use, plot size,hhsize,age,gender,variety.
- 11,000 MCMC (Gibbs Sampling) runs. First 1000 runs as burn-in and next 10,000 for inference.
- Normal-inverse gamma conjugate prior, non-informative/flat prior: 0 prior mean and 0.001 prior precision ($1/\tau^2$).

Baseline regressions: Non-informative prior

Table: Baseline regressions

	Experimental			Observational		
Parameter	2.50%	50%	97.50%	2.50%	50%	97.50%
(Intercept)	894.45	1116.62	1353.47	96.38	1015	1950
Fert	27.72	29.4	31.02	3.15	3.44	3.74
Fert squared	-0.14	-0.12	-0.11	-0.001	-0.0008	-0.0005

- Under profit maximization, optimal x^* is given by $x^* = \frac{\frac{P_x}{P_y} - \beta_1}{2\beta_2}$
- If fertilizer to maize price ratio is 2.35:1 (2010 estimates) then
  - Optimal experimental $x^* = 111$
  - Optimal observational $x^* = 0.000436$!

Prior robust Bayesian analysis results

Table: Low precision scenarios

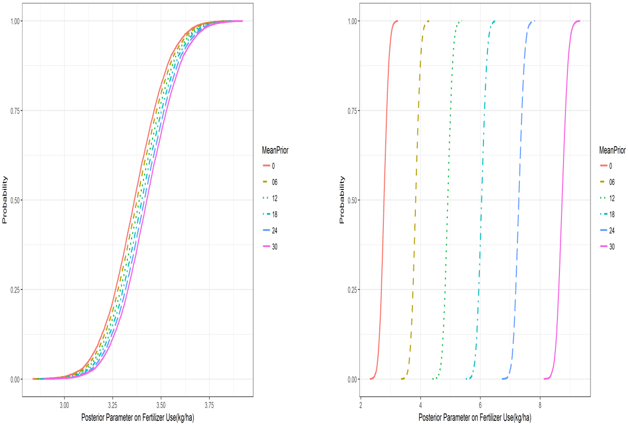
Prior Precision	Prior Mean	2.50%	50%	97.50%
0.1	0	3.08	3.36	3.65
0.1	6	3.10	3.38	3.66
0.1	12	3.11	3.39	3.68
0.1	18	3.12	3.40	3.69
0.1	24	3.13	3.41	3.70
0.1	30	3.15	3.43	3.72
1	0	3.02	3.30	3.59
1	6	3.15	3.42	3.71
1	12	3.27	3.55	3.84
1	18	3.40	3.68	3.96
1	24	3.52	3.80	4.09
1	30	3.65	3.93	4.21

More simulations

Table: High precision scenarios

Prior Precision	Prior Mean	2.50%	50%	97.50%
10	0	2.52	2.77	3.04
10	6	3.58	3.83	4.10
10	12	4.65	4.91	5.17
10	18	5.77	6.04	6.32
10	24	6.99	7.29	7.58
10	30	8.41	8.73	9.06

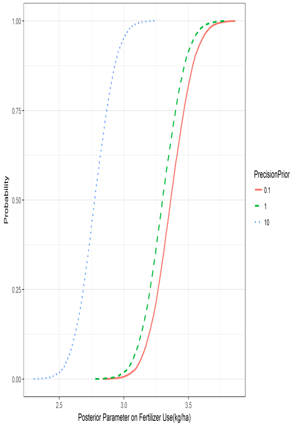
Precision Prior Comparison



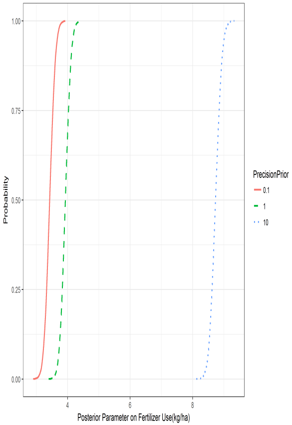
(a) Precision prior of 0.1 (b) Precision prior of 10

Figure: Precision prior comparisons

Mean Prior Comparison



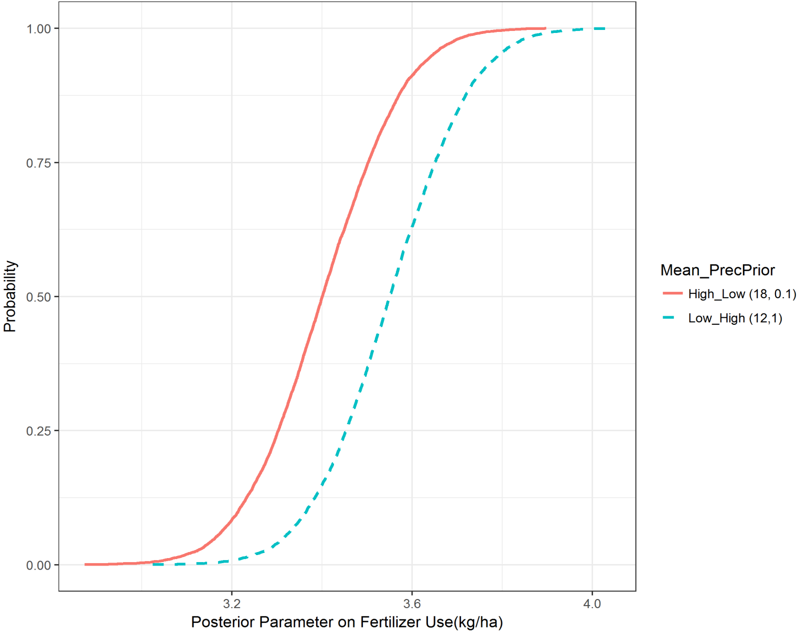
(a) Mean prior of 0



(b) Mean prior of 30

Figure: Mean prior comparisons

Posterior response scenario 5, Mix



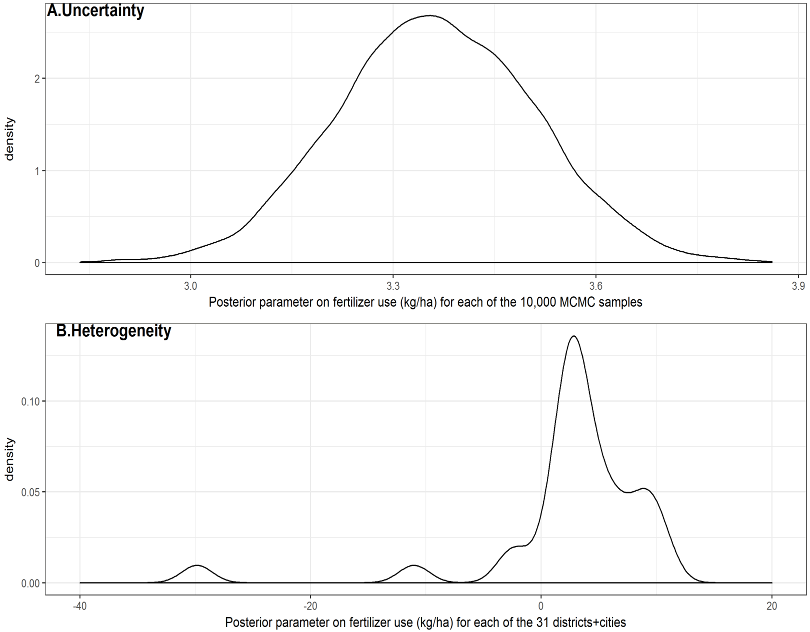
Adding heterogeneity

- **Estimating equation (2): Bayes Hierarchical Model**:

$$y_i = \beta_0 + \beta_1 x_i + \beta_2 x_i^2 + \alpha z_i + W_i b_k + \mu_i \tag{2}$$

- Where k is the district
- Non-informative and conjugate priors
  - Multivariate normal prior for fixed parameters
  - Inverse-gamma prior on the residual error variance
  - Inverse-Wishart prior on the random effects variance matrix

Result 2:Heterogeneity vs. Uncertainty



Conclusion

- The paper has incorporated three themes negleted in crop response literature i.e. parameter uncertainty, heterogeneity and multiple sources of information.
- Ignoring these three issues leads to "tripple miss" in policy prescriptions.
- Heterogenous model in crop responses may be more appropriate to identify non-responsive plots.
- Overall, crop responses appear to be low (about 9kg of maize per unit of nitrogen fert applied).
- Should recommendations be based on this middle ground?

Next steps

- Show analytically and numerically whether Bayesian recommendations are better than experimental and observational based recommendations.
- Use hold out samples and panel data to prove whether Bayesian approach predicts crop responses better.
- Combine experimental and survey data after using quasi-experimental econometric methods e.g., DiD, and IVs.
- Bayesian experimentation where farmers tryout new farming methods or whatever they want to try at small scale.
- From on-farm trials to farmer trials with big N.

THANK YOU! ZIKOMO!