Duke UNIVERSITY

The *Other* Shale Revolution

How the fracking boom helped Indian farmers

Faraz Usmani

August 7, 2017

Joint work with T. Robert Fetter
Camp Resources XXIV Wrightsville Beach, NC

Preview

- Natural experiment in northwest India

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- Smallholders in Rajasthan grow majority of world's guar, a key input in fracking

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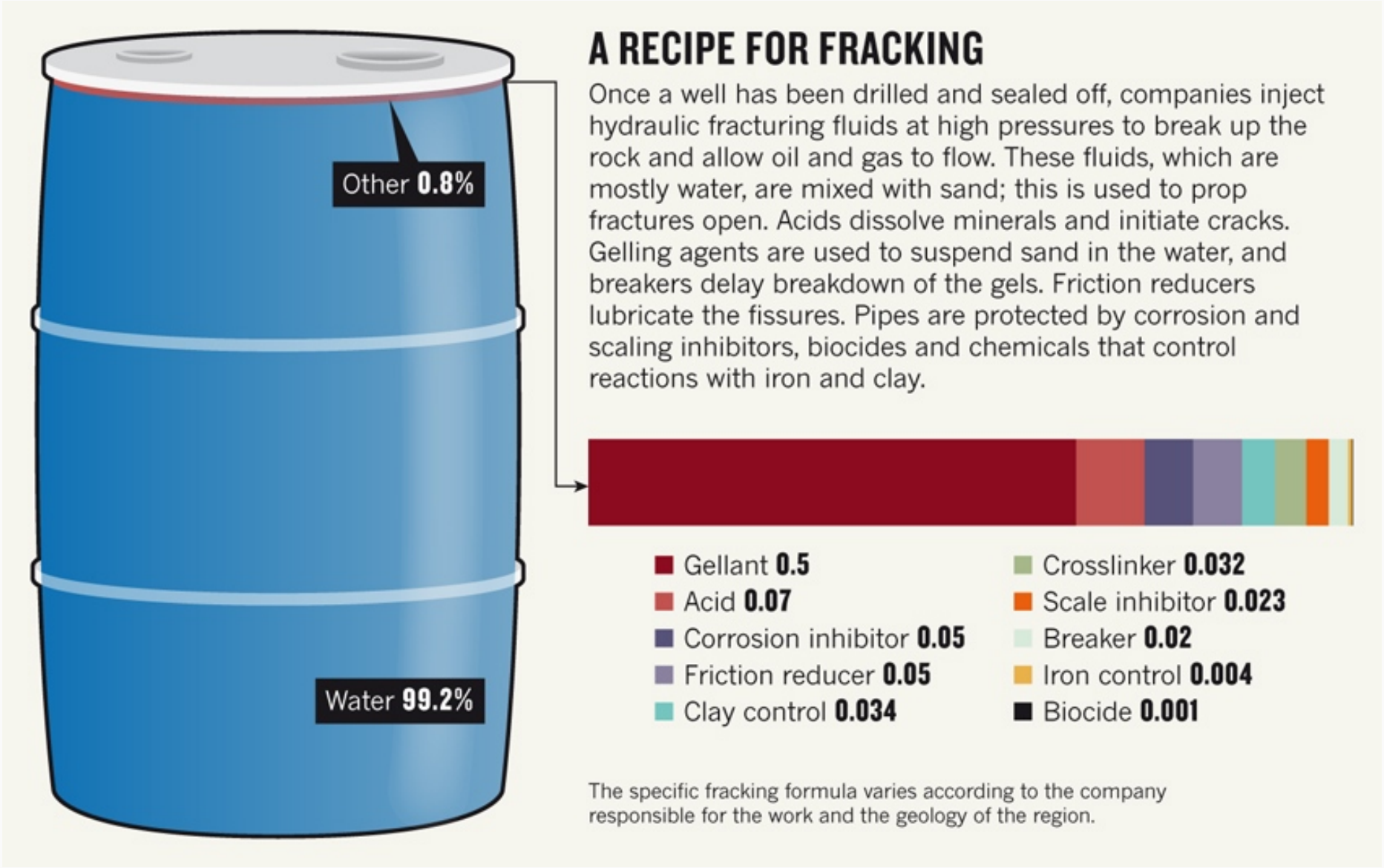
Preliminary result

Rajasthan shines significantly brighter at night, suggestive of socioeconomic benefits

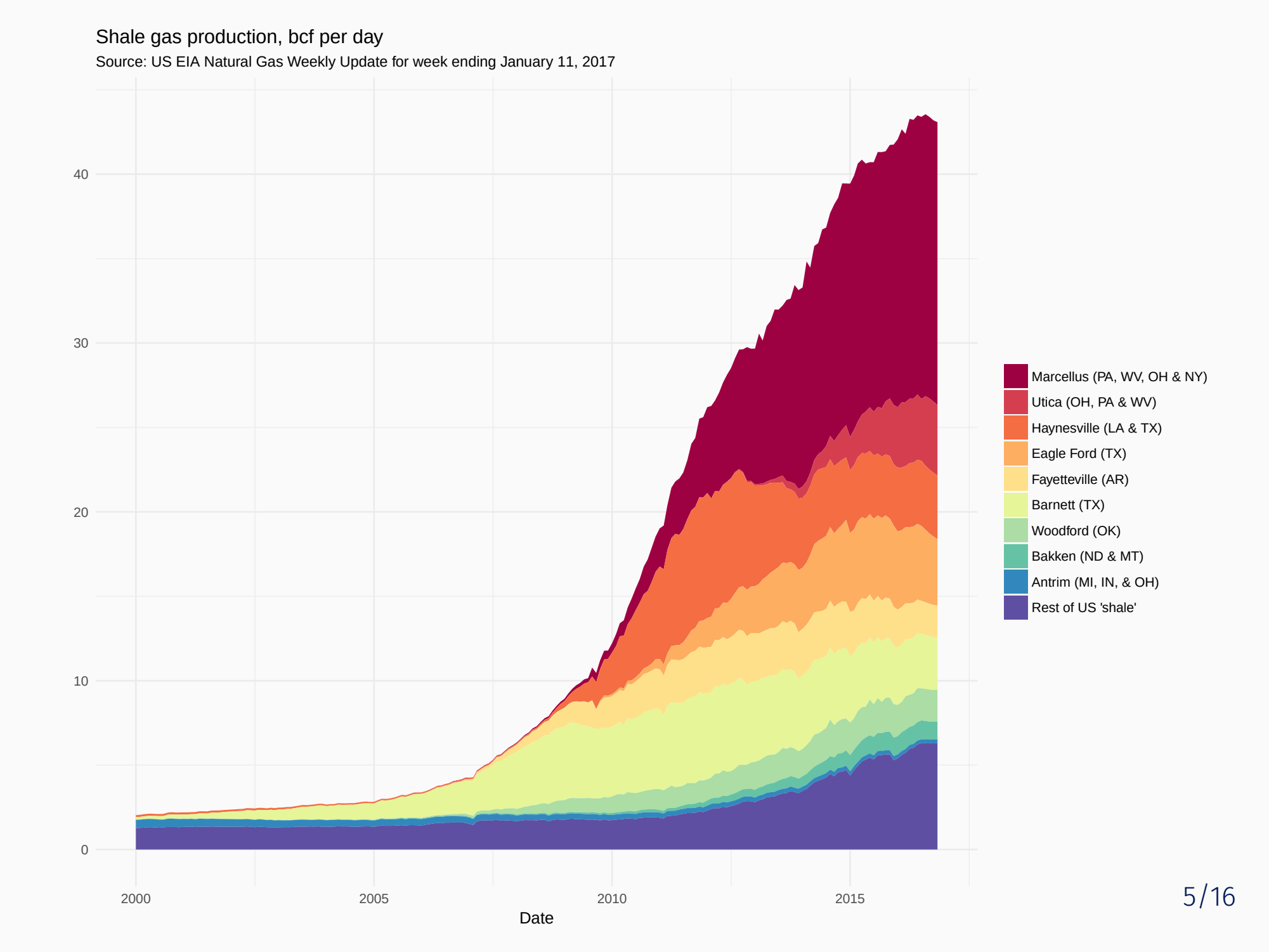


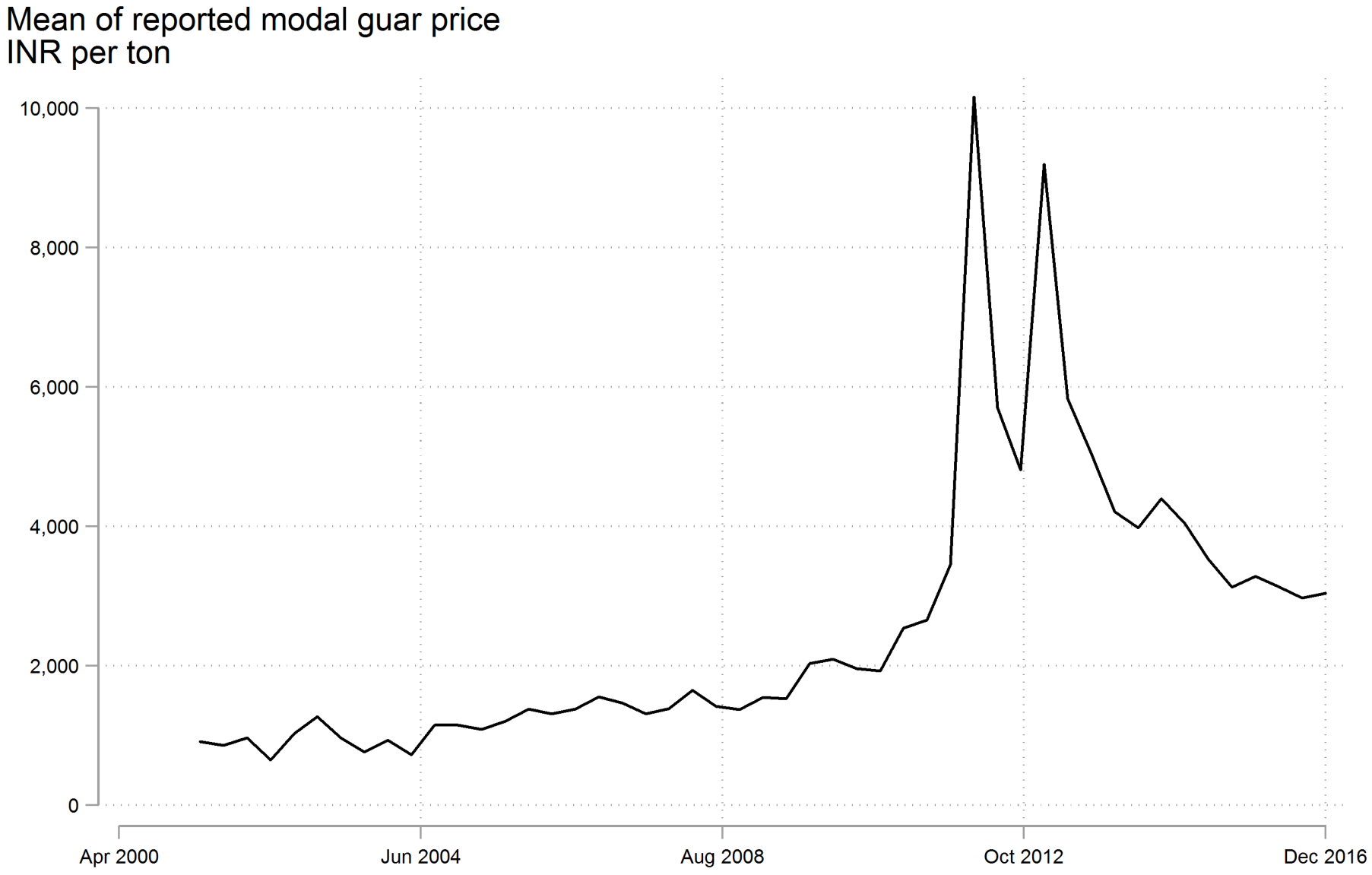
Source: Tollefson (2013)

What is guar?

- Drought-resistant legume primarily grown in the semi-arid tracts of northwestern India
- Rajasthan: ~65% of global supply (Mudgil et al. 2011)

Source: The Hindu BusinessLine


Shale gas production, bcf per day
Source: US EIA Natural Gas Weekly Update for week ending January 11, 2017
40
30
20
10
0
2000
2005
2010
2015
Date
Marcellus (PA, WV, OH & NY)
Utica (OH, PA & WV)
Haynesville (LA & TX)
Eagle Ford (TX)
Fayetteville (AR)
Barnett (TX)
Woodford (OK)
Bakken (ND & MT)
Antrim (MI, IN, & OH)
Rest of US 'shale'



Source: Daily agricultural price/quantity data scraped from Ministry of Agriculture

The New York Times | https://nyti.ms/SDJ0uM

ASIA PACIFIC

In Tiny Bean, India's Dirt-Poor Farmers Strike Gas-Drilling Gold

By GARDINER HARRIS JULY 16, 2012

LORDI, India — Sohan Singh's shoeless children have spent most of their lives hungry, dirty and hot. A farmer in a desert land, Mr. Singh could not afford anything better than a mud hut and a barely adequate diet for his family.

But it just so happens that when the hard little bean that Mr. Singh grows is ground up, it becomes an essential ingredient for mining oil and natural gas in a process called hydraulic fracturing.

THE WALL STREET JOURNAL.
WSJ.com

theguardian

COMMODITIES | November 25, 2011

Farmer Says: Hitch Your Wagons to Some 'Guar'

By RYAN DEZEMBER

Without guar, crystals would co
and that cranberry sauce leftove
shortage of the legume also coul

Beans mean high profits for guar farmers of Rajasthan

Price of little known seed has rocketed on new-found use as water thickener in controversial fracking process

CNN

The little green bean demand

Printed from
THE TIMES OF INDIA

Humble guar gum is India's top farm export

TNN | Mar 10, 2013, 12.37 AM IST

Does Rajasthan shine brighter than the (synthetic) counterfactual?

Following Abadie and Gardeazabal (2003), pick W^* such that

$$Y_{i,t} = Y^j_{0,t} W^*$$

where

$$Y_{1,t} \equiv \text{Mean nighttime luminosity in Rajasthan in } t \quad (1)$$

$$Y^j_{0,t} \equiv \text{Mean nighttime luminosity in } J \text{ states in } t \quad (2)$$

$$W = (w_1, \ldots, w_J) \, ; \sum_{j=1}^{J} w_j = 1 \quad (3)$$

$$W^* = \arg\min_W \left\{ \sum_{t<t^*} \left(X_{1,t} - X^j_{0,t} W \right) V \left(X_{1,t} - X^j_{0,t} W \right)' \right\} \quad (4)$$

Model specification is a black box.

At least **fifteen different state-level characteristics** available from World Bank's India CPS

Question

How to pick model predictors rigorously and transparently in the absence of theoretical guidance?

Our solution? Monte Carlo Model Selection

For each s of $S = 10{,}000$ simulations:

1. Randomly choose normalized predictors $\mathbf{X}_t^{(s)} \subseteq \mathbf{X}_t$

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   and save $\beta^{(s)}$

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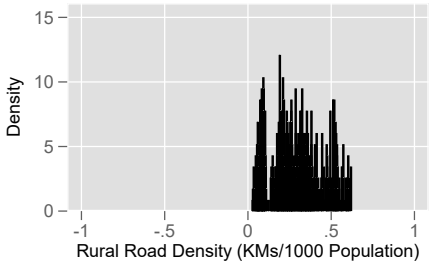
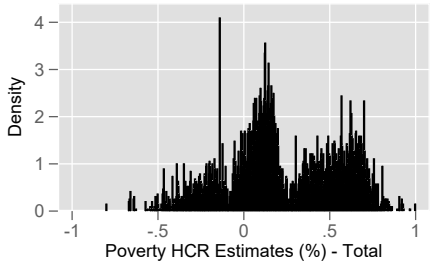
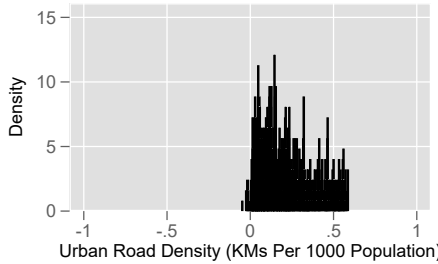
3. Repeat S times in total to obtain $\mathbf{B} = \left\{ \beta^{(1)}, \ldots, \beta^{(S)} \right\}$


Density
Rural Road Density (KMs/1000 Population)


Density
Poverty HCR Estimates (%) - Total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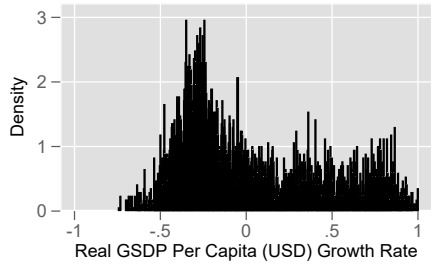
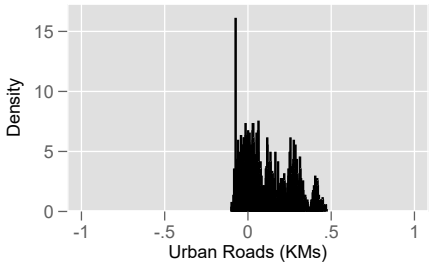
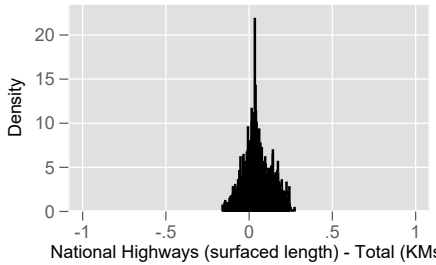
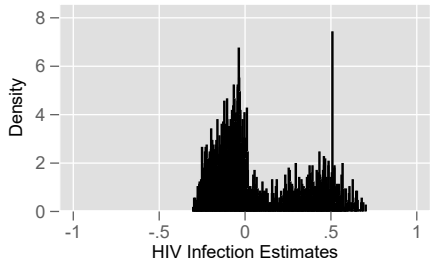
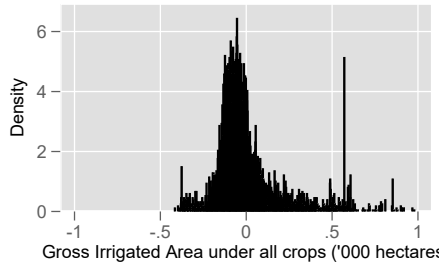
Urban Road Density (KMs Per 1000 Population)

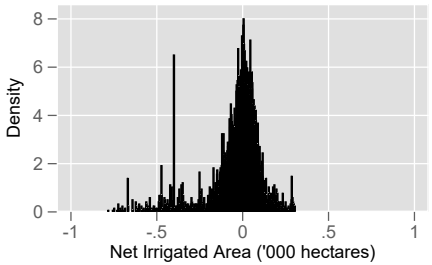

Density
Real GSDP Per Capita (USD) Growth Rate

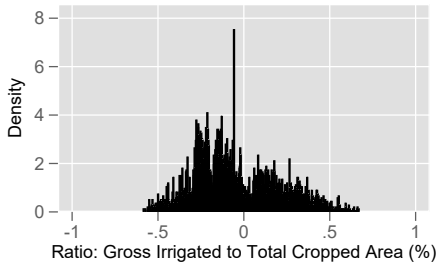

Density
Urban Roads (KMs)

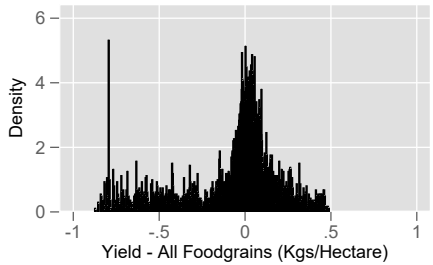

Density
National Highways (surfaced length) - Total (KMs)

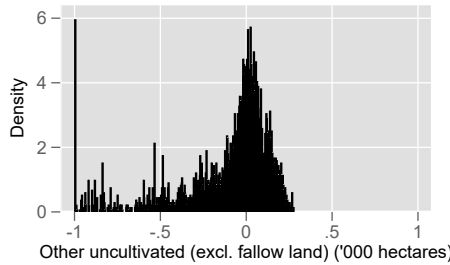

Density
HIV Infection Estimates

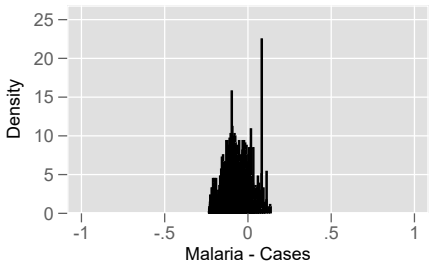

Density
Gross Irrigated Area under all crops ('000 hectares)

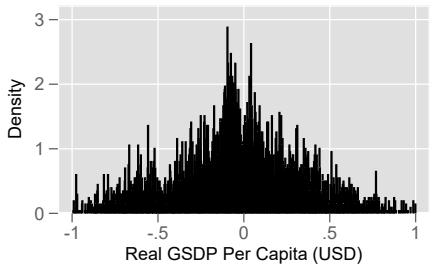

Density
Net Irrigated Area ('000 hectares)

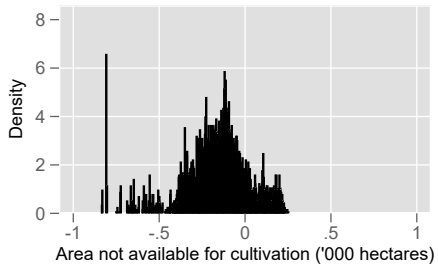

Density
Ratio: Gross Irrigated to Total Cropped Area (%)

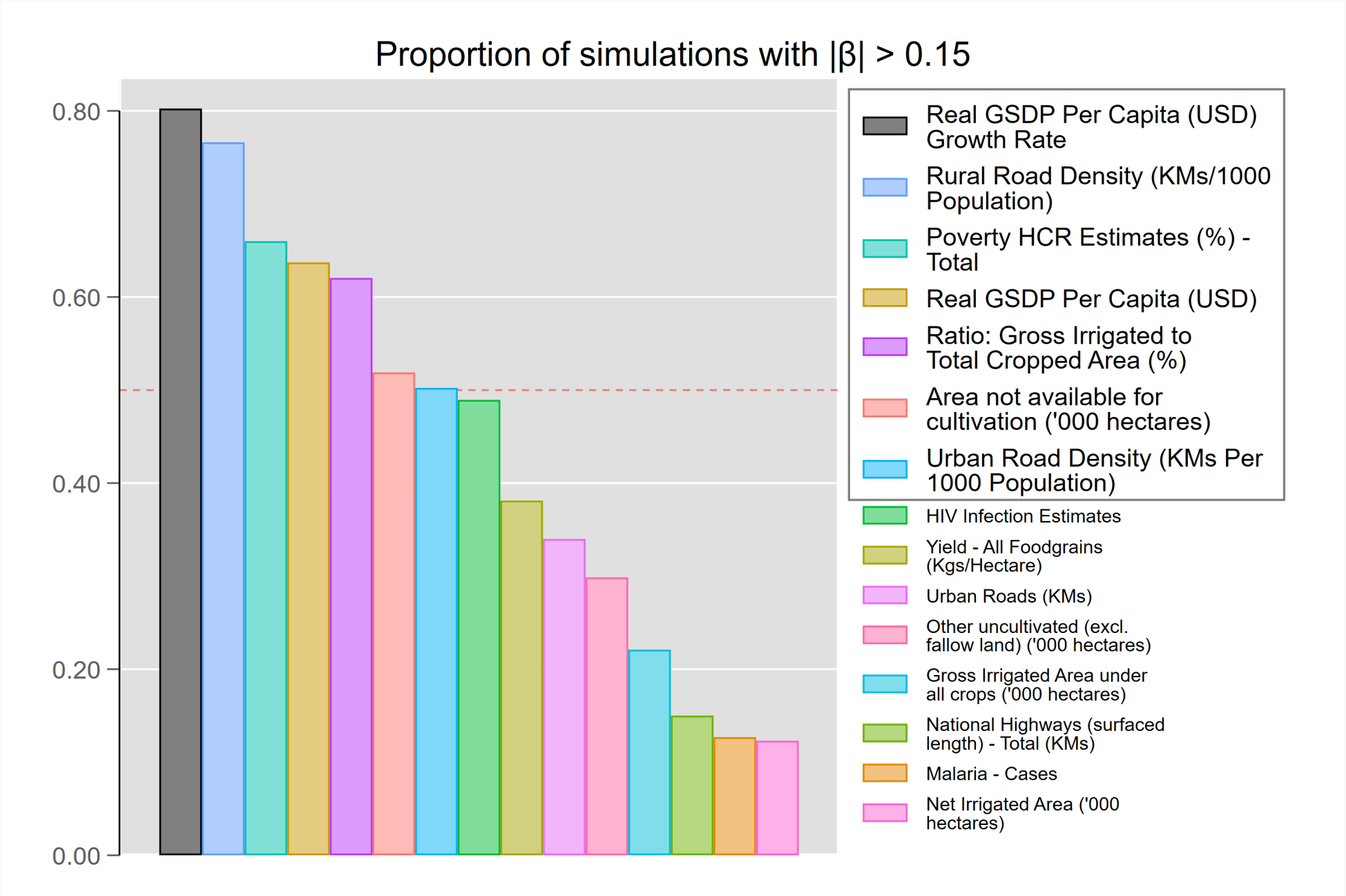

Density
Yield - All Foodgrains (Kgs/Hectare)


Density
Other uncultivated (excl. fallow land) ('000 hectares)


Density
Malaria - Cases


Density
Real GSDP Per Capita (USD)


Density
Area not available for cultivation ('000 hectares)


Proportion of simulations with |β| > 0.15
0.80
0.60
0.40
0.20
0.00
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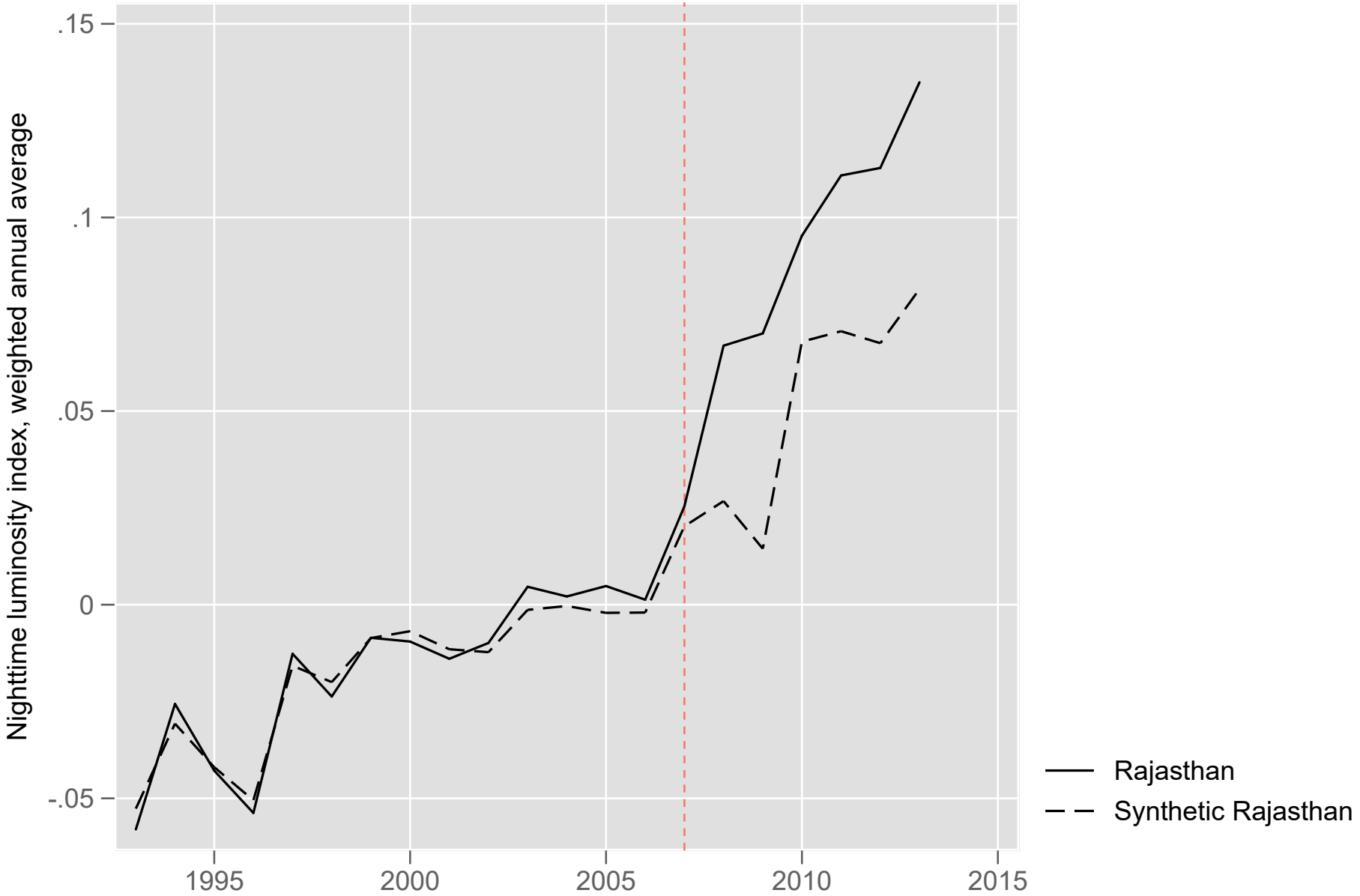
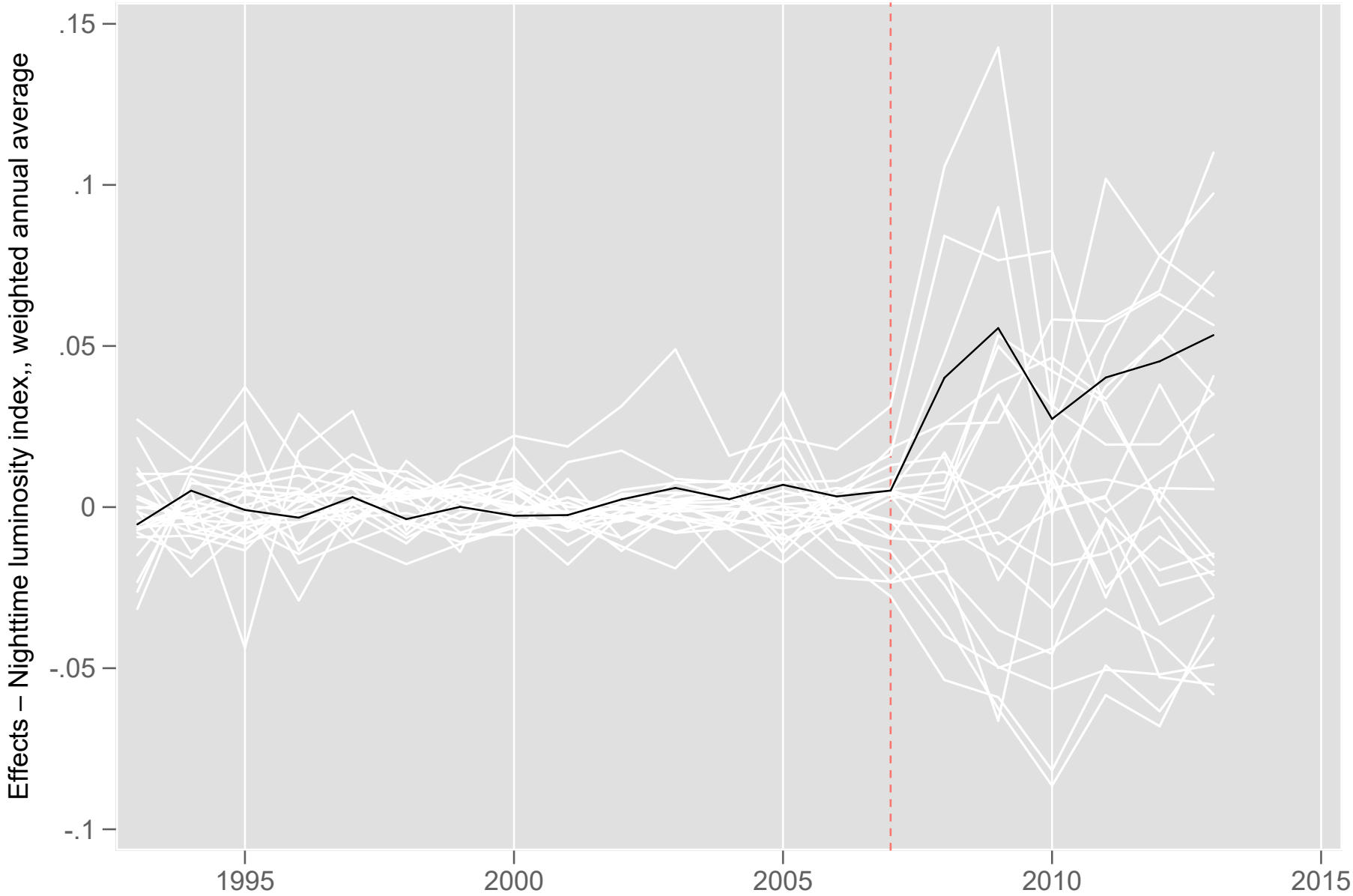
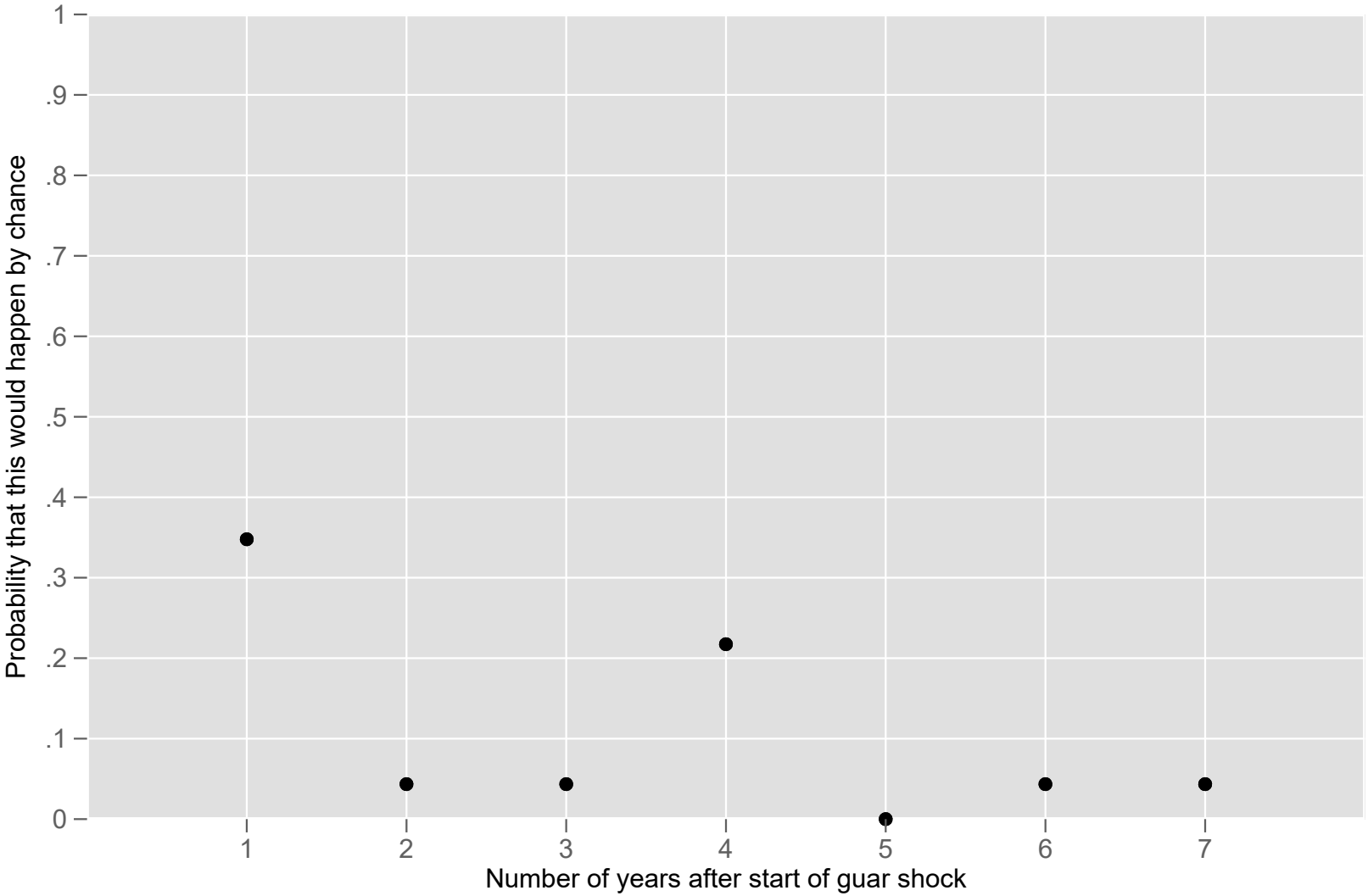

.15
.1
.05
0
-.05
Nighttime luminosity index, weighted annual average
1995
2000
2005
2010
2015
Rajasthan
Synthetic Rajasthan


Effects – Nighttime luminosity index,, weighted annual average
.15
.1
.05
0
-.05
-.1
1995
2000
2005
2010
2015



Note. Lead-specific significance levels (p-values) adjusted by the j^{th} unit's pre-treatment root mean squared prediction error (Cavallo et al. 2013; Quistorff and Galiani 2017)

Next steps: guar shock $\rightarrow$ energy/development outcomes

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Other empirical approaches

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Richer set of outcomes: Household-level data in India Human Development Survey (IHDS)

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Thank You!

Comments welcome at `faraz.usmani@duke.edu`