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## **Modeling Nonresponse in Establishment Surveys: Using an Ensemble Tree Model to Create Nonresponse Propensity Scores and Detect Potential Bias in an Agricultural Survey**

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# Purpose

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- Developed classification trees to identify hardcore nonrespondents
- Assessed relationship between classification tree nonresponse propensity and actual nonresponse
- Created 10 classes based on classification tree nonresponse propensities to assess and compare nonresponse bias

# Motivation

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- Attempt to reduce nonresponse bias, by identifying and targeting influential nonrespondents prior to survey administration

# ARMS

## Nonresponse Rates

*Table 1. ARMS response rates 2000–2008*

Year	Sample size	Response rate (%)
2000	17,903	63
2001	13,313	64
2002	18,219	74
2003	33,861	63
2004	33,908	68
2005	34,937	71
2006	34,203	68
2007	31,924	70
2008	36,388	66

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# Methods

- Used an ensemble of classification trees to identify likely nonrespondents
- Used nonresponse propensity deciles to classify nonrespondents and assessed bias using the relative difference of the mean

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# Classification Trees

- A “data mining” technique which segments a dataset using a series of simple rules to maximize dichotomies
- Creates subsets of records exhibiting a higher percentage of the “target”(respondent or nonrespondent)

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# Splitting Criteria

## ■ Optimal Splitting Criteria

### ▶ Significance Testing

- Uses the  $p$  value as the stopping rule after applying a Bonferroni adjustment to mitigate bias toward variables w/ many values
  - Interval ( $F$  test)
  - Nominal (Chi-Square)

### ▶ Variance Reduction

- Measures the reduction in entropy, after adjusting for ordinal differences
  - Ordinal (Entropy)

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# Classification Tree

## Proxy Data

- Imported Census of Agriculture (COA) response history for the ARMS III 2000-2008 Samples ( $n = 254,632$ )
- Imported and matched 2002 COA data to be used as proxies of these operations characteristics
  - ▶ 78% match rate for 2002

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The image shows a portion of the 2008 Agricultural Resource Management Survey (ARMS) form. It includes the title "2008 AGRICULTURAL RESOURCE MANAGEMENT SURVEY" and the ERS logo. The form contains various sections for data entry, including a "FARM TYPE" section with checkboxes for different types of operations (e.g., "I have only one type of farm", "I have more than one type of farm") and a "FARM SIZE" section with checkboxes for different sizes (e.g., "I have less than 10 acres", "I have 10 to 24.9 acres").



The image shows a portion of the United States 2007 Census of Agriculture form. It includes the title "UNITED STATES 2007 CENSUS OF AGRICULTURE" and the USDA logo. The form contains various sections for data entry, including a "FARM TYPE" section with checkboxes for different types of operations (e.g., "I have only one type of farm", "I have more than one type of farm") and a "FARM SIZE" section with checkboxes for different sizes (e.g., "I have less than 10 acres", "I have 10 to 24.9 acres").



# Types of Proxy Data

- Proxy data included 70 COA variables significantly related to ARMS nonresponse

- ▶ Operator Demographics
- ▶ Farm Type
- ▶ Size
- ▶ Commodities Raised
- ▶ Expenses
- ▶ Location



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# Example Tree

ARMS III Matched Sample (Training Data)

**37%**  
*n* = 79,616

Sum of Poultry Inventory Data

**< 4**  
**38%**  
*n* = 71,644

**≥ 4**  
30%  
*n* = 7,972

Total Value of Products Sold + Government Payments

**< \$110,005**  
27%  
*n* = 30,904

**≥ \$110,005**  
**45%**  
*n* = 40,740

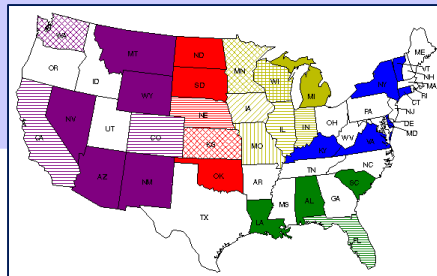
Total Sales – Not Under Production Contract (NUPC)

**< \$844,879**  
41%  
*n* = 31,211

**≥ \$844,879**  
**57%**  
*n* = 9,529

States

AL, AZ, CA, CO, CT, DE, FL, IL, IN, IA, KS, KY, LA, MI, MN, MO, MT, NE, NV, NM, NY, ND, OK, SC, SD, VT, WA, & WY



**Yes**  
**70%**  
*n* = 3,346

**No**  
52%  
*n* = 1,118

# Analyses

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- Assessed the relationship between classification propensity scores and nonresponse rates using logistic regression
- Assessed the relationship between classification propensity scores and nonresponse bias by plotting the relative bias of the mean by classification propensity score decile

# Variables

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## ■ Inputs

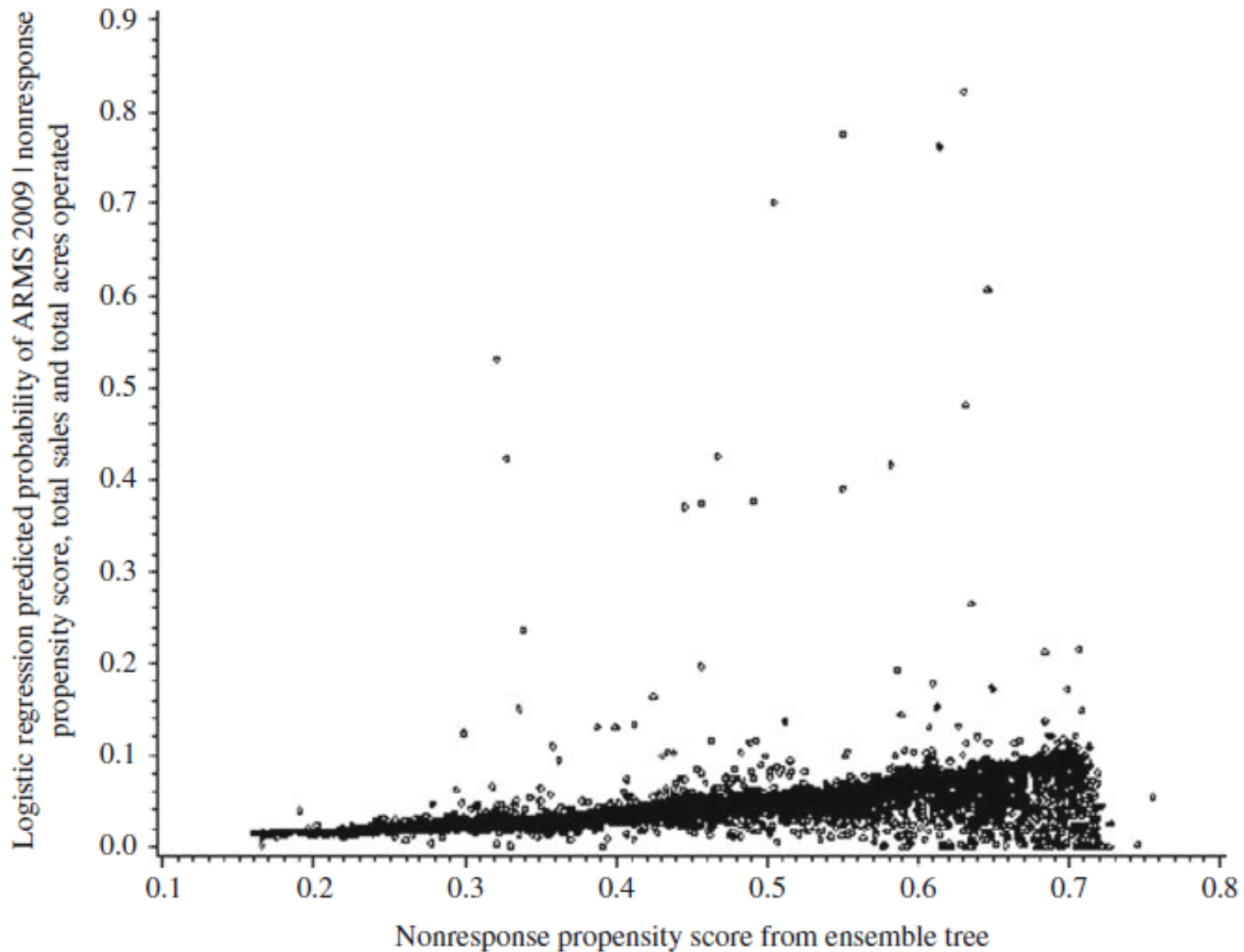
- ▶ Classification Tree Propensity Score
  - ARMS 2000-2008 nonresponse
  - Census 2002 operation characteristics

## ■ Controls

- ▶ Total Sales & Total Acres Operated
  - Census 2007

## ■ Target

- ▶ ARMS 2009 Nonresponse



*Fig. 1. Plot of the logistic regression predicted probability of 2009 ARMS nonresponse given the ensemble tree nonresponse propensity score, 2007 total sales, and 2007 total acres operated, by the ensemble tree nonresponse propensity score*

# Logistic Regression Results

Table 2. *Logistic regression model fit statistics*

Analysis of maximum likelihood estimates					
Predictor	$\beta$	SE $\beta$	Wald's $\chi^2$ ( <i>df</i> = 1)	<i>p</i>	$e^\beta$ Odds Ratio
Constant	-4.77	0.14	1191.55	<.0001	
Propensity score	3.76	.34	118.99	<.0001	42.93
Total sales	-9.02E-08	2.11E-08	18.35	<.0001	1.00
Total acres operated	2.0E-05	3.19E-06	40.67	<.0001	1.00

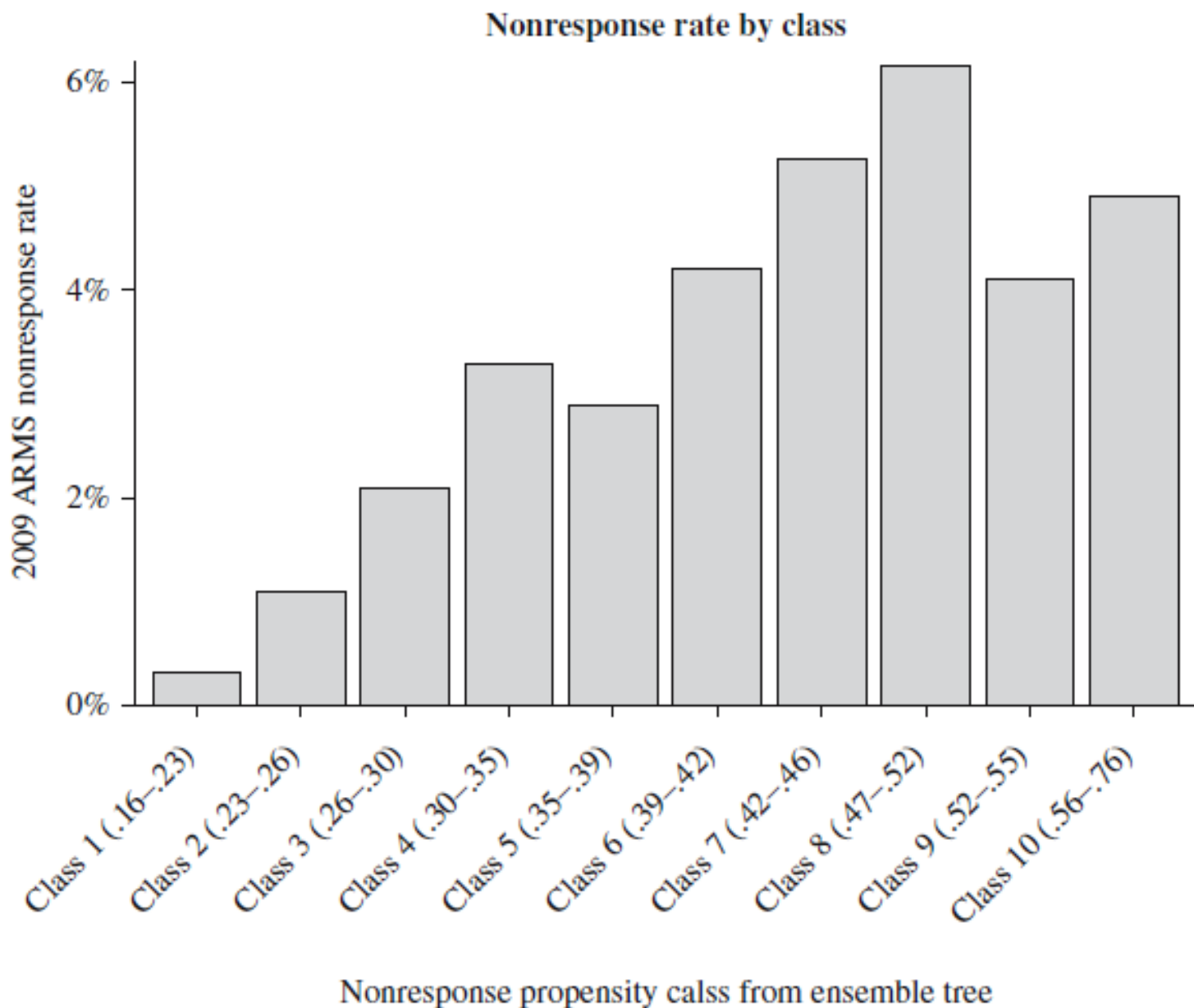
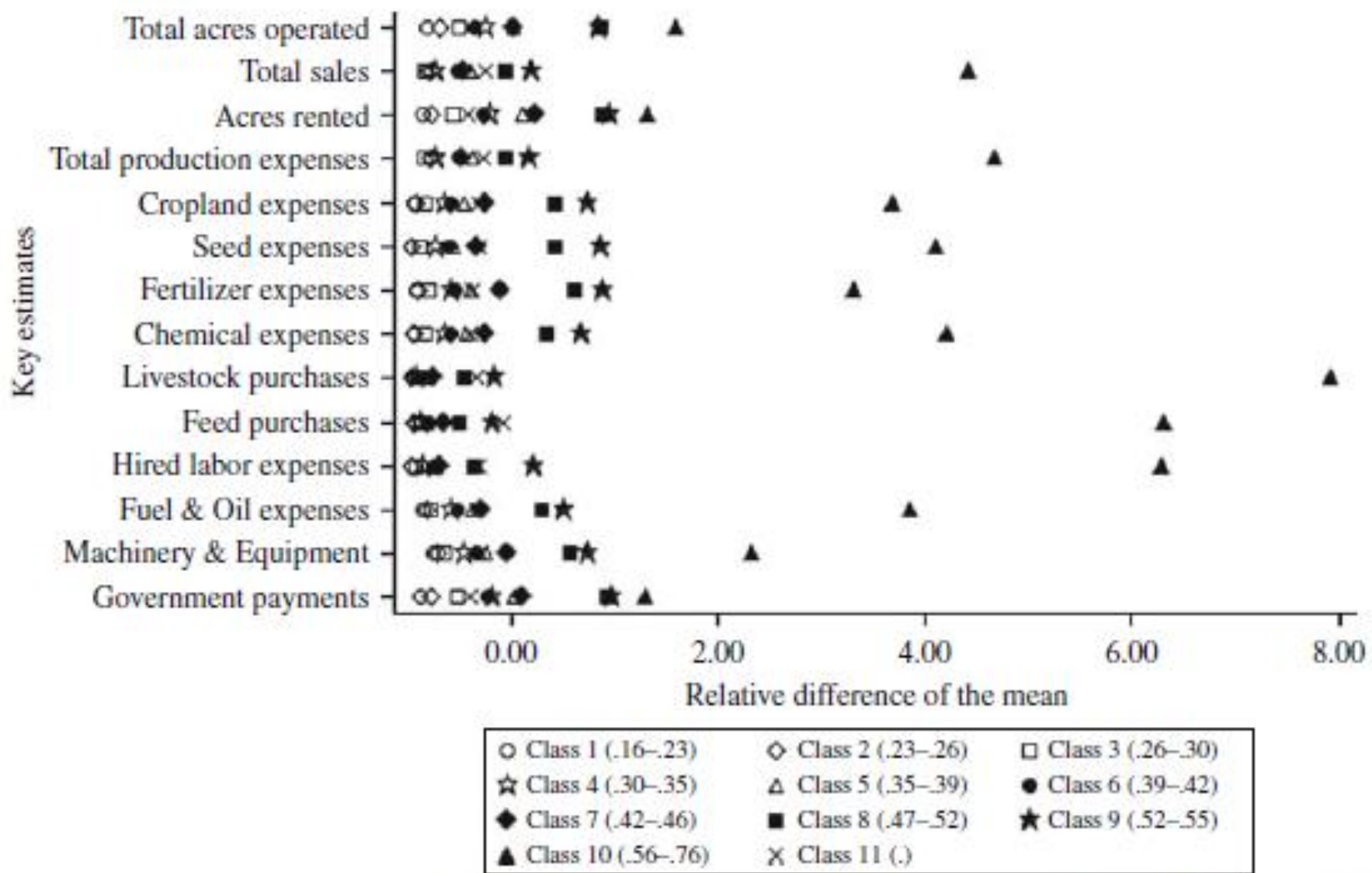


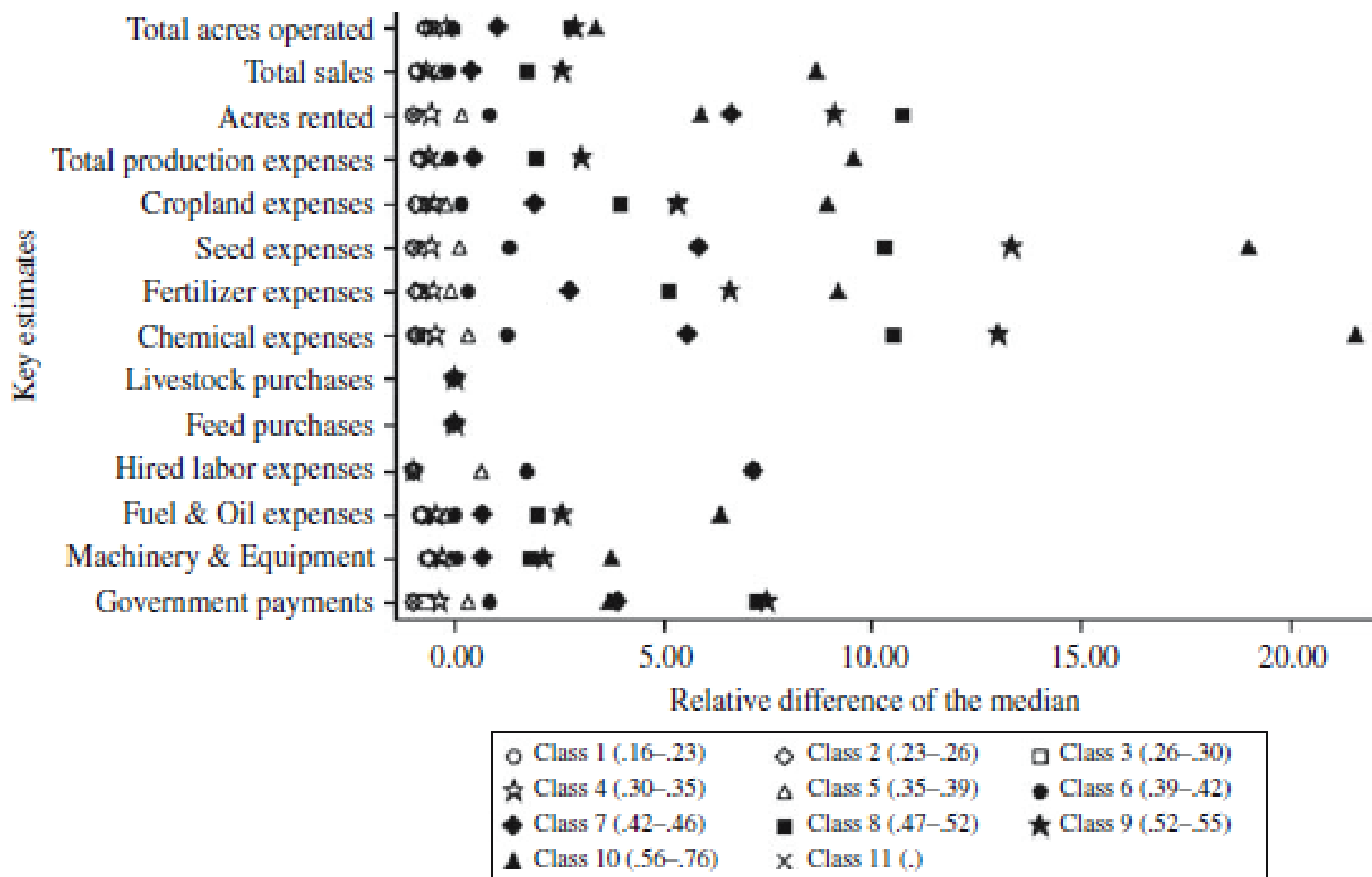
Fig. 2. ARMS 2009 nonresponse rate by ensemble tree nonresponse propensity class



$$\text{Relative difference of the mean} = [(\text{class mean} - \text{overall mean}) / \text{overall mean}]$$

Fig. 3. Relative difference of the mean for key estimates by nonresponse propensity class





$$\text{Relative difference of the median} = [(\text{class median} - \text{overall median}) / \text{overall median}]$$

Fig. 4. Relative difference of the median for key estimates by nonresponse propensity class

# Conclusion

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- Easily identify characteristics associate w/ nonresponse
- Can ensure that each variable is considered once in the overall average model
- These propensity scores were positively correlated with the amount of potential bias across several key estimates

# Conclusion

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- We would like to compare this tree method w/ random forests
- They are currently being used to pre-score samples prior to data collection to ensure that those farms that are least likely to respond and most likely to bias estimates as a result receive special attention.

# Contact Information

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## Contact Information

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