Models and Interventions in Adaptive and Responsive Survey Designs

Andy Peytchev
Center for Survey Methodology, RTI International

DC-AAPOR Panel on Adaptive Survey Design
February 10, 2014

Outline

1. Goals of statistical models in responsive and adaptive designs
2. Models
   - 2.1 Timing
   - 2.2 Variables
   - 2.3 Statistical methods
3. Examples
4. Interventions
5. Examples

Goals of Models and Interventions

- Identify key goals and their relative importance
  - Cost
  - Nonresponse bias
  - Measurement error bias
  - Variance
  - Nonresponse rates
  - Other…

- Identify key drivers that can be influenced, such as:
  - Continuing to work nonproductive cases
  - Bias from underrepresenting groups
  - Measurement error bias associated with a mode
  - Design effect due to weighting (selection and nonresponse)
  - More effective protocol cannot be afforded for the full sample

But Why Models?

- Formalize data-driven decision criteria
- Leverage more data to better achieve goals
  - Frame variables
  - Auxiliary data from other sources (e.g., ACS)
  - Survey data from survey iterations or waves
  - Paradata from current and prior implementations
  - Interviewer observations
- Balance multiple objectives
- Models are often employed, but lacking one or more of the features above (for example, deterministic decisions based on a single auxiliary variable)

Types of Models by Purpose and Implementation, and Examples

		Implementation	
		By Phase/Group-Level (Responsive Design*)	**Continuous/Case-Level (Adaptive Design*)**
Main Objective	**Error Reduction**	Multiphase designs often with targeting of cases. Phases are implemented at a point in time. (e.g., Peytchev et al., 2010; Pratt et al., 2013)	Changing treatment on a case basis, during the course of the study (simulations, Calinescu, 2013).
	Cost Reduction	Stopping rules for the entire study. Can be based on changes in estimates or imputed estimates (e.g., Wagner and Raghunathan, 2009). Targeting of more productive cases (G&H, 2006).	Attempt cases by propensity in a call window (Couper and Wagner, 2011). Mode switch (Chesnut, 2013). Stop cases based on propensity (Peytchev, 2013).

* Couper and Wagner (2011) argue these to be the features distinguishing Responsive from Adaptive designs, but for convenience, refer to both as Responsive Design.

Types by Features of Models

1. Timing
2. Variables
3. Statistical Methods

1.1 Timing of Modeling

1. Prior to data collection
   - Strengths:
     - Stable estimates
     - Model final outcome
   - Weaknesses:
     - Limited to auxiliary data prior to data collection
     - Not responsive to current data collection outcomes
2. During data collection using prior parameter estimates
   - Strengths
     - Leverage relevant (para)data from current data collection
3. During data collection using current outcome and current covariates
   - Strengths:
     - Fully responsive to what is happening in data collection
   - Weaknesses:
     - Estimates can be unstable, especially early
4. A hybrid approach combining estimates from (1) and (3)

1.2 Variables in Models

- Choice of dependent variable
  - To match primary objective(s)
  - To match intervention (e.g., noncontacts, refusals, or both)
  - To include stability criteria (e.g., current vs. prior wave)
  - One vs. two or more
- Choice of covariates
  - Demographic characteristics
  - Survey variables
  - Frame and administrative data
  - Various types of paradata

1.3 Choice of Statistical Methods

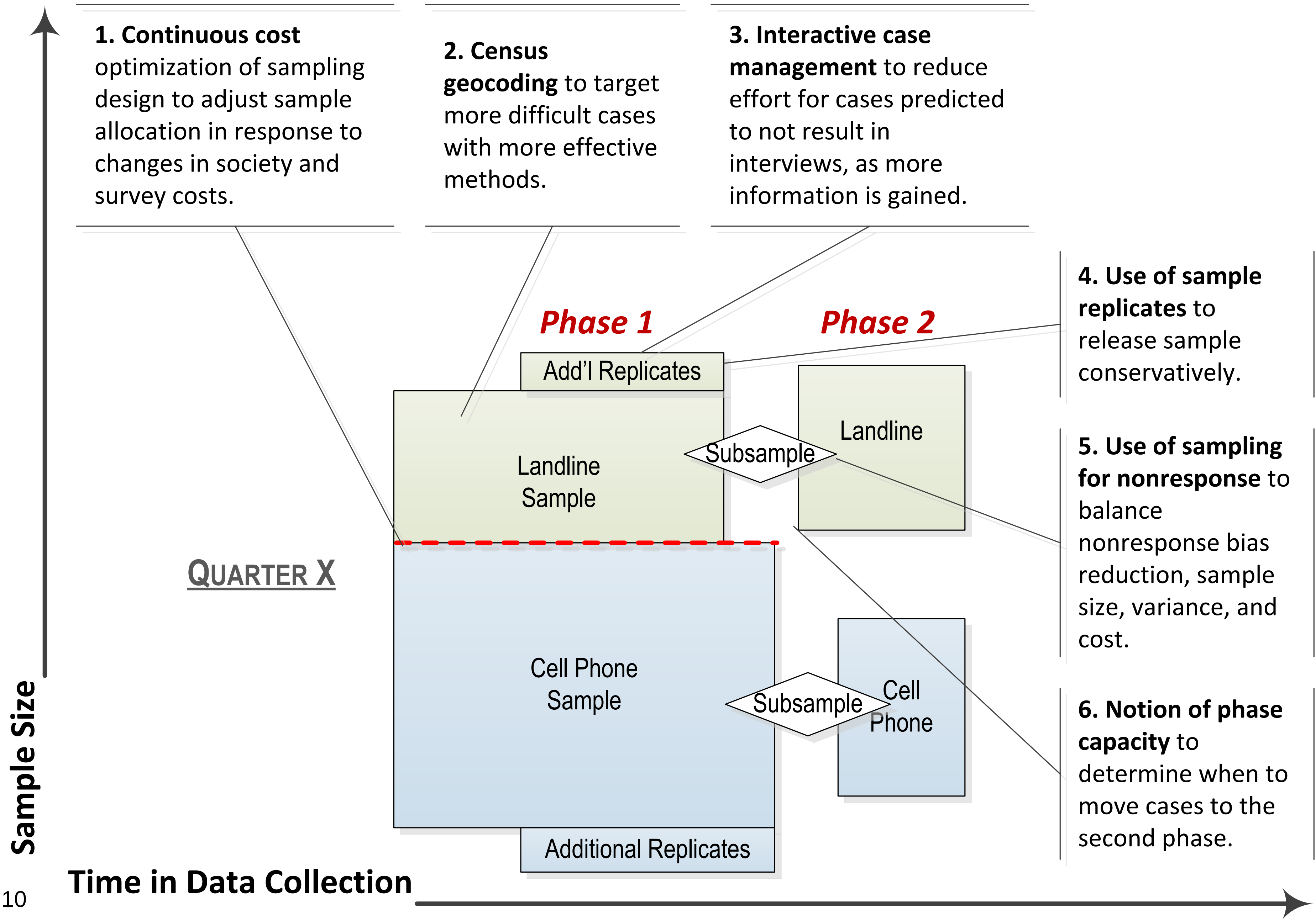
- Vary by purpose
  - Likelihood of an interview at the case or call attempt level
    - E.g., logistic regression
  - Phase capacity at the sample level
    - Fraction of Missing Information (Wagner, 2010), Propensity-based R-indexes (Schouten and Cobben, 2007)
- Vary by data structure
  - Call record vs. case-level
    - Discrete time event history models
  - Presence of nesting and need to estimate nesting effects
    - Multilevel survival models (Durrant, D'Arrigo, and Steele, 2011)
- Vary by statistical methodology preference
  - E.g, Logistic regression, Mahalanobis Distances, R-indexes

Example: Responsive Design in an RDD Survey

1. Continuous cost optimization of sampling design to adjust sample allocation in response to changes in society and survey costs.

2. Census geocoding to target more difficult cases with more effective methods.

3. Interactive case management to reduce effort for cases predicted to not result in interviews, as more information is gained.



4. Use of sample replicates to release sample conservatively.

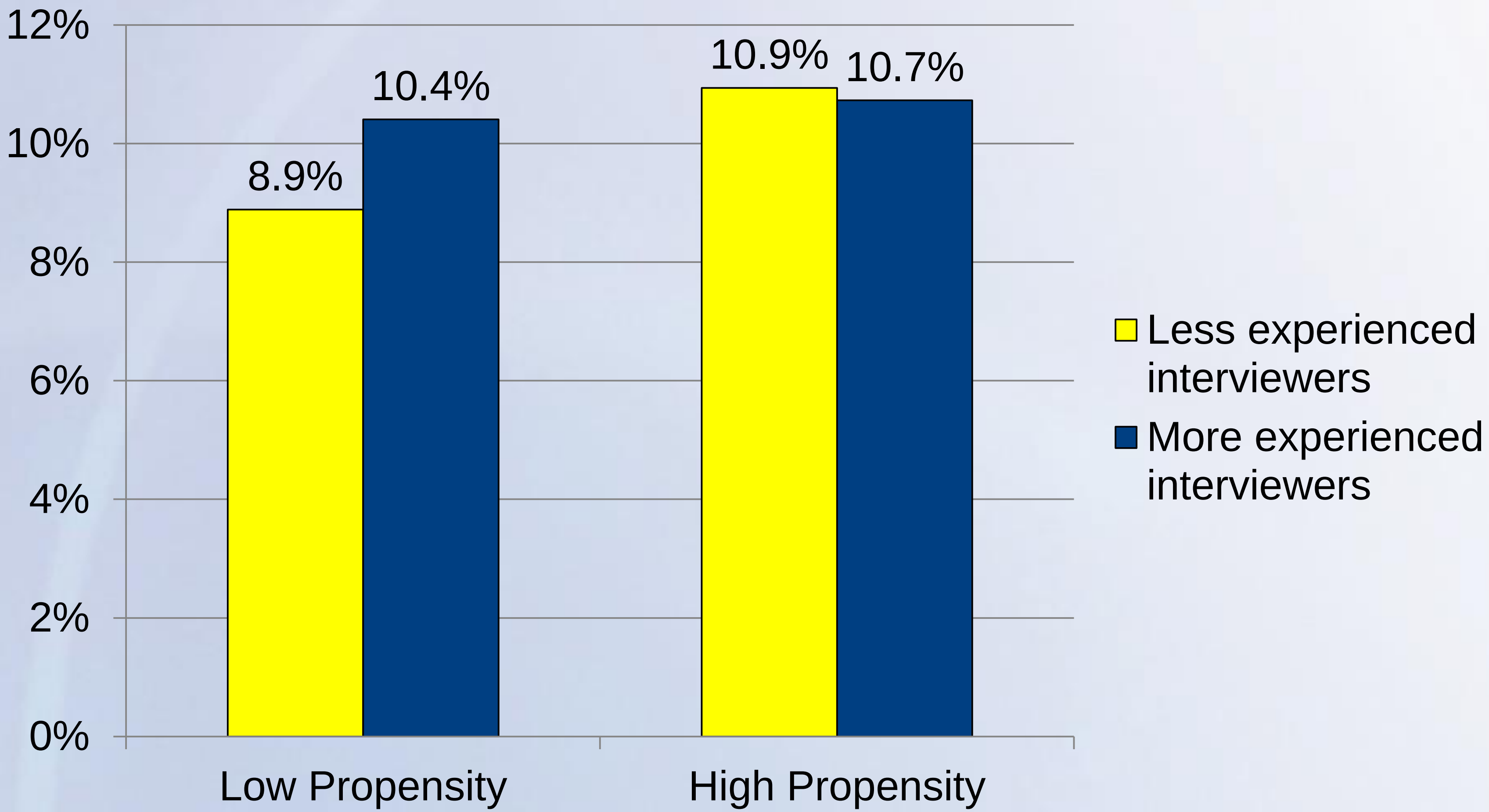
5. Use of sampling for nonresponse to balance nonresponse bias reduction, sample size, variance, and cost.

6. Notion of phase capacity to determine when to move cases to the second phase.

Census Geocoding to Target Cases

- Objective:
  - Increase response rates
- Approach:
  - Augment samples with Census data
    - For *landline* telephone numbers that can be matched to an address, append information at the census block group level
    - For *landline* telephone numbers that cannot be matched, use telephone exchange to match to postal code (ZIP)
    - For *cell* phone numbers use telephone exchange to match to county or state level data
  - Fit model to prior data, apply coefficients to current sample, estimate response propensities prior to data collection
  - Assign low propensity cases to more experienced interviewers until first contact with a sample member

Census Geocoding to Target Cases - Results



Interactive Case Management - Background

- Survey case management systems include rules with fixed parameters, such as:
  - A minimum and/or maximum number of call attempts for the entire sample
  - Ensuring numbers are dialed at different times and days of week
- The rules do not adapt to the particular survey and sample; they are quite *static*
- Unproductive numbers are dialed when the same effort could have been directed to numbers more likely to produce an interview

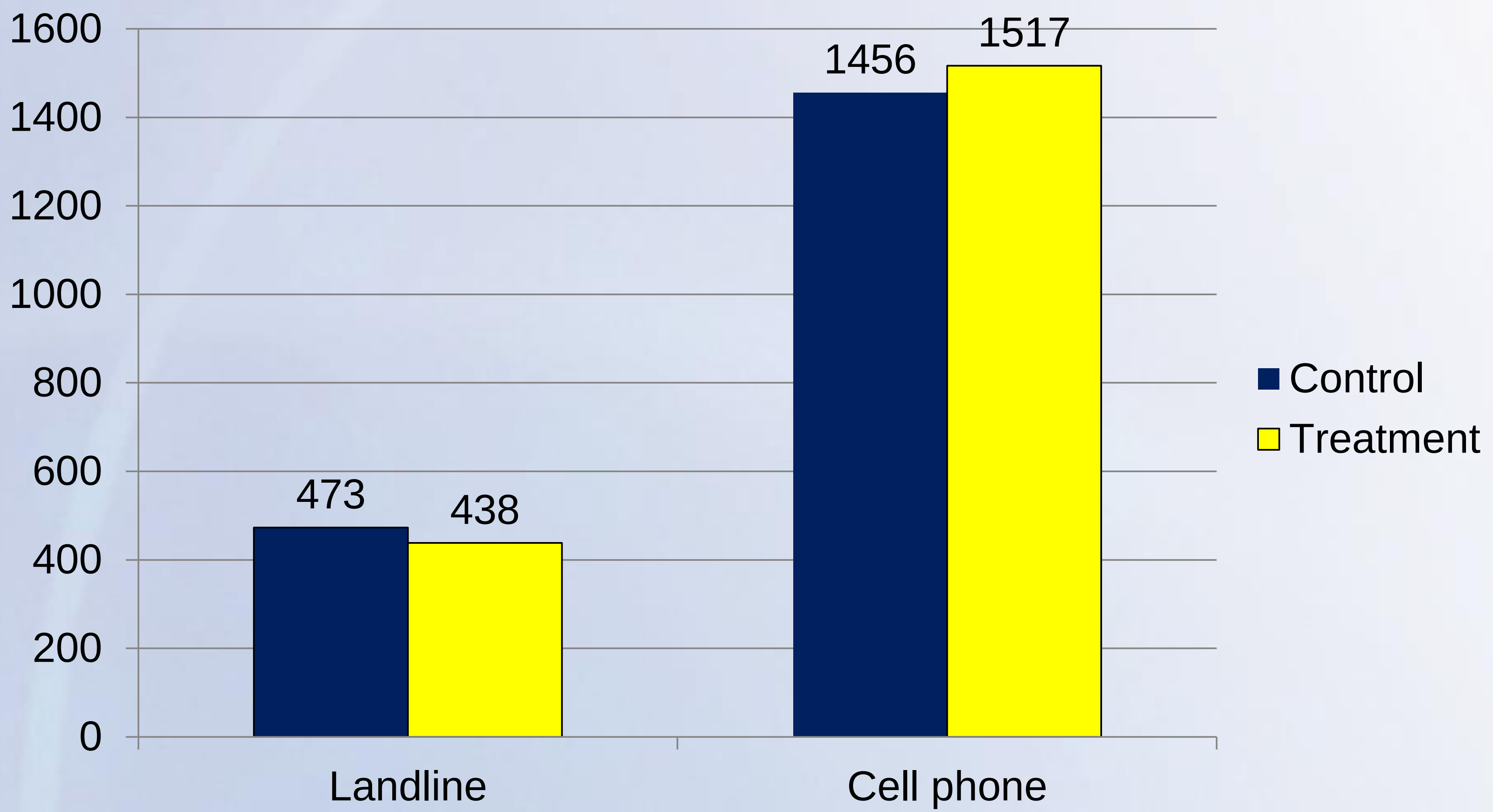
Interactive Case Management

- Objective:
  - Reduce data collection cost without impacting response rates
- Approach
  1. Build response propensity models:
     - Using past data, predicting end-of-phase interview outcome
     - Using current data, predicting interview outcome on the next call
  2. Decide on propensity thresholds and other parameters to put cases on hold, balancing cost efficiency and possible effect on response rates
  3. Apply the estimated model coefficients from (1), obtaining response propensities on a recurring basis.
  4. Stop dialing for cases that fail to reach the response propensity threshold. Include a control condition.
  5. Evaluate cost efficiency and response rates, foremost.

Implementation

- Planned as an automated nightly process during data collection
- Used models to evaluate:
  - Impact on number of call attempts to be saved
  - Impact on lost interviews
  - Ran for different combinations of
    - Day in data collection
    - Minimum number of call attempts
    - Propensity threshold
- Tested as a single stop on a subset of cases
  - 46.1% (4,897 cases) of active landline cases
  - 5.7% (2,032 cases) of active cell phone cases
  - Randomized into Treatment and Control from beginning of study

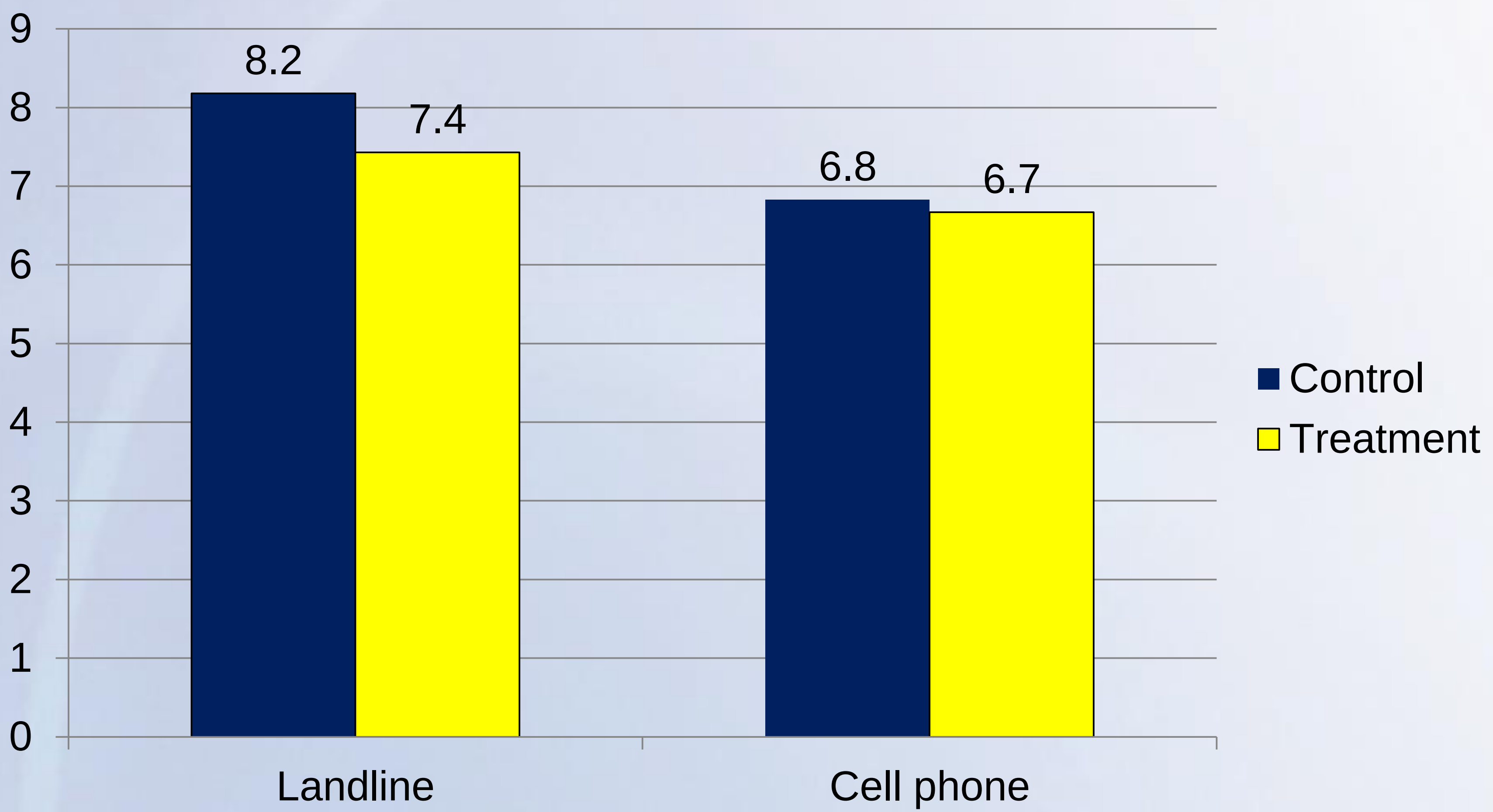
Number of Interviews



p=.23

p=.25

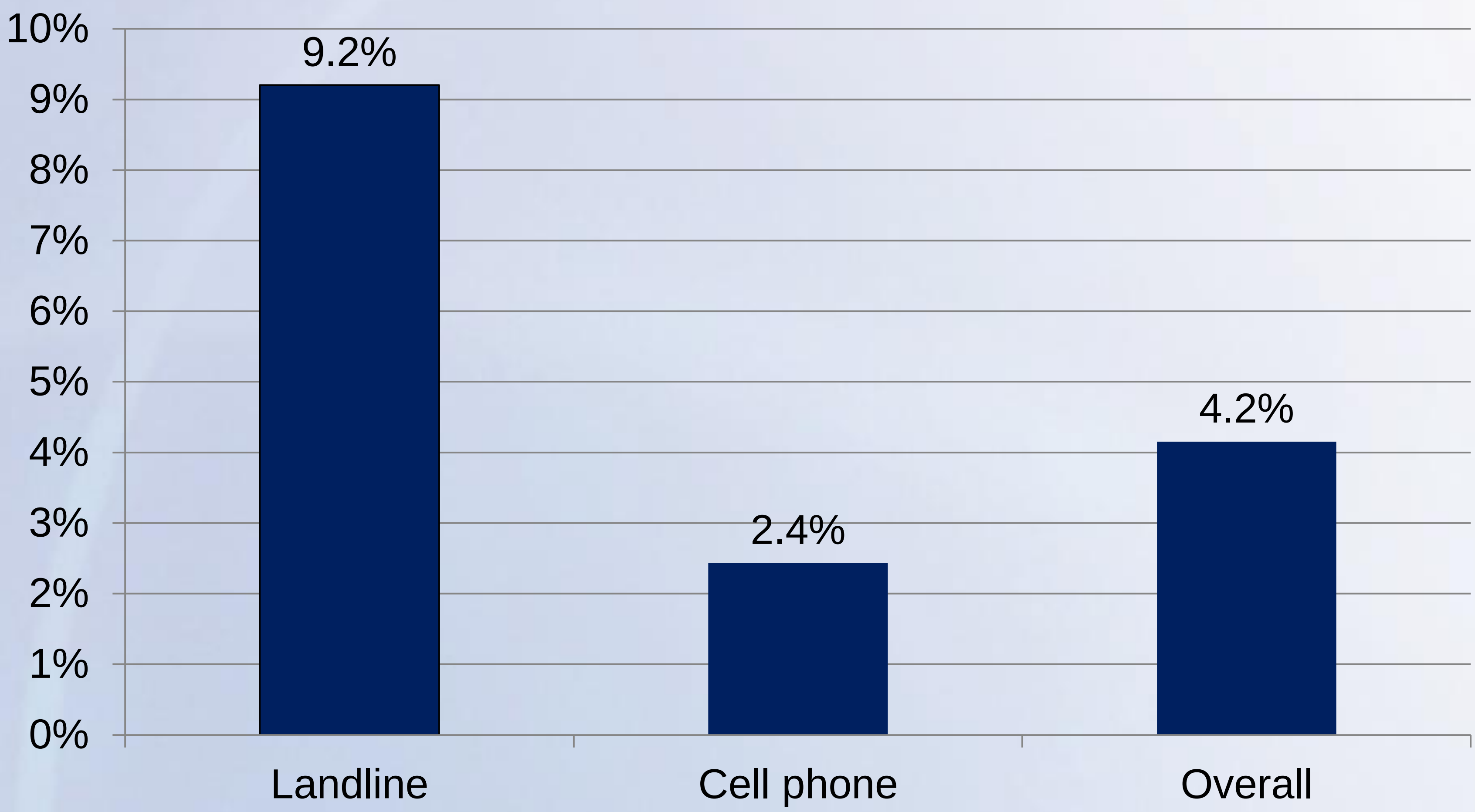
Mean Number of Call Attempts



p<.001

p<.001

Percent Reduction in Total Call Attempts



Improving Models to Meet Objectives

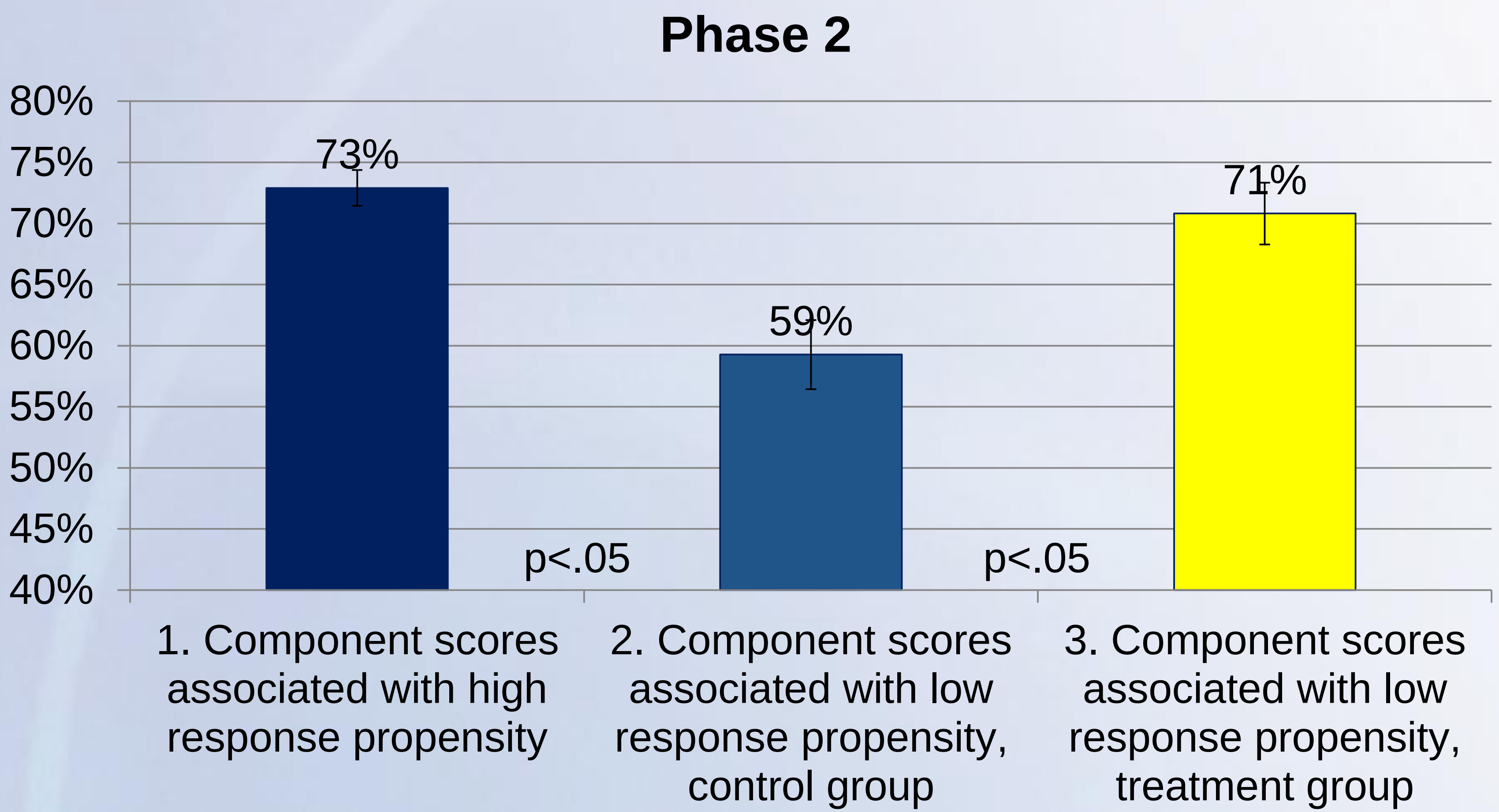
- Objective:
  - Reduce nonresponse bias in panel survey estimates
- Approach:
  - Estimate response propensities before/during data collection
  - Target cases with low propensities with more intensive protocol (respondent & interviewer incentives)
- Two examples of models evolving
  - Community Advantage Panel Survey
  - High School Longitudinal Study

Improving Models to Meet Objectives

- Community Advantage Panel Survey, 2008-2009
  - Estimated model to maximize prediction, including demographic, substantive (economic) frame and prior wave, and paradata variables
  - Estimated prior to data collection
  - No difference in estimates between the control and experimental conditions, but could be attributable to the intervention
- Community Advantage Panel Survey, 2011-2012
  - Used two models
    - Likelihood of participating
    - Summary variable of all key survey variables
    - Combine the likelihood of participation and summary variable
  - Estimated during data collection

Sources: Peytchev, Riley, Rosen, Murphy, and Lindblad, 2009, 2010, 2012

CAPS Owners Sample – Response Rates by Group with Standard Errors



- Yet, weighted survey estimates remained largely the same across the two scenarios.

Improving Models to Meet Objectives

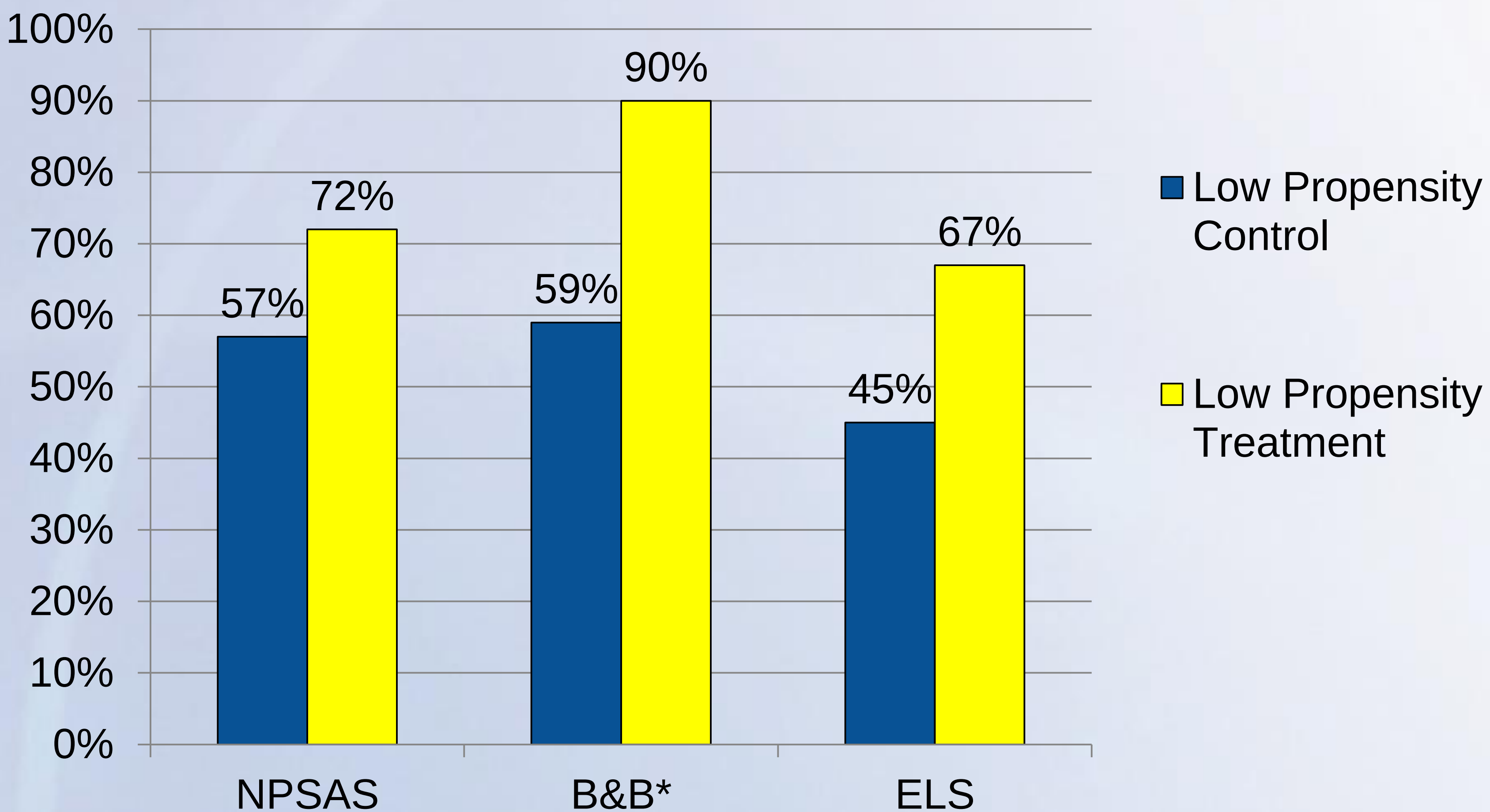
- High School Longitudinal Study 2012 update
  - Estimated Mahalanobis Distance model to maximize separation of respondents and nonrespondents, using demographic, frame, prior wave, and paradata variables
  - Paradata variables were among the strongest predictors
- High School Longitudinal Study 2013 update
  - Estimated “nonresponse bias” propensities, deliberately excluding paradata from the logistic regression, and *not* aiming to maximize model fit
    - Protects against overwhelming the model with paradata that can be unrelated to the survey variables, such as prior wave participation
    - A statistically simple way to combine the “R” and “Y” models
  - Model estimated during data collection prior to each phase

Source: Pratt, 2013

2. Interventions

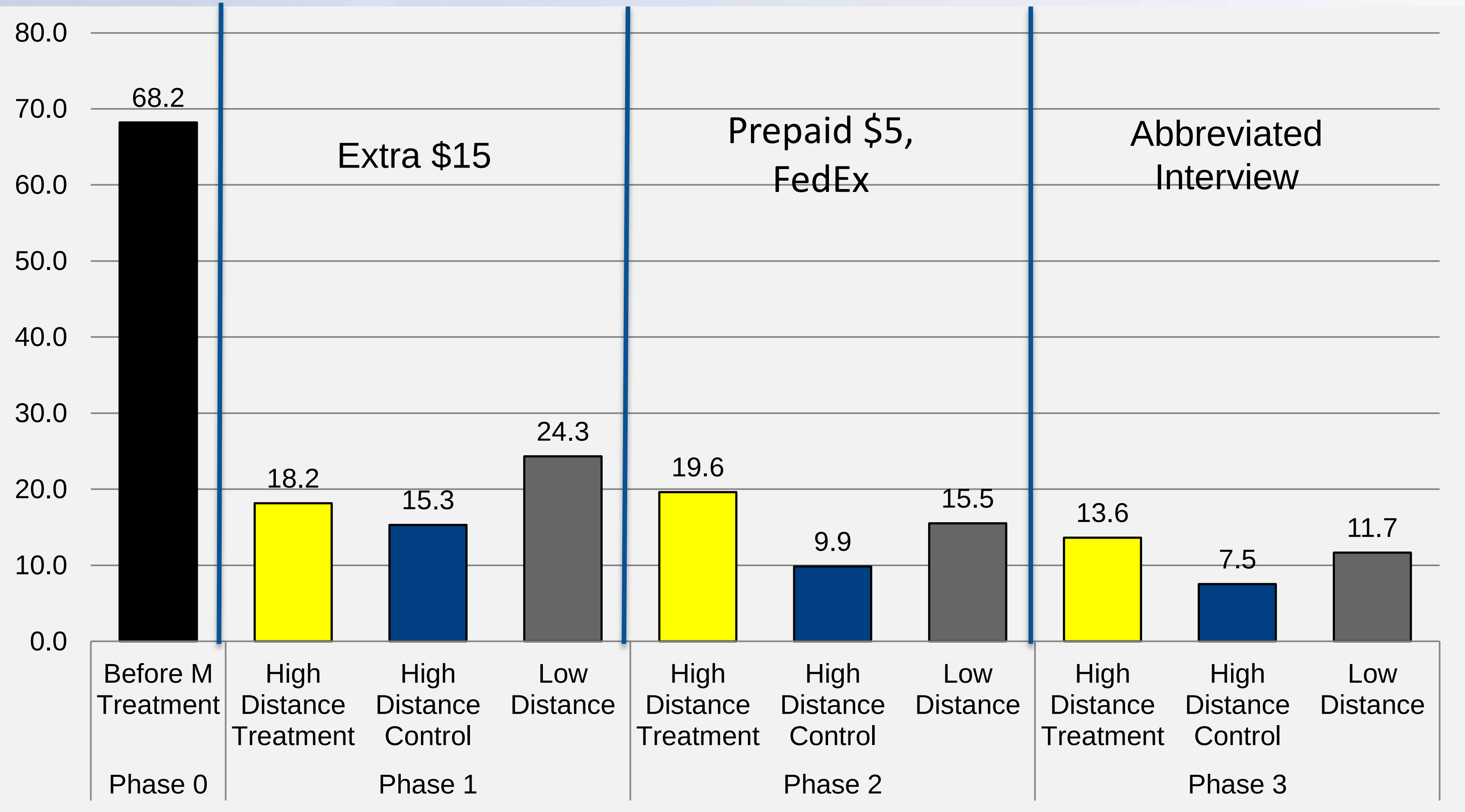
- Near-infinite number of permutations of features (mode, incentive, letters, etc.) and timing of the change
  - A key strength of the responsive design framework is that the optimal intervention is not necessarily known
- Match intervention to goals, models, and theory
  - For example, incentives are a common feature in interventions, but could be ineffective when nonresponse is due to noncontact
- Could more than one intervention be needed?
  - Different interventions for different subgroups
- Progress depends on ability to evaluate the intervention
  - Absence of a control group can make it impossible to evaluate
- Caution when applying findings to other studies
  - An effective intervention for study A may not be so for study B

Interventions across Studies



Source: Pratt, Cominole, Peytchev, Rosen, Shepherd, Siegel, Wilson, and Wine (2013). Using Predicted Response Propensities for Bias Reduction. Paper presented at the AAPOR annual conference.

Interventions within a Study (Baccalaureate & Beyond study)



Source: Cominole, Peytchev, Pratt, Shepherd, Siegel, Wilson, and Wine (2013). Using Mahalanobis Distance Measures for Bias Reduction. Paper presented at the AAPOR annual conference.

Summary

- Models play a critical role in many responsive designs
  - Have demonstrated utility
  - Leverage more data
  - They could play a larger role, as examples are still limited
- Further development of models is needed
  - For example, blending of multiple models (at different points in time, different sources of data, different sources of error being addressed)
- Interventions
  - Incentives are generally effective, along with other commonly used methods
  - Could tailoring interventions to sample subgroups help further?
    - Or even case-level?