

Morris H. Hansen Memorial Lecture

# **Exploring the Assumption That Online Opt-in Respondents Are Answering in Good Faith**

**Courtney Kennedy**

*Director of Survey Research*

# Pew Research Center's Lens on Nonprobability



## Overview of Our Nonprobability Work

**Main collaborators:** Andrew Mercer\*, Arnold Lau, Nick Hatley, Dorene Asare-Marfo, Scott Keeter, Nick Bertoni

# A well-known finding: estimates from opt-in surveys tend to be less accurate

Found online opt-in surveys were less accurate	Found online opt-in surveys were just as accurate
Malhotra and Krosnick (2007)	Vavrek and Rivers (2008)
Chang and Krosnick (2008)	Ansolabehere and Schaffner (2014)
Yeager et al. (2011)	
Szolnoki and Hoffmann (2013)	
Erens et al. (2014)	
Sturgis et al. (2016)	
Dutwin and Buskirk (2017)	
MacInnis et al. (2018)	
Pennay et al. (2018)	
Silver (2018)	
Mercer et al. (forthcoming)	

## **This holds even when relatively advanced statistical approaches are used**

### **Dutwin and Buskirk (2017)**

“advanced techniques such as propensity weighting and sample matching did not improve these measures, and in some cases made matters worse”

### **Mercer et al. (2018)**

“even the most effective adjustment strategy [sample matching, propensity modeling, and raking] was only able to remove about 30% of the original bias.”

# Why?

# Why?

**Are our adjustment models not sophisticated enough?**

**Or is the data not genuine and, thus, immune to modeling fixes?**

# **Prior research on nonprobability respondents being not genuine or fraudulent**

## **Fraudulent interviews from outside the U.S.**

Kennedy et al. 2018; Moss 2018; Ahler et al. 2019; Kennedy et al. 2021

## **Click farms**

Pasternak 2019

## **Trolling**

Lopez and Hillygus 2018

## **Cases failing various data quality checks**

Fan et al. 2006; Oppenheimer et al. 2009; Walker et al. 2009; Hopper 2012; Baxter 2016; Vannette 2017; Liu and Wronski 2018; Shanahan 2018; McDowell 2019; Puleston 2019; Kennedy et al. 2021

## Advancing the conversation

- Bogus interviews are not randomly distributed across opt-in samples. They are concentrated in certain subgroups.
- For some subgroups, sizeable shares of cases may not actually belong to that subgroup.
- Statistical models assume respondent demographic info is accurate, but in some cases that may be untrue.
- Whether a hybrid design reduces or increases MSE may depend on the subgroup.

# Research design of 2021 benchmarking study

## In 2021 we fielded six samples

- Opt-in panel 1 n = 4,912
- Opt-in panel 2 n = 4,931
- Opt-in panel 3 n = 4,955
- ABS panel 1 n = 5,027
- ABS panel 2 n = 5,147
- ABS panel 3 n = 4,965

## We used a common questionnaire with 27 benchmark questions

## We weighted each sample independently on 12 variables

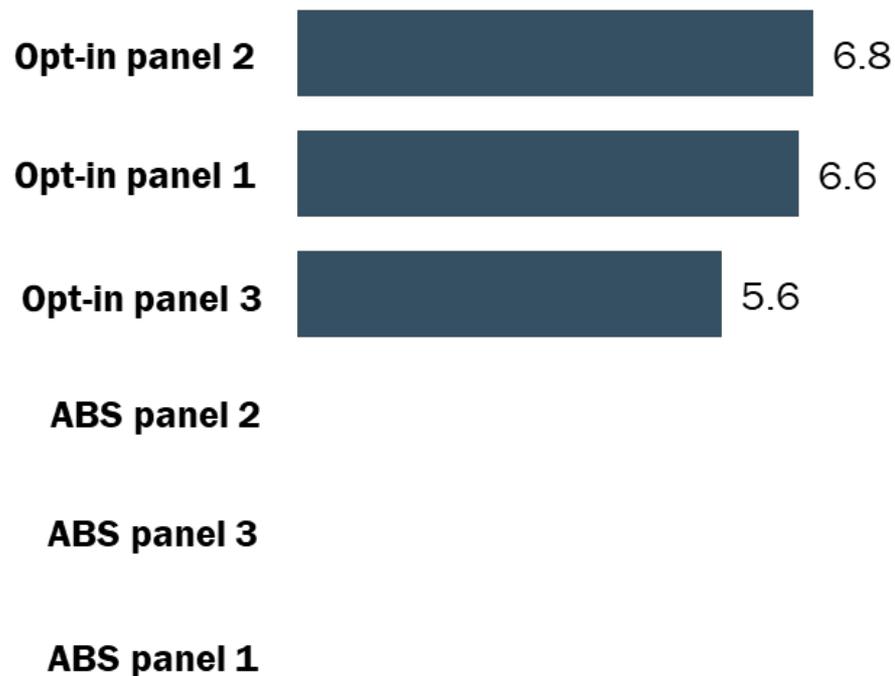
- core demographic interactions (e.g., race/ethnicity x education, age x sex)
- civic, political participation (volunteerism, registered voter status)
- other known online panel biases (internet frequency, religion, partisanship)

# **Consistent with other studies, opt-in sample estimates contained larger errors on average**

*Average (abs) deviation from 27 benchmarks*

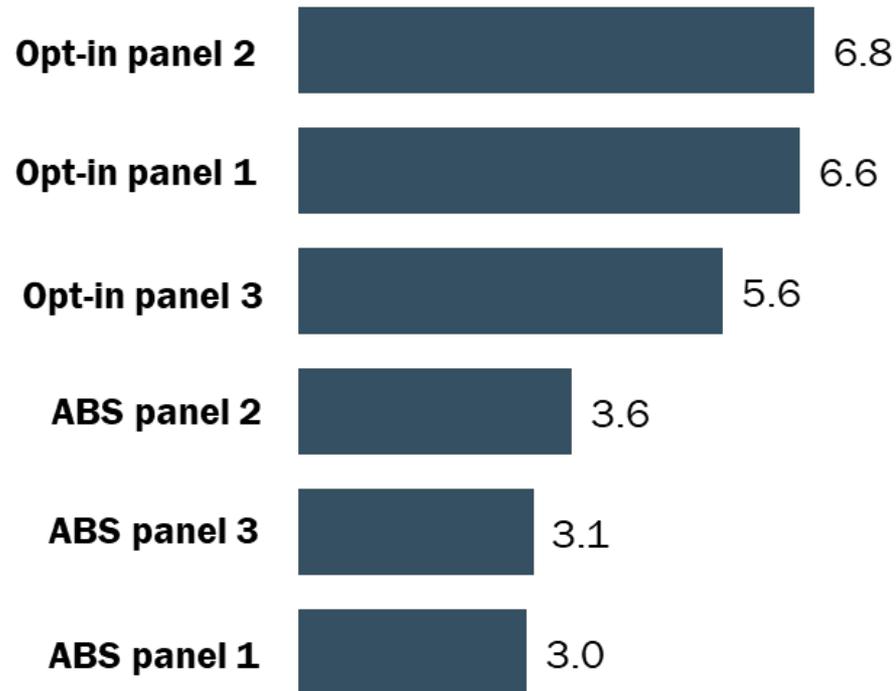
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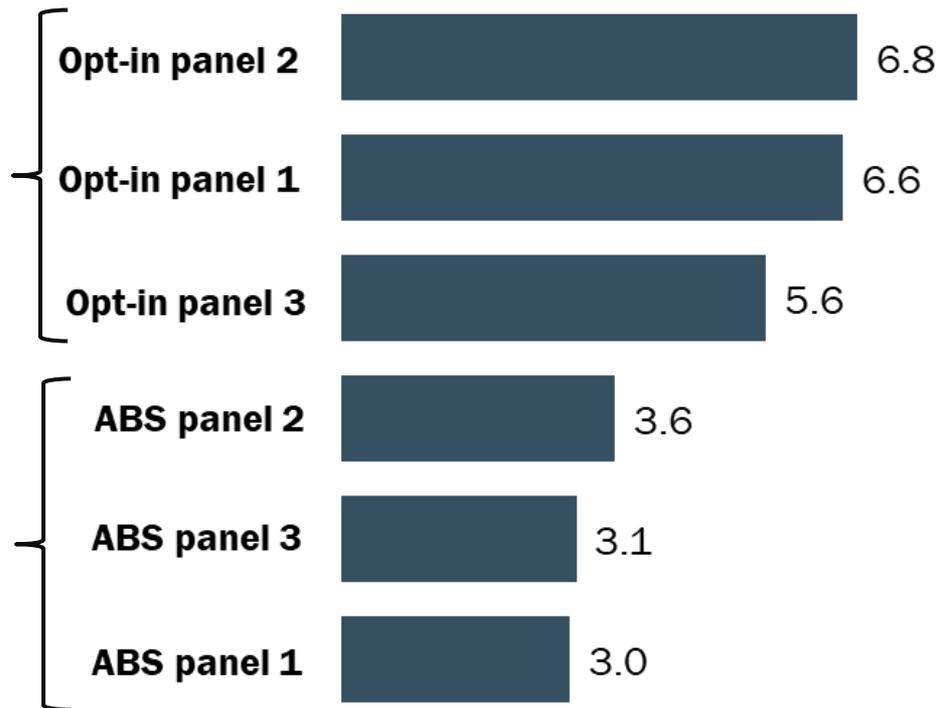
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# Consistent with other studies, opt-in sample estimates contained larger errors on average

*Average (abs) deviation from 27 benchmarks*

Subsequent slides show the average for the opt-in panels and the average for the ABS panels

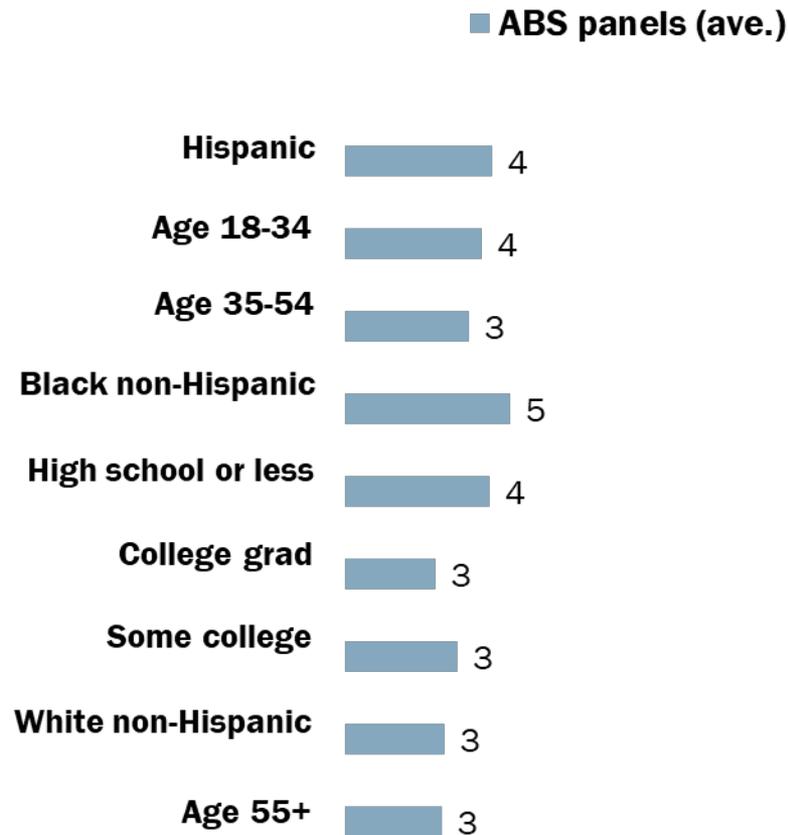


# Where are the large opt-in sample errors coming from?

*Average (abs) deviation from benchmarks, **by subgroup***

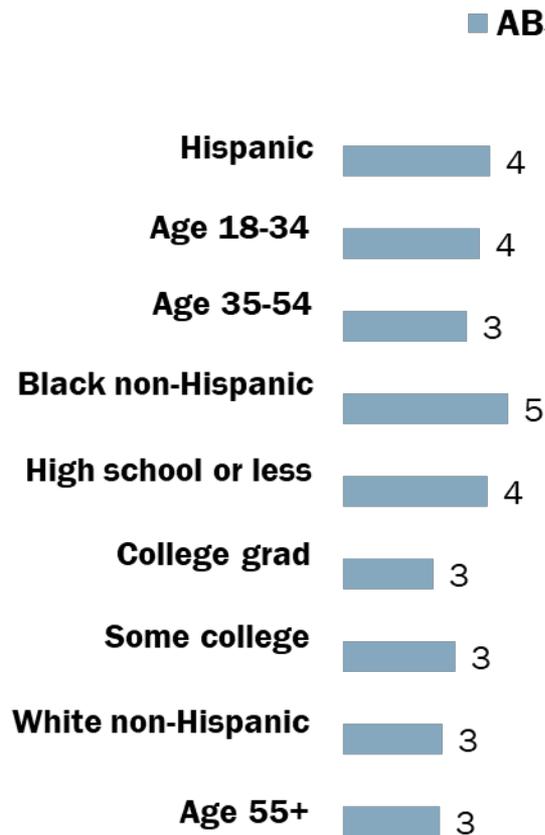
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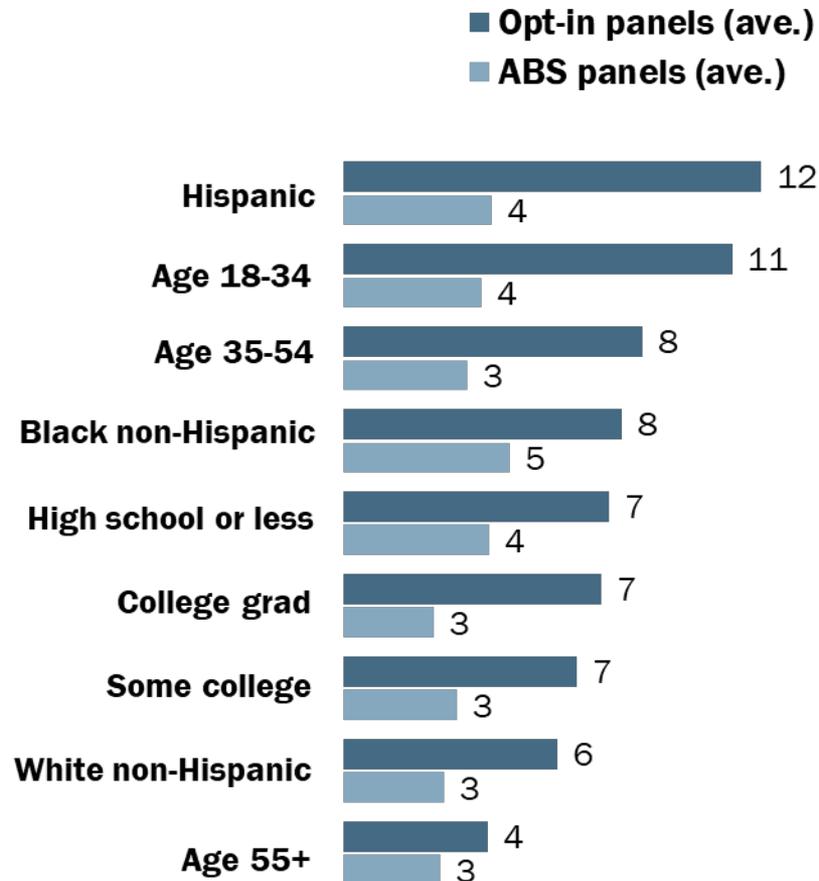
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The accuracy of ABS sample estimates does not vary much by subgroup

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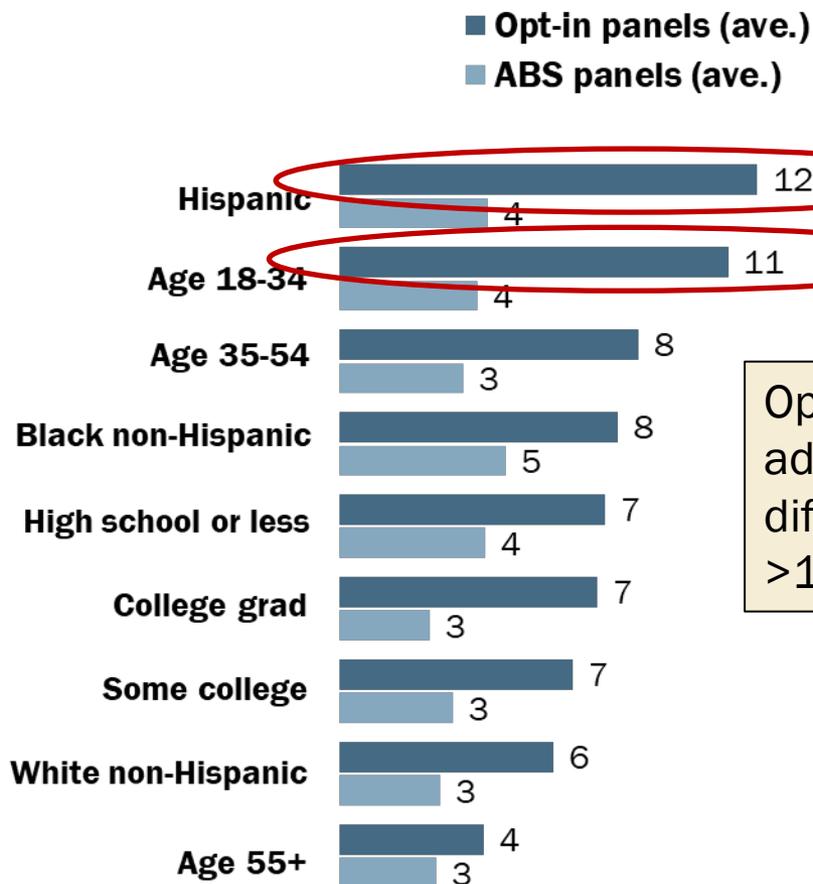
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But the accuracy of opt-in estimates varies greatly by subgroup

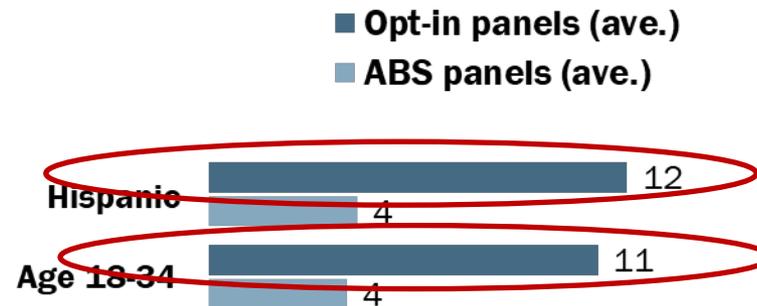
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*Average (abs) deviation from benchmarks, by subgroup*



Opt-in estimates for Hispanic adults and young adults differed from benchmarks by >10 p.p. on average

## Average (abs) deviation from benchmarks, *by subgroup*



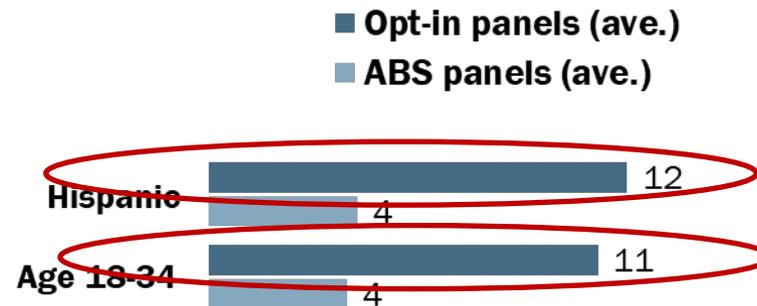
Should we attribute this to:

### **Nonresponse/Noncoverage error**

These opt-in respondents are genuine (answering in good faith) and just adorably unique or quirky



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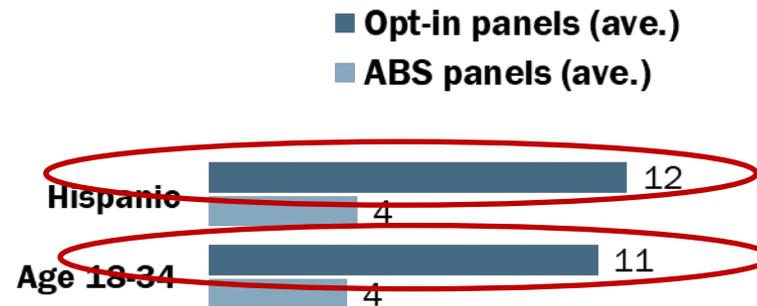
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These opt-in respondents are not who they pretend to be (answering in bad faith)



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OR

A combination of the two



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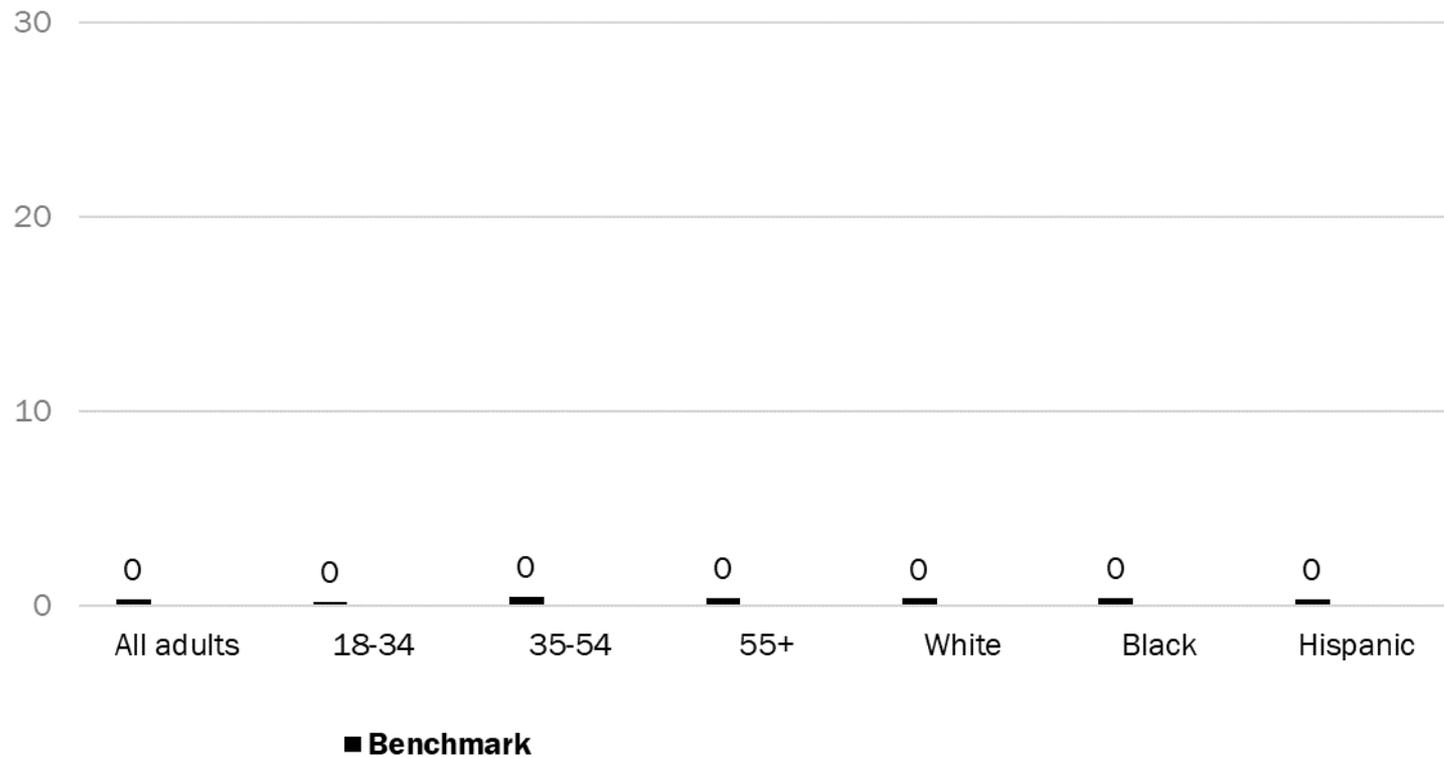
Answers would not be plausible, reflective of bad faith

# Do opt-in errors stem from respondents being adorably unique or bogus?

*% of adults receiving Worker's Compensation payments in 2020*

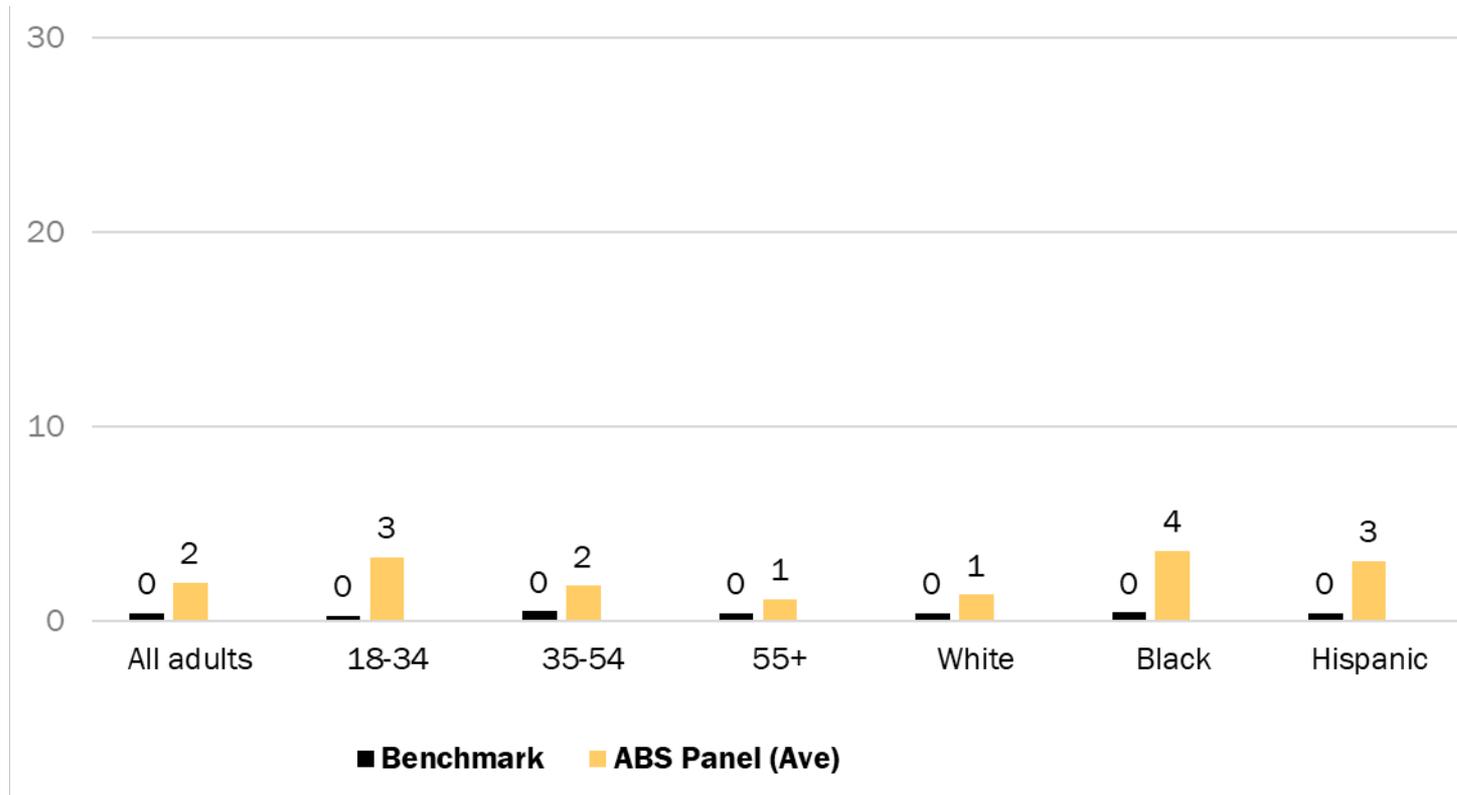
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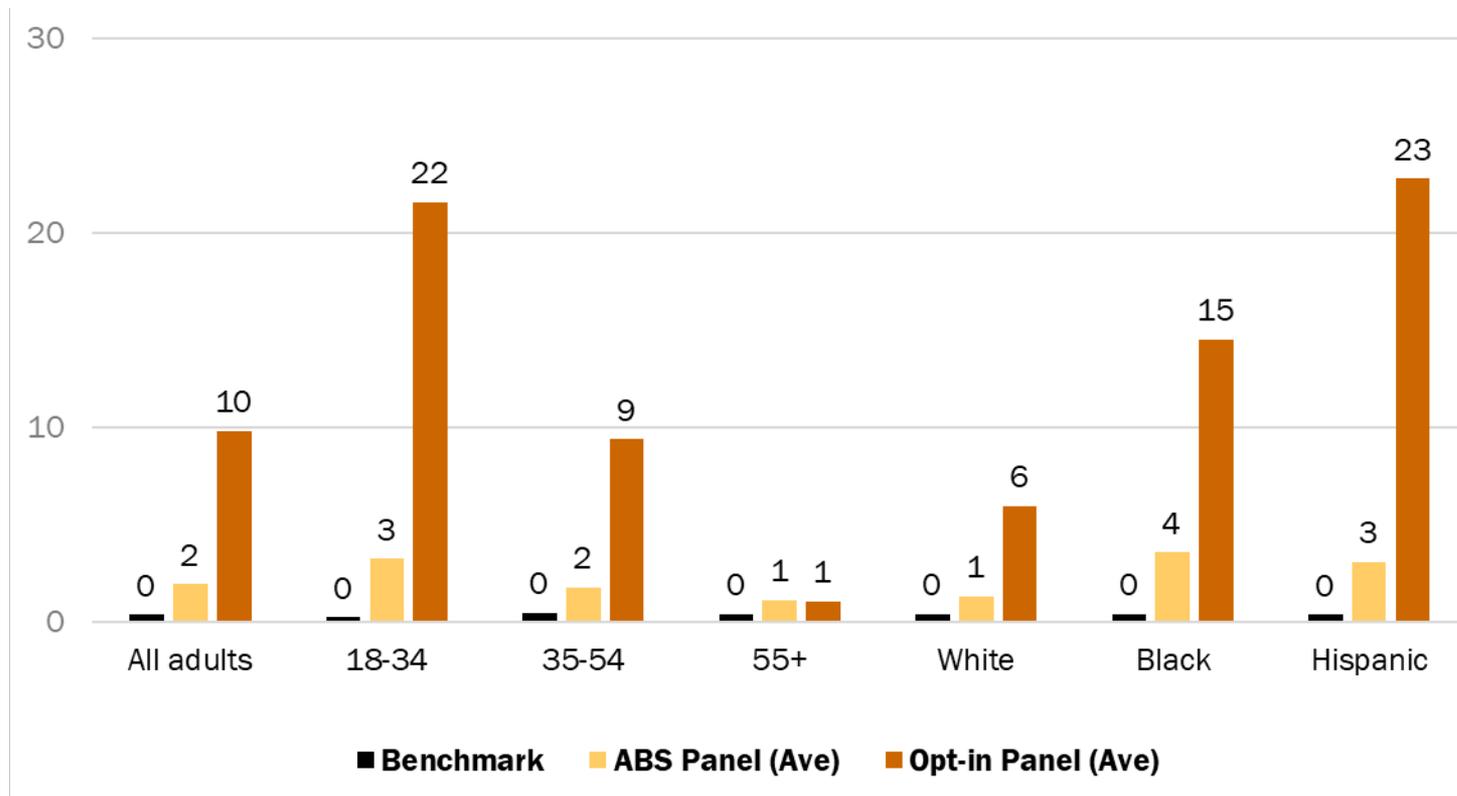
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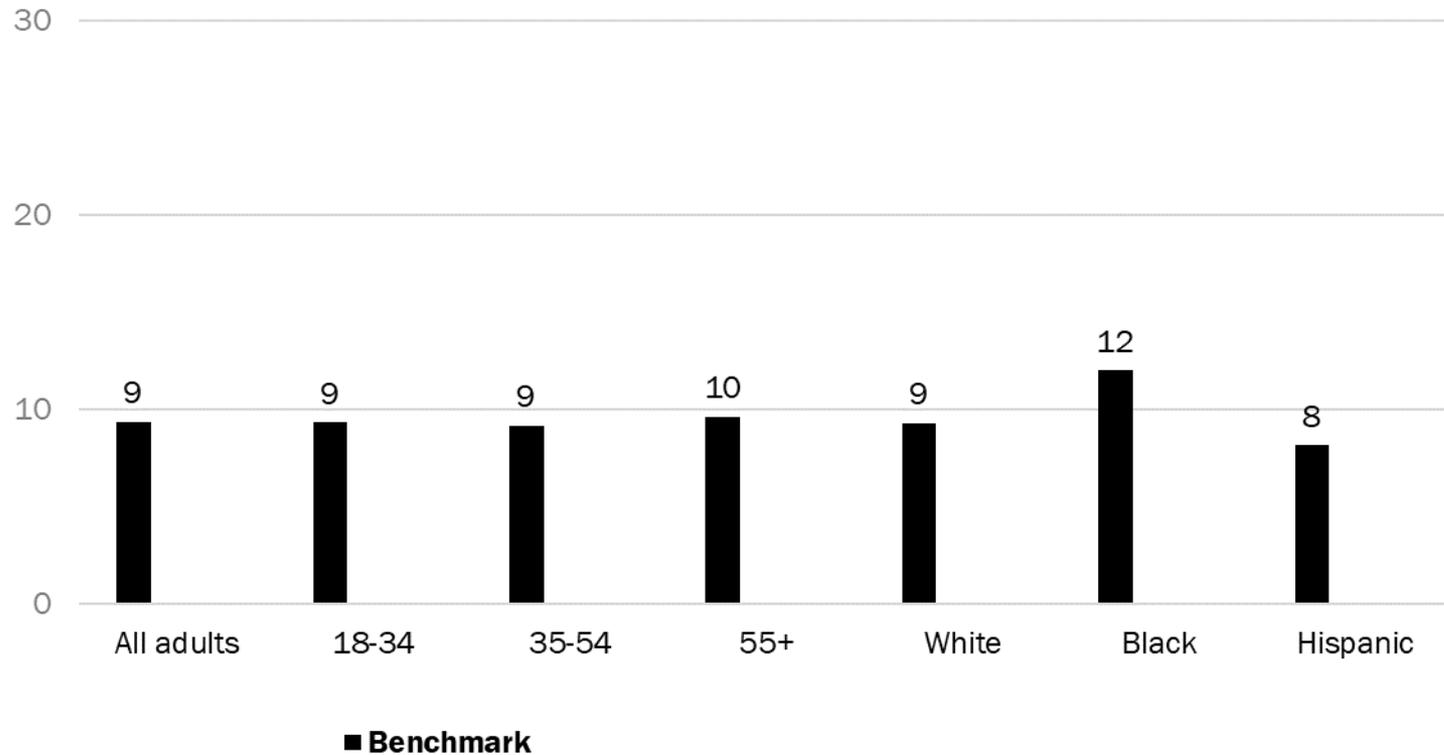


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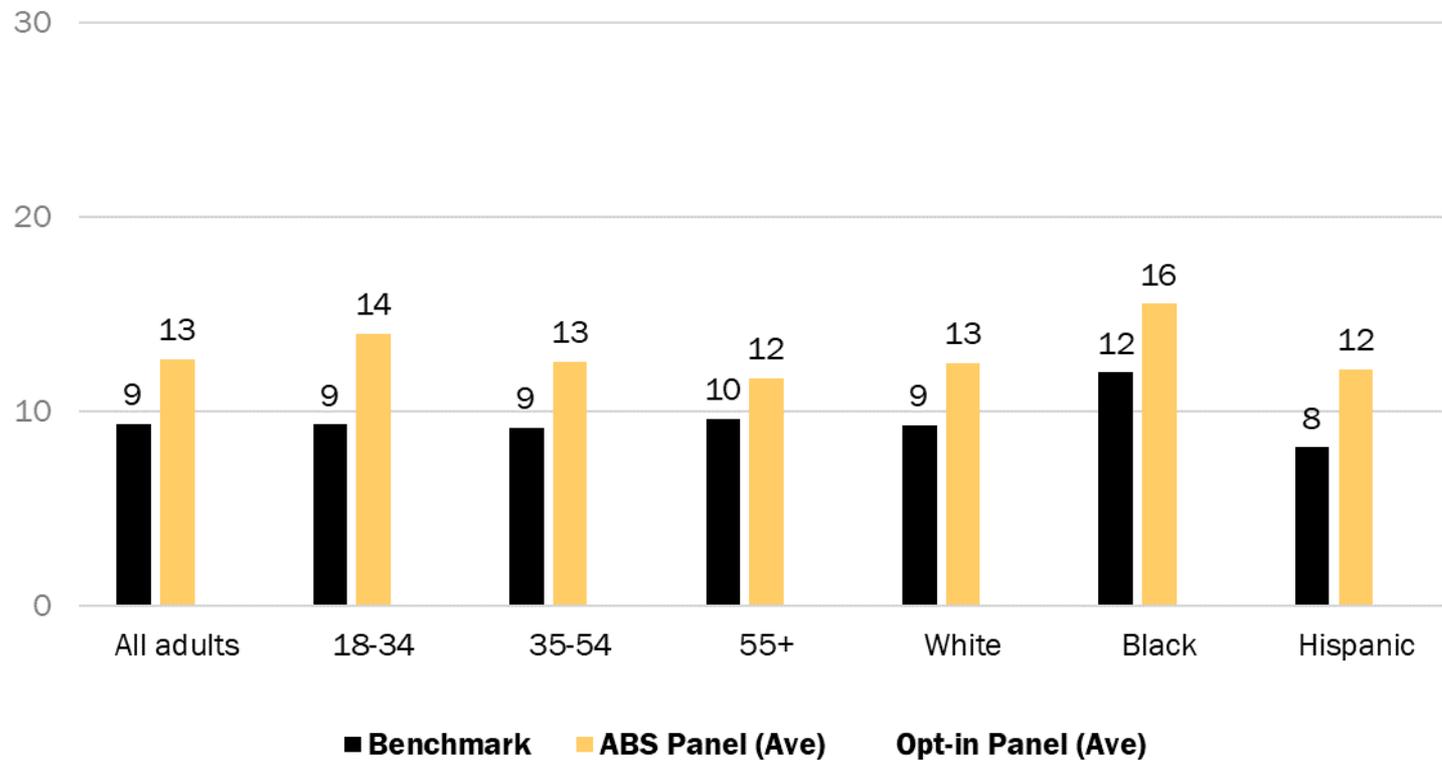
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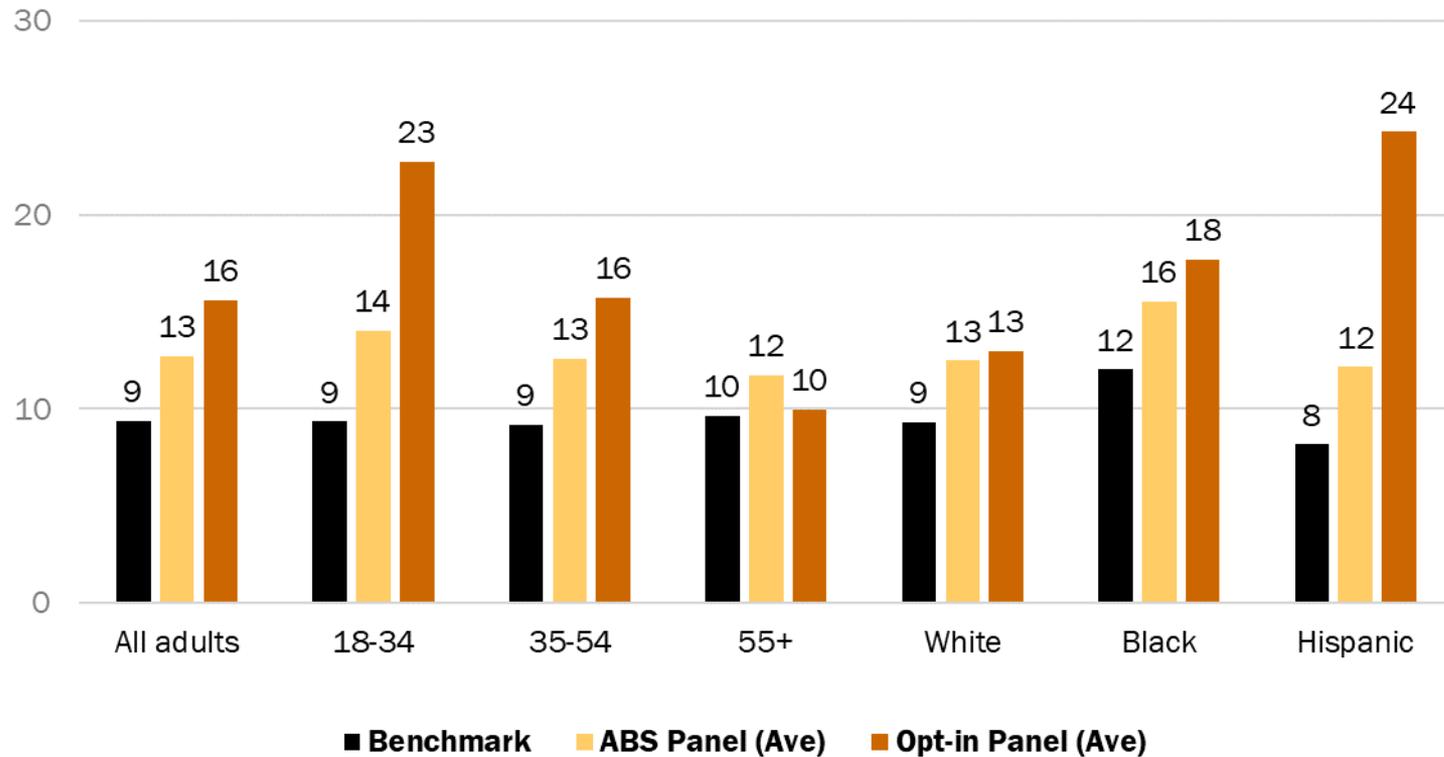
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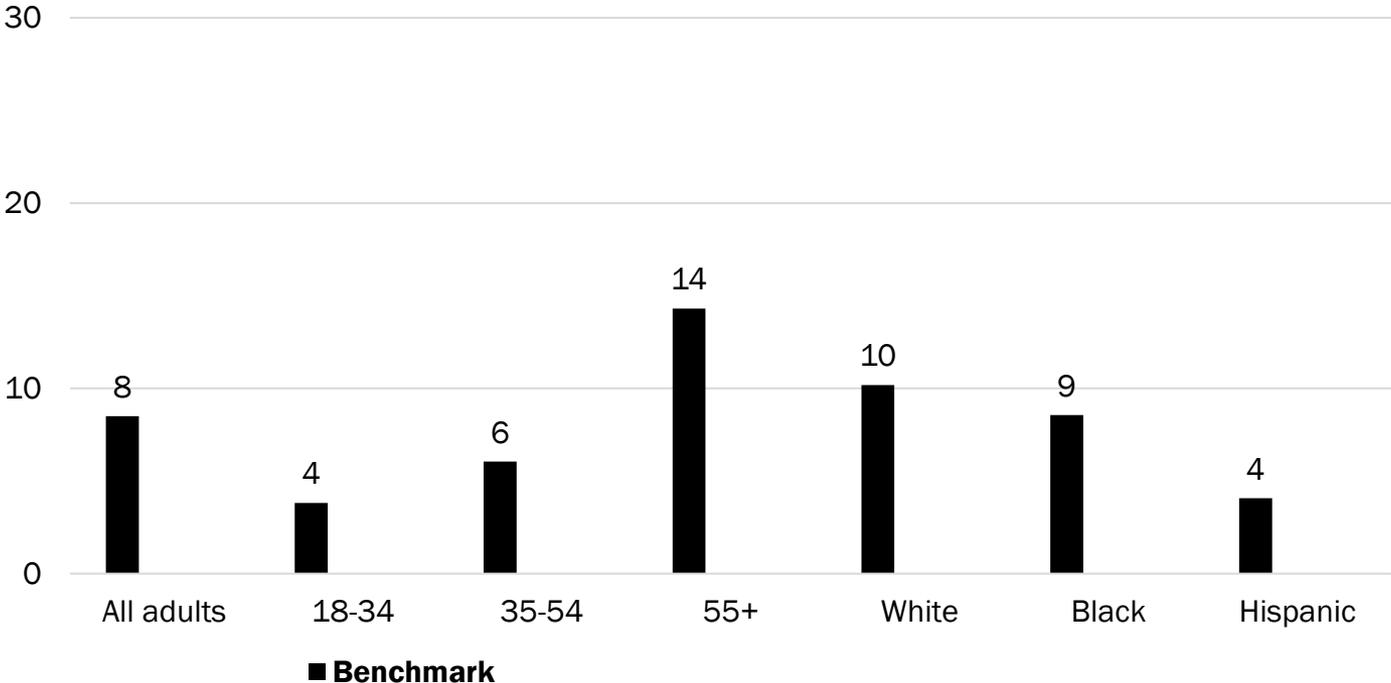
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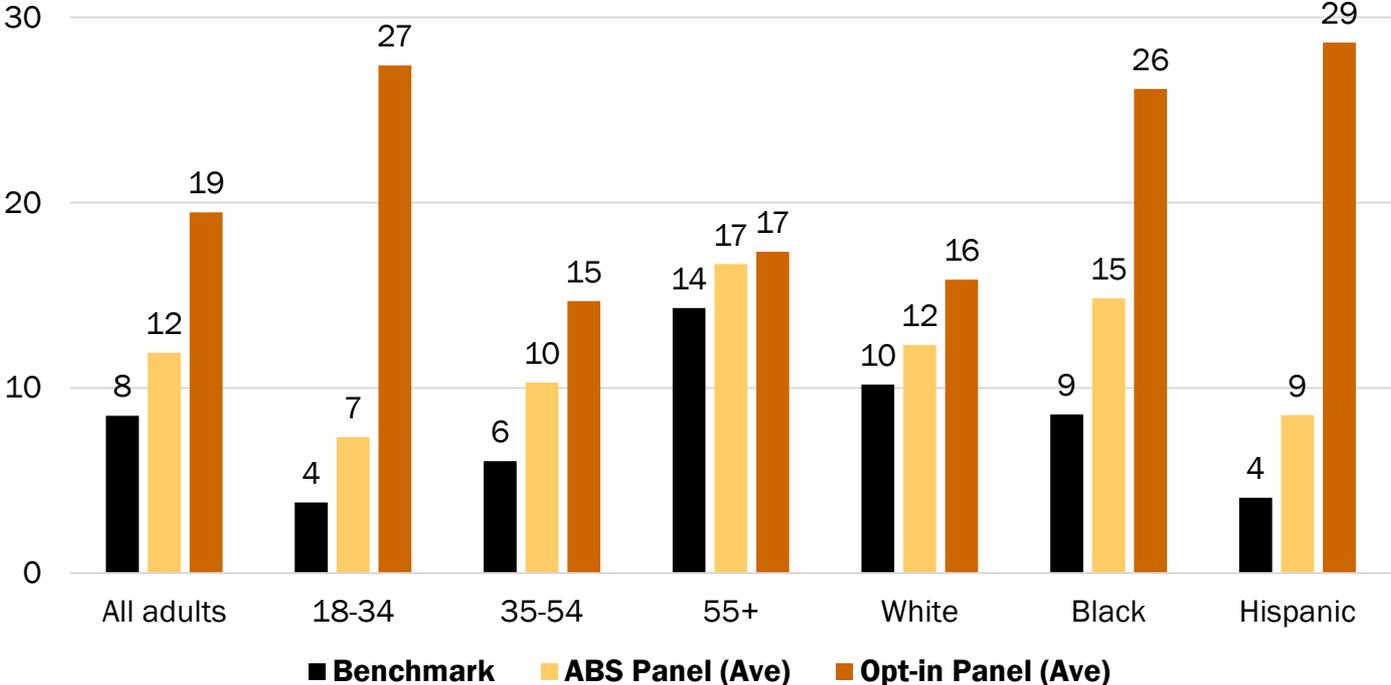
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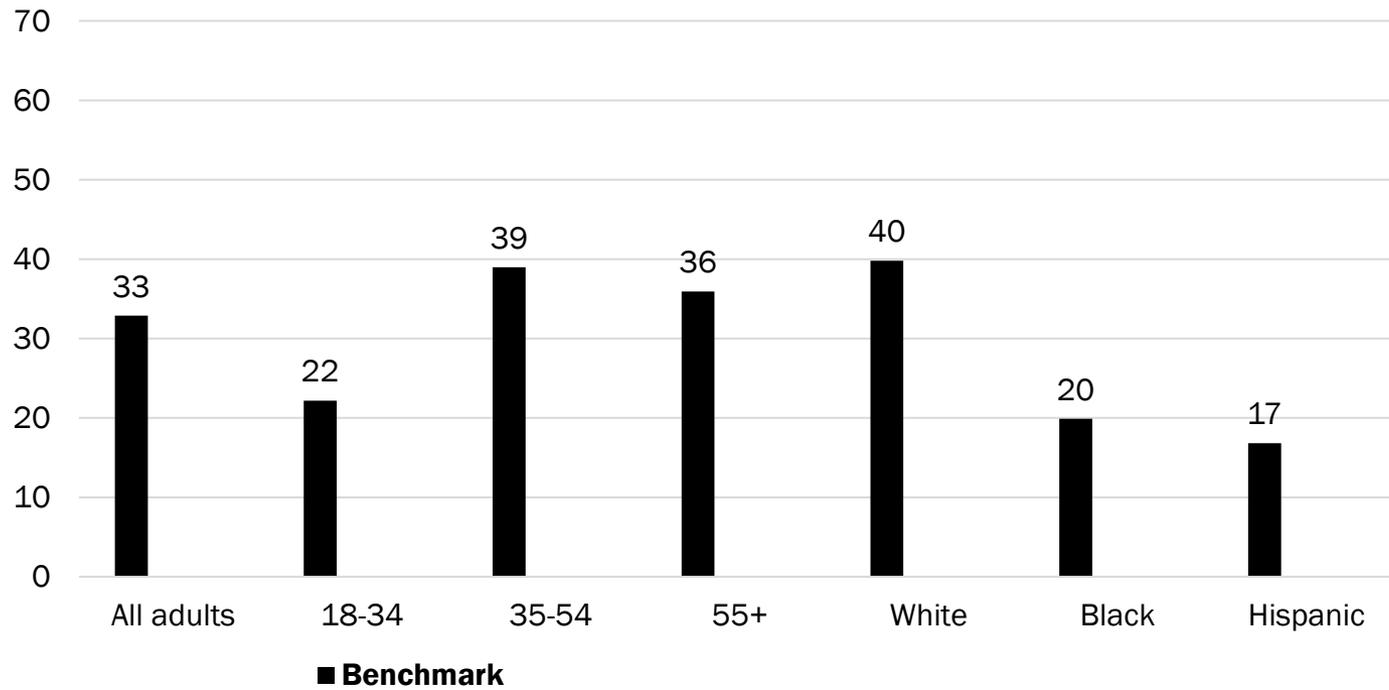
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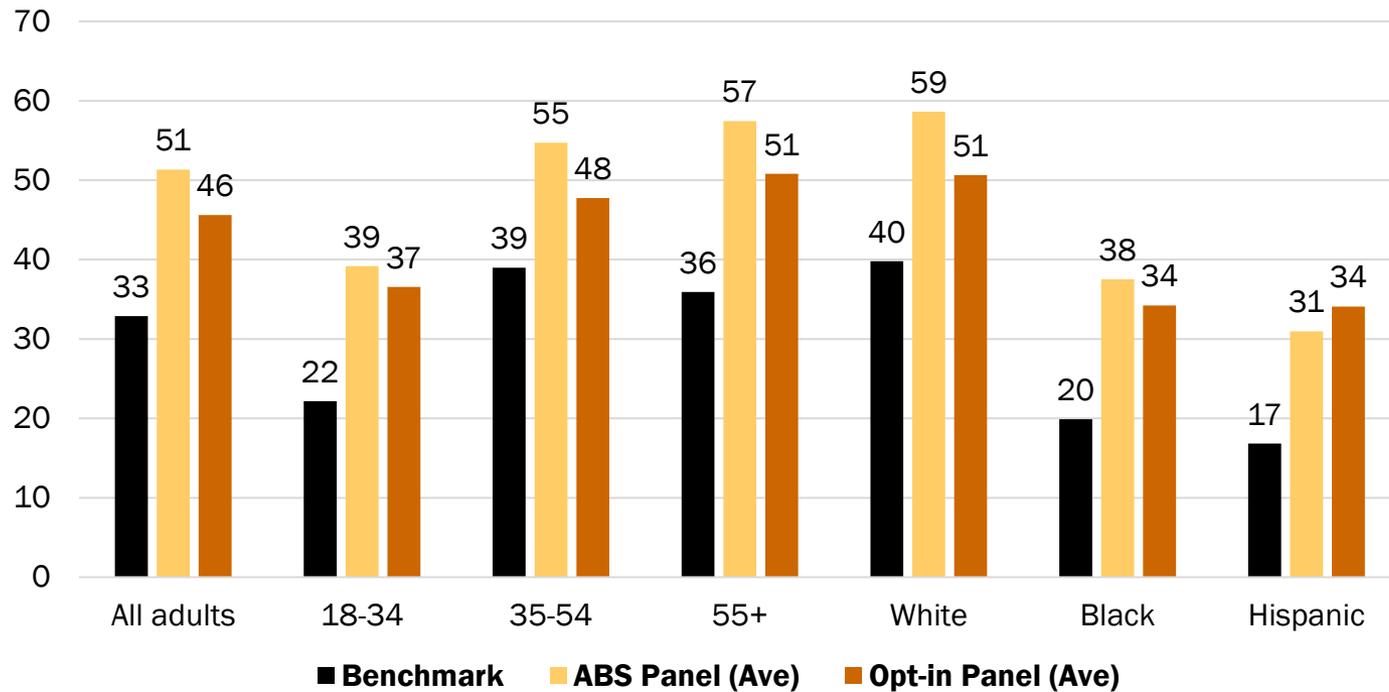
# A counter example

*% of adults who have a retirement savings account*



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**ARE WE SURE THESE HISPANIC OPT-IN CASES ARE  
ACTUALLY HISPANIC?**

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## **Why might a substantial share of Hispanic opt-in cases not actually be Hispanic?**

1. Lying to qualify for more surveys (e.g., Downes-Le Guin et al. 2006)

**Are you of Hispanic, Latino, or Spanish origin, such as Mexican, Puerto Rican or Cuban?**

- Yes
- No

## **Why might a substantial share of Hispanic opt-in cases not actually be Hispanic?**

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2. Positivity bias (e.g., Kennedy et al. 2021)
3. Haphazard responding

**Are you of Hispanic, Latino, or Spanish origin, such as Mexican, Puerto Rican or Cuban?**

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## Testing for bogus cases more directly

- We fielded an opt-in survey using a different vendor
- n=569 completed interviews with U.S. adults
- Included questions to detect clearly bogus data

## Testing for bogus cases more directly

Are you licensed to operate a class SSGN submarine?

- Yes
- No

# Testing for bogus cases more directly

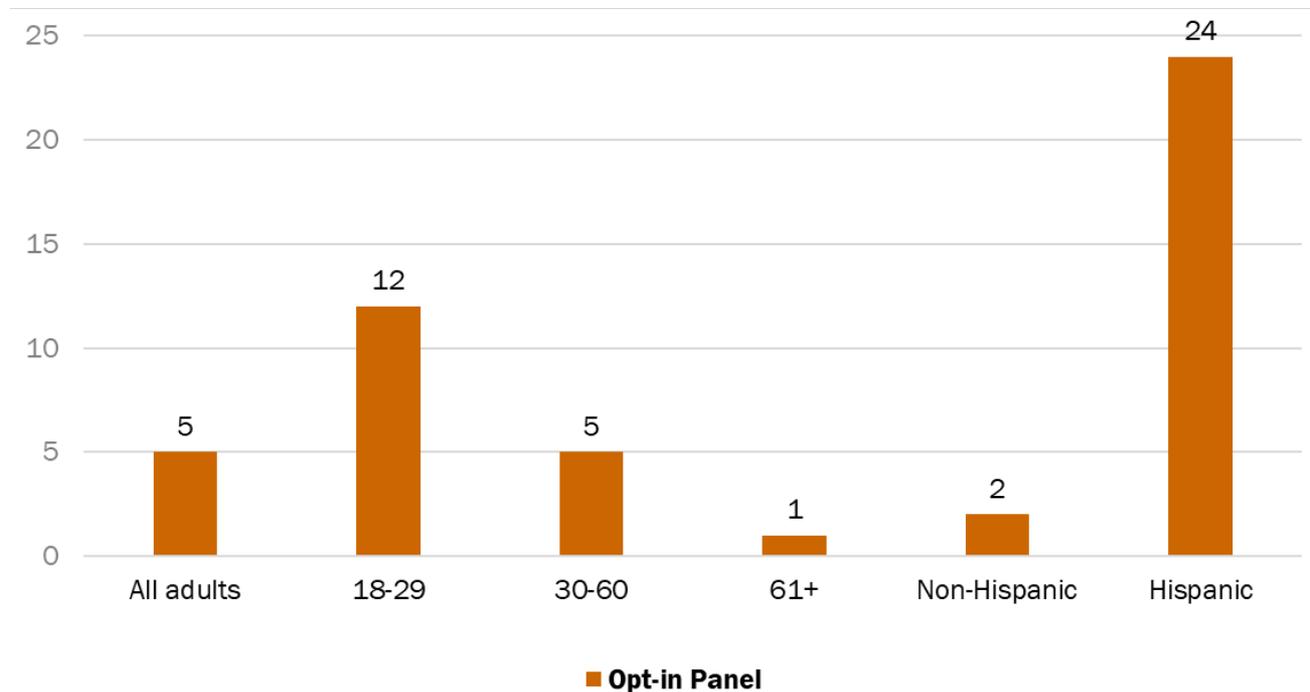
Are you licensed to operate a class SSGN submarine?

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# Testing for bogus cases more directly

*% of respondents saying they are licensed to operate a class SSGN sub*



## Testing for bogus cases more directly

Which of the following did you do in the past week?  
*Check all that apply.*

- Purchased a private jet
- Climbed a peak in the Karakoram Mountains
- Watched TV
- Learned to cook halusky
- Played jai alai
- Read a book
- None of the above

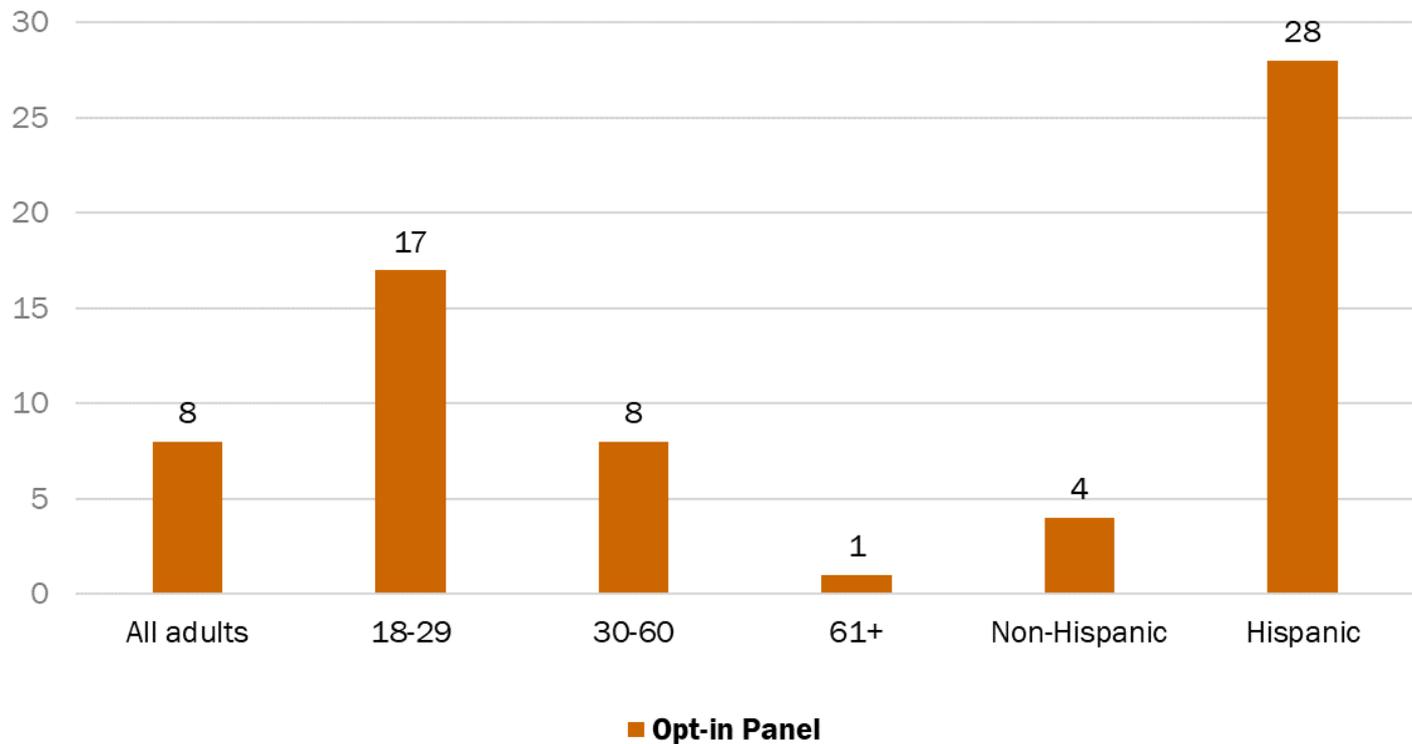
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- Learned to cook halusky
- Played jai alai
- Read a book
- None of the above

## Testing for bogus cases more directly

*% of respondents saying they purchased a jet, climbed a Karakoram mountain, cook halusky, or played jai alai in the past week*



## Conclusions

- Statistical models for nonprobability data tend to assume that respondents are who they say they are.
- But we find evidence invalidating that assumption for a sizable portion of young and/or Hispanic nonprobability cases.
- This leads to erroneous patterns concerning effects from age and ethnicity.
- We do not think that ethnicity or race is a causal mechanism.
- Nonprobability estimates for older adults are much more accurate. We see few bogus respondents in that age group.
- Whether supplementing a probability sample with nonprobability cases increases or decreases MSE may vary by subgroup. More research is needed to test that.

# PewResearchCenter

**Courtney Kennedy**

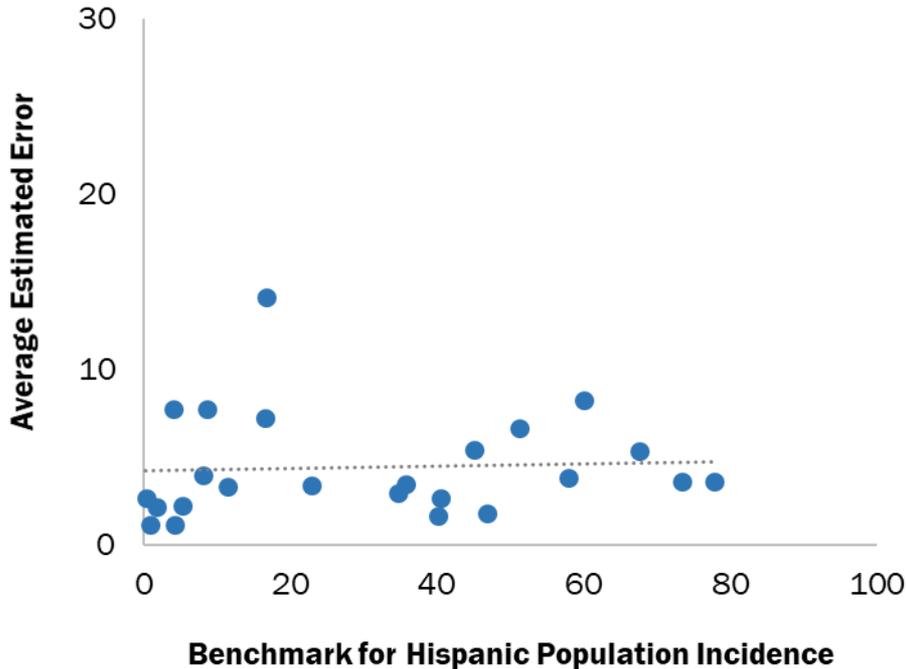
*Director of Survey Research*

**[ckennedy@pewresearch.org](mailto:ckennedy@pewresearch.org)**



# Opt-in estimate errors are particularly high for low-incidence outcomes

**ABS Panel (Ave.)**



**Opt-in Panel (Ave.)**

