Sample Smoothie: Blending Probability-based and Non-probability Samples with Differing Bias

Megan A. Hendrich [1], Randall K. Thomas [2], Ryan Tully [1], & Chris Jackson [1]

[1] Ipsos Public Affairs
[2] AccuSurvey Consulting

CIPHER 2025

Wednesday, 26 February through Friday, 28 February 2025

USC Capital Campus in Washington, D.C.

1771 N St NW | Washington, DC 20036

Study Background

The first online poll in the U.S. occurred over 30 years ago (Maisel et al., 1995). Since then, online samples have increasingly been used for polling.

However, there are questions about the efficacy and accuracy of online samples.

There are two main types of online samples:

- **Opt-in samples: Non-probability convenience or access panels**
- **Probability-based samples: Panels built with random sampling in recruitment**

Generally, online probability-based samples have been found to be more accurate and have lower bias than opt-in samples for national samples of adults (MacInnis et al., 2018; Yeager et al., 2011).

Study Background

The Ipsos KnowledgePanel, established in 1999, is the most well-established online probability-based panel in the U.S. and is one of the largest, with 60,000 active members.

However, there are times when we need to supplement the KnowledgePanel sample with non-probability opt-in sample due to sample size requirements and the finite size of the panel.

This is often true for studies interested in sub-national estimates.

Study Background

However, we often see that opt-in samples can be highly variable in their quality and accuracy.

These sample quality issues can be especially problematic for smaller geographies. We have seen researchers introduce detailed quotas to try to counteract this lower quality, believing that controlling the demographic composition will bring about more accurate results.

Study Purpose

As part of a larger study focusing on political issues and vote choice in the 2022 midterm election in Wisconsin, we fielded three different sample sources in parallel:

- **Address-based sample (ABS) using primarily a mail-back survey**
- **Probability-based online sample from KnowledgePanel (KP)**
- **Opt-in online sample**

While studies like MacInnis et al. (2018) and Yeager et al. (2011) looked at bias by sample type at the national level, we wanted to see if the results were replicated when looking at subnational estimates.

Study Purpose

After establishing the average bias by sample, we wanted to see if blending the samples together could reduce the overall bias.

We examined two types of blending methods:

1. **Pooling the samples without regard to their weighted effective sample size**
2. **Combining the weights based on relative effective sample size**

We first blended the two probability-based samples (ABS + KP) to determine if each could offset the other's bias and improve the collective bias.

Next, we blended in the opt-in sample to see if the average bias would decrease or increase due to the increased sample size.

Methodology

Study Design: Fielding

Sample	Field Period	Completion Mode	Fielded Sample	Completes	Response/ Completion Rate
ABS	09/09/22 to 11/07/22	93% mail, 7% online	6,100	1,610	26.4%
KP	09/30/22 to 11/07/22	Online	1,371	946	69.0%
Opt-in	09/30/22 to 10/26/22	Online	-	1,922	-

Study Design: Fielding

ABS sample: 4 mailings – invitation with mail-back survey, postcard reminder, reminder letter with mail-back survey + online option, and second postcard reminder.

KnowledgePanel sample: Used standard KP fielding procedures.

Opt-in sample:

- **Primarily used Ipsos' iSay panel, a panel of opt-in participants recruited via various methods but where participants have a verified physical address.**
- **Additional sample came from panel-only providers.**
- **We implemented minimum quotas for age, gender, education, and race-ethnicity (minimum quotas do not cap off any specific category but try to ensure minimum numbers in each category).**

Study Design: Benchmarks

Our Wisconsin-specific benchmarks varied widely from low to high prevalence and across a mix of topics.

General Benchmarks	Benchmark
People vaccinated with at least 1 COVID-19 dose	83.7%
Own their own home	75.2%
Born in state of residence	70.8%
Currently married	52.8%
Works full time	50.1%
Valid U.S. passport	42.4%
Valid fishing license	30.5%
At least 1 child under 18 in household	27.6%
Valid hunting license	13.9%
Has a motorcycle	13.2%
Valid concealed carry license	10.6%
Veteran	6.6%

Study Design: Benchmarks

Beyond the more general Wisconsin-specific benchmarks, we also had three politically-related benchmarks. This gave us a total of 15 benchmarks (12 general + 3 politically-related benchmarks).

Politically-related Benchmarks	Benchmark
Currently registered to vote in Wisconsin	81.7%
Vote for Senator for 2022 WI – Republican	30.3%
Vote for Governor for 2022 WI – Republican	28.7%

Study Design: Weighting

For standard demographic weighting, we used the following variables based on demographic values for Wisconsin:

- **Age by gender**
- **Race-ethnicity**
- **Education**
- **Income**
- **Region of state (not available with opt-in sample)**
- **Urbanicity (not available with opt-in sample)**

Study Design: Weighting

The following table shows the variance of the weights, weighting efficiencies, and effective sample sizes used for combining weights (all weights untrimmed):

Weight	N	Min	Max	Mean	Std. Dev.	Efficiency	Effective Sample Size
ABS Demo Wt	1,610	0.173	8.379	1.000	0.882	0.562	905.57
KP Demo Wt	946	0.171	16.770	1.000	1.126	0.441	417.11
Opt-in Demo Wt	1,922	0.269	7.084	1.000	0.754	0.637	1,225.21
ESS Wt: ABS + KP	2,556	0.145	14.289	1.000	0.966	0.517	1,322.68
ESS Wt: ABS + KP + Opt-in	4,478	0.132	12.996	1.000	0.870	0.569	2,547.89

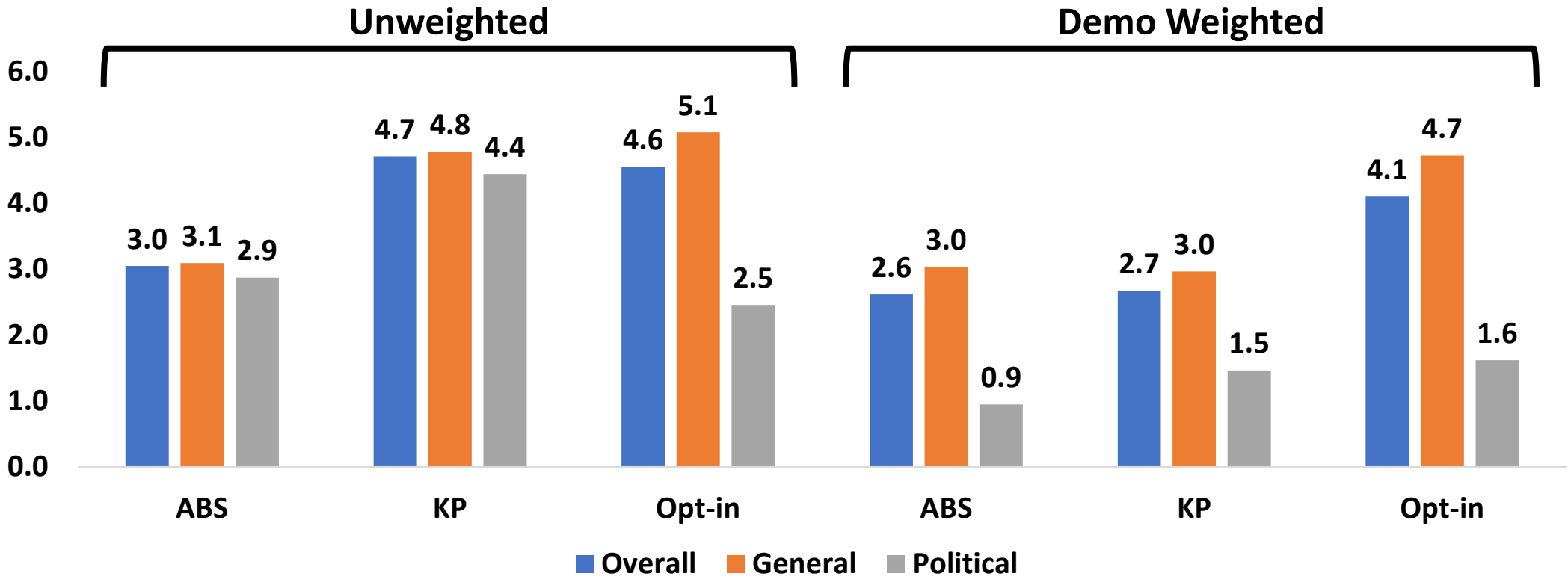
Results

Results: Benchmark Estimates by Sample

Benchmark Items	Benchmark	Unweighted			Demo Weighted		
		ABS	KP	Opt-in	ABS	KP	Opt-in
People vaccinated with at least 1 COVID-19 dose	83.70%	82.17%	82.45%	73.52%	77.42%	76.88%	74.86%
Own their own home	75.20%	77.45%	79.28%	60.09%	73.63%	76.58%	67.20%
Born in state of residence	70.80%	71.12%	72.09%	69.98%	71.60%	74.64%	71.41%
Currently married	52.80%	54.97%	62.58%	44.07%	53.55%	55.25%	49.27%
Works full time	50.10%	43.85%	40.91%	35.12%	56.30%	50.17%	39.31%
Valid U.S. passport	42.40%	49.25%	50.63%	41.16%	49.16%	47.83%	47.44%
Valid fishing license	30.50%	29.50%	25.16%	30.33%	30.04%	26.43%	33.61%
At least 1 child under 18 in household	27.60%	22.98%	23.47%	29.55%	29.97%	29.27%	31.46%
Valid hunting license	13.90%	17.83%	11.10%	14.00%	20.77%	13.96%	15.95%
Has a motorcycle	13.20%	10.50%	8.03%	8.84%	11.64%	7.31%	10.47%
Valid concealed carry license	10.60%	11.12%	12.37%	12.80%	11.62%	13.01%	15.46%
Veteran	6.60%	11.55%	10.89%	7.65%	8.36%	8.08%	9.82%
Currently registered to vote in Wisconsin	81.70%	85.34%	90.17%	84.65%	79.71%	85.22%	85.29%
Vote for Senator for 2022 WI – Republican	30.30%	32.48%	33.09%	28.20%	30.46%	30.73%	30.08%
Vote for Governor for 2022 WI – Republican	28.70%	31.49%	30.76%	26.38%	29.39%	29.14%	27.65%

Results: Absolute Deviations from Benchmarks

For each sample and benchmark, we computed the average absolute difference between the sample and benchmark proportions for unweighted and weighted data. Demo weighting reduced bias for all samples, substantially more so for KP than Opt-in.



Results: Combined Samples

Next, we combined the samples in two ways:

1. **Pooled Weight: Pooled the samples without regard to their weighted effective sample sizes (based on the total sample size)**

2. **ESS Weight: Combined the weights based on their relative effective sample sizes/weighting efficiencies**

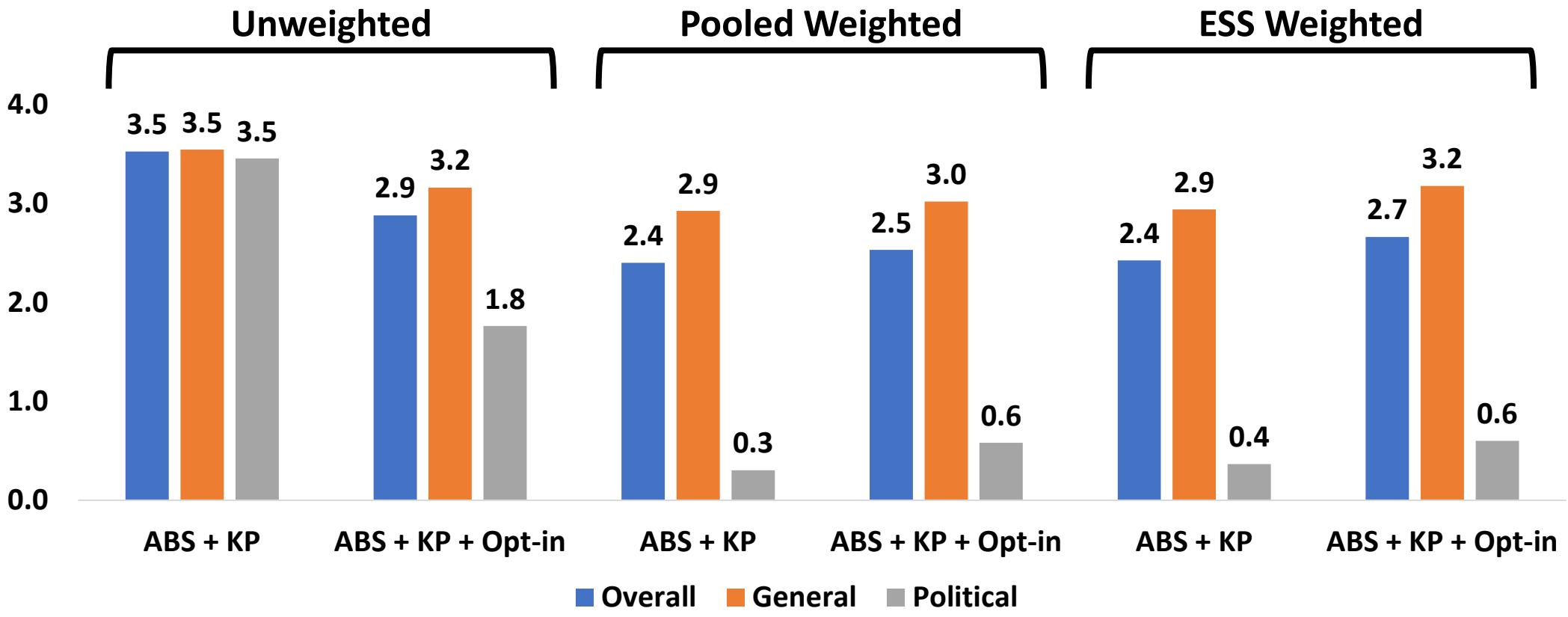
With both combinations, we first blended the two probability-based samples (ABS + KP) and then blended in the opt-in sample (ABS + KP + Opt-in).

Results: Benchmark Estimates by Sample Combination

Benchmark Items	Benchmark	Unweighted		Pooled Weighted		ESS Weighted	
		ABS + KP	ABS + KP + Opt-in	ABS + KP	ABS + KP + Opt-in	ABS + KP	ABS + KP + Opt-in
People vaccinated with at least 1 COVID-19 dose	83.70%	82.28%	78.52%	77.22%	76.21%	77.25%	76.10%
Own their own home	75.20%	78.13%	70.39%	74.72%	71.49%	74.56%	71.02%
Born in state of residence	70.80%	71.48%	70.84%	72.73%	72.16%	72.56%	72.01%
Currently married	52.80%	57.79%	51.90%	54.18%	52.08%	54.09%	51.77%
Works full time	50.10%	42.76%	39.48%	54.03%	47.71%	54.37%	47.13%
Valid U.S. passport	42.40%	49.77%	46.07%	48.67%	48.14%	48.74%	48.12%
Valid fishing license	30.50%	27.90%	28.94%	28.70%	30.81%	28.90%	31.16%
At least 1 child under 18 in household	27.60%	23.16%	25.90%	29.71%	30.46%	29.75%	30.57%
Valid hunting license	13.90%	15.34%	14.76%	18.25%	17.26%	18.62%	17.34%
Has a motorcycle	13.20%	9.59%	9.27%	10.04%	10.22%	10.28%	10.37%
Valid concealed carry license	10.60%	11.58%	12.10%	12.14%	13.56%	12.06%	13.69%
Veteran	6.60%	11.31%	9.74%	8.26%	8.93%	8.27%	9.02%
Currently registered to vote in Wisconsin	81.70%	87.13%	86.07%	81.75%	83.27%	81.45%	83.29%
Vote for Senator for 2022 WI – Republican	30.30%	32.71%	30.77%	30.56%	30.36%	30.54%	30.32%
Vote for Governor for 2022 WI – Republican	28.70%	31.22%	29.14%	29.30%	28.59%	29.31%	28.51%

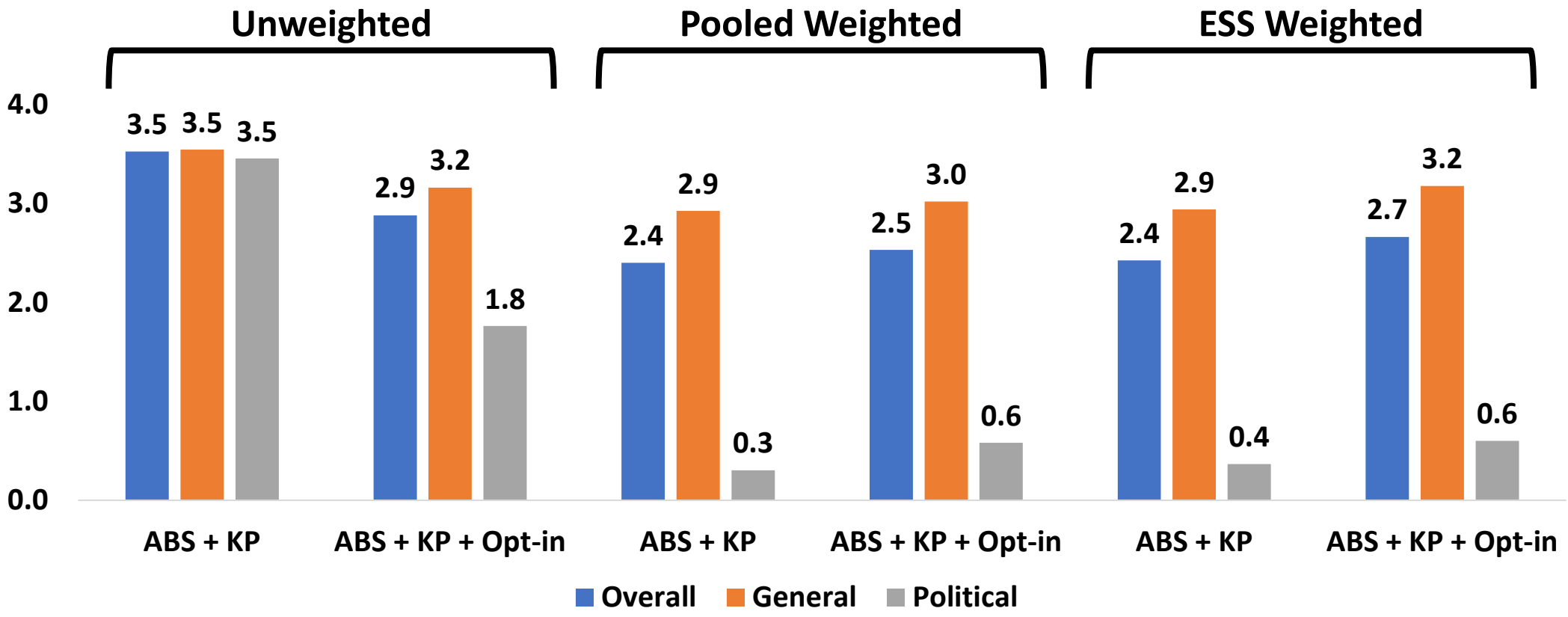
Results: Absolute Deviations from Benchmarks

For each sample combination and benchmark, we again computed the average absolute difference between the sample and benchmark proportions.



Results: Absolute Deviations from Benchmarks

Demo weighting reduced bias for all sample combinations. However, the combination weighting based on relative effective sample size did not have lower bias than the combination based on simple pooling.



Discussion

Discussion and Conclusions

Generally, the probability-based samples had lower bias than the opt-in sample, especially after demographic weighting.

Blending the probability-based samples together did lower bias somewhat (success!).

However, blending in the opt-in sample with the probability-based samples increased overall bias, albeit modestly.

Discussion and Conclusions

In contrast to expectations, the results for the ESS weight actually showed slightly more bias than the Pooled weight.

This points to the importance of three main factors affecting the influence of samples in the ESS method – a more biased sample that has both a larger effective sample size combined with more participants can increase bias in blending (as is often the case with opt-in sample).

These results again demonstrate that there is no empirically supported blending technique that consistently leads to significantly lower bias than other techniques.

Thank you!

Megan Hendrich

Megan.Hendrich@ipsos.com

Ipsos U.S. Public Affairs is a Charter Member of AAPOR's Transparency Initiative