

Federal Committee on  
Statistical Methodology



# Scrubbed Clean: Does Data Cleaning Improve the Quality of Analytic Models?

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# Study Background



Many researchers believe that it is necessary to clean survey data before analysis in order to improve data quality and accuracy. **Sub-optimal response** is believed to be a source of lower quality data due to dishonest, mistaken, inattentive, or approximate responses.

Data cleaning is often based on many sub-optimal behaviors:

- **Speeding through the survey**
- **Grid non-differentiation or straight-lining**
- **Item nonresponse (i.e., skipping items)**
- **Extreme responding on numeric entry**
- **Failure at trap questions (e.g., compliance traps)**
- **Consistency checks**

# Study Background



While there is little research on data cleaning and its effects on measurement bias, what does exist seems to start with the **assumption that data cleaning is necessary** to improve the accuracy of survey results.

However, there are potential disadvantages to data cleaning:

- Takes time
- Has implications for sample costs
- May clean out harder-to-reach respondents more often

# Study Background



**In an initial study using data collected from both probability and non-probability online samples, we used extensive cleaning criteria based on the following:**

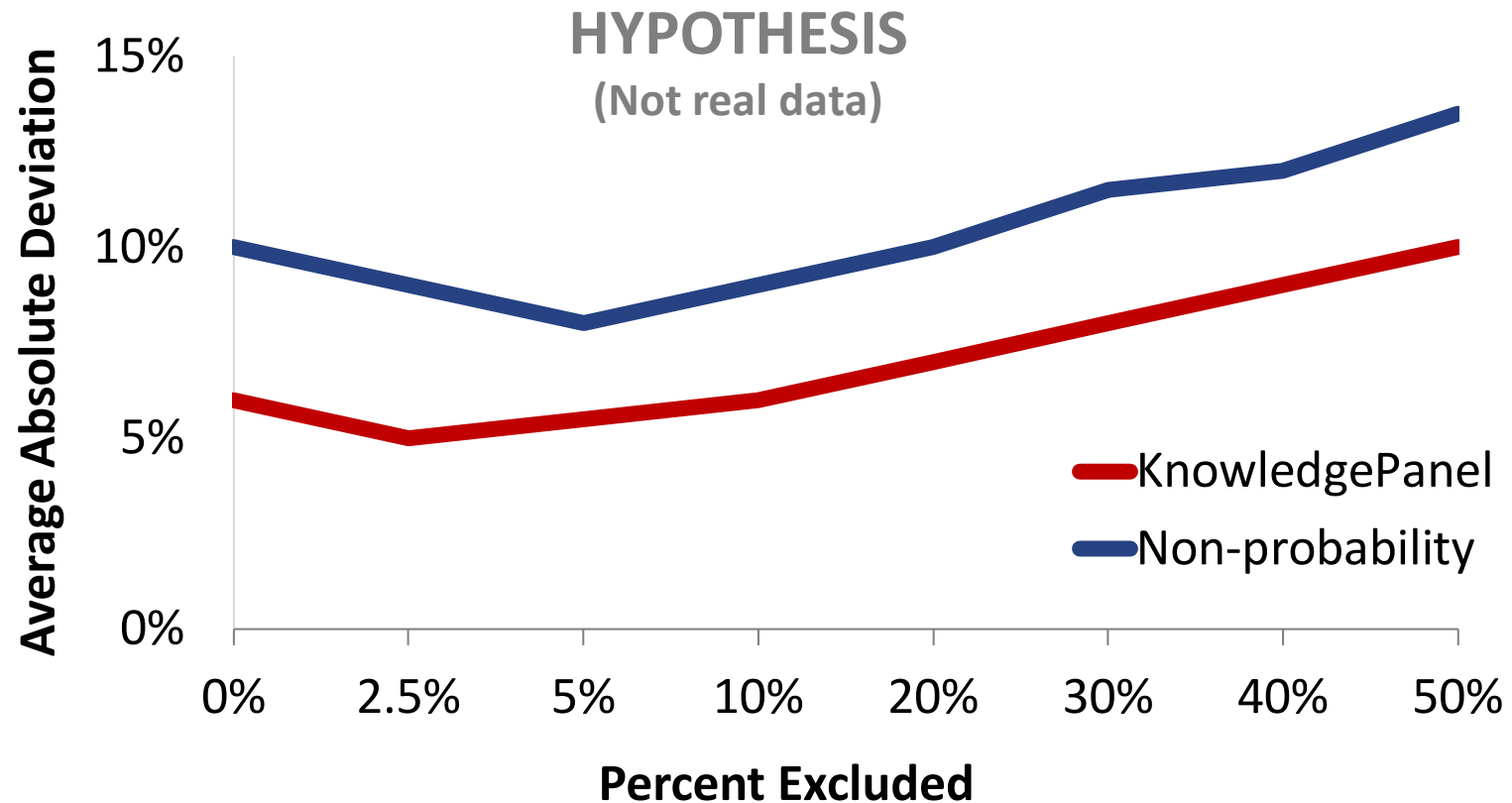
- **Item nonresponse**
- **Completion speed**
- **Grid non-differentiation**
- **Extreme numeric entry**

**Using this cleaning criteria, we deleted cases in gradations from 2.5% up to 50%.**

# Study Background



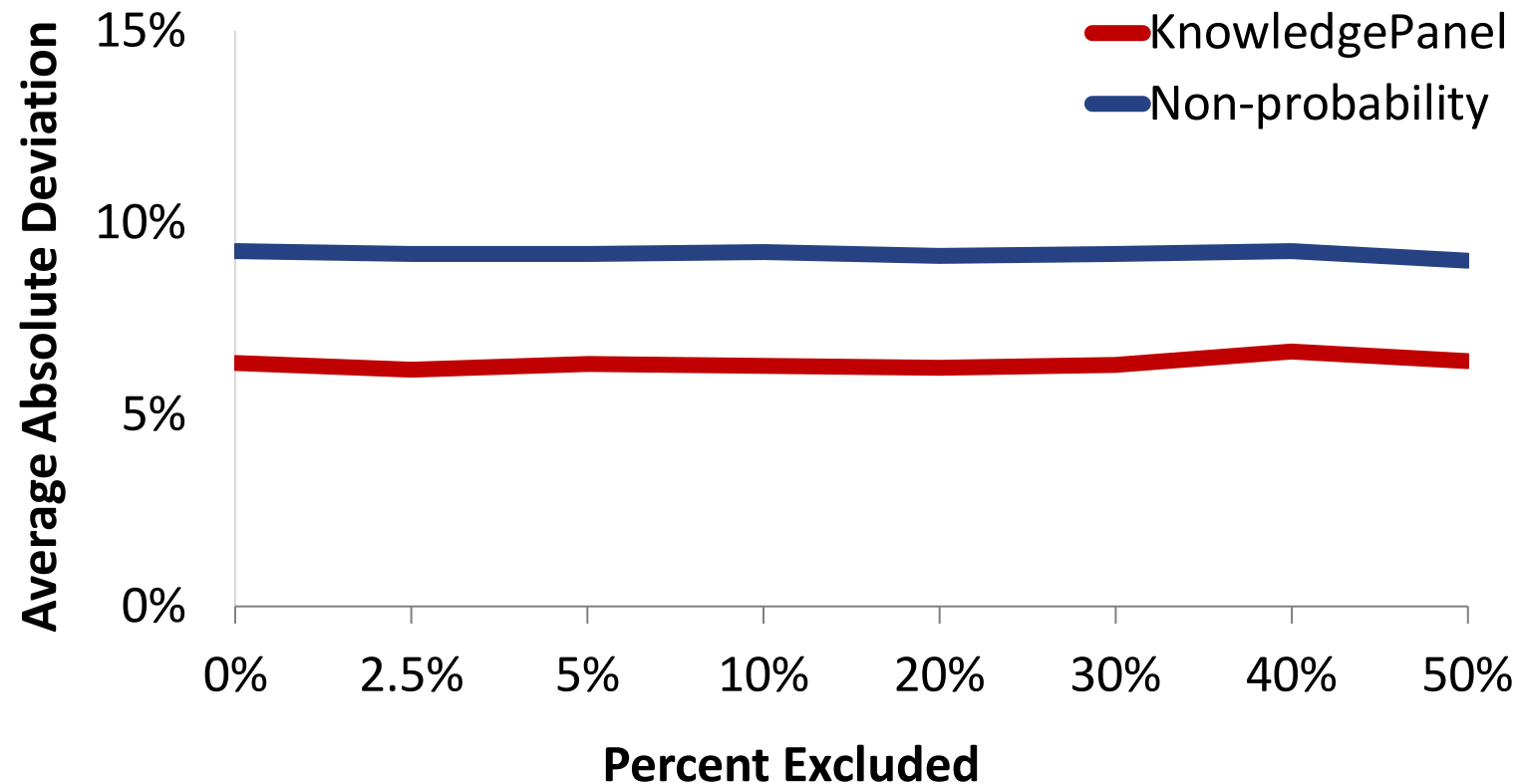
We hypothesized that minimal data cleaning, around 2.5% to 5%, would reduce bias, but extensive cleaning would do more harm than good:



# Study Background



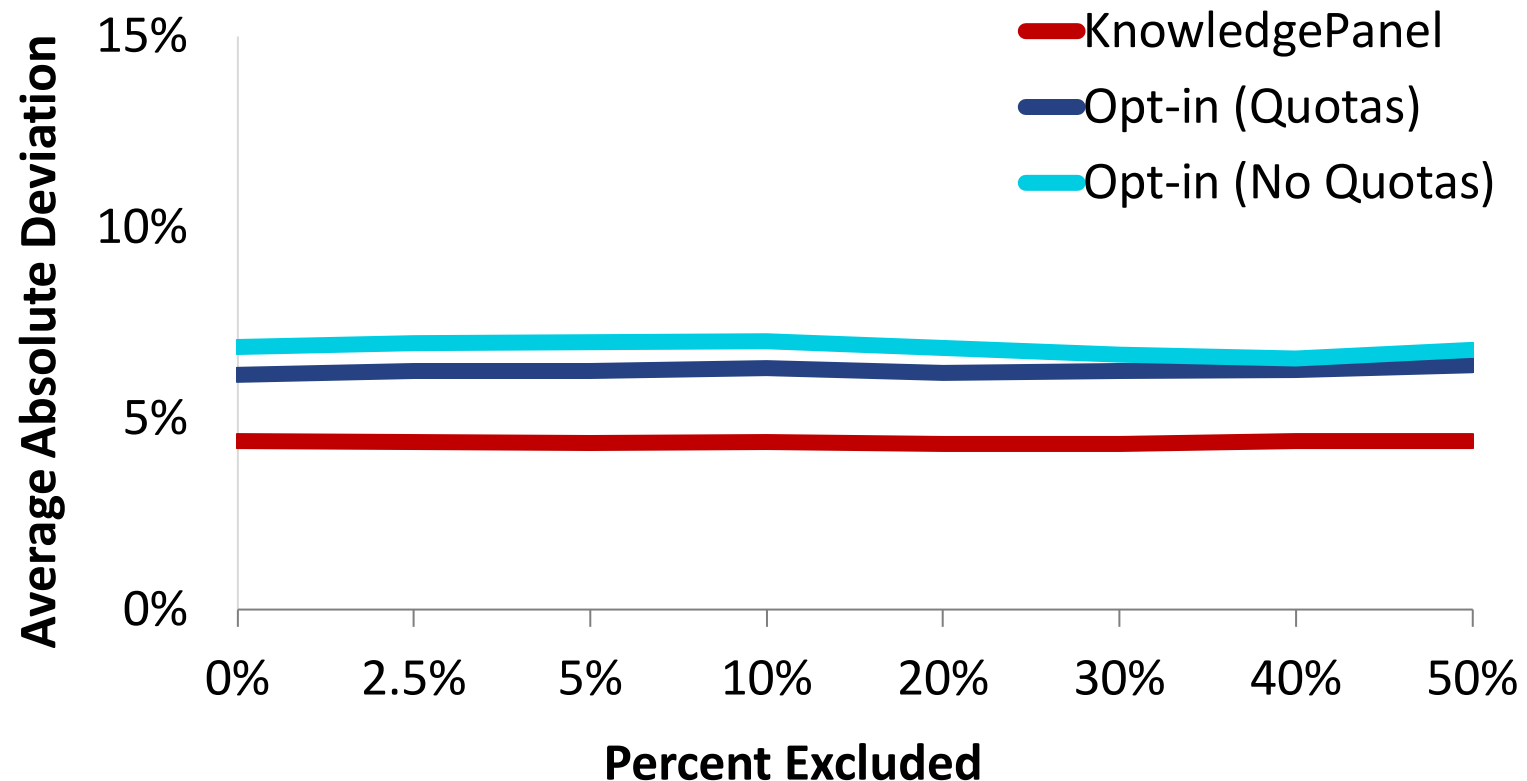
However, we instead found that there was **no effect** on bias for point estimates with increasingly rigorous exclusion criteria:



# Study Background



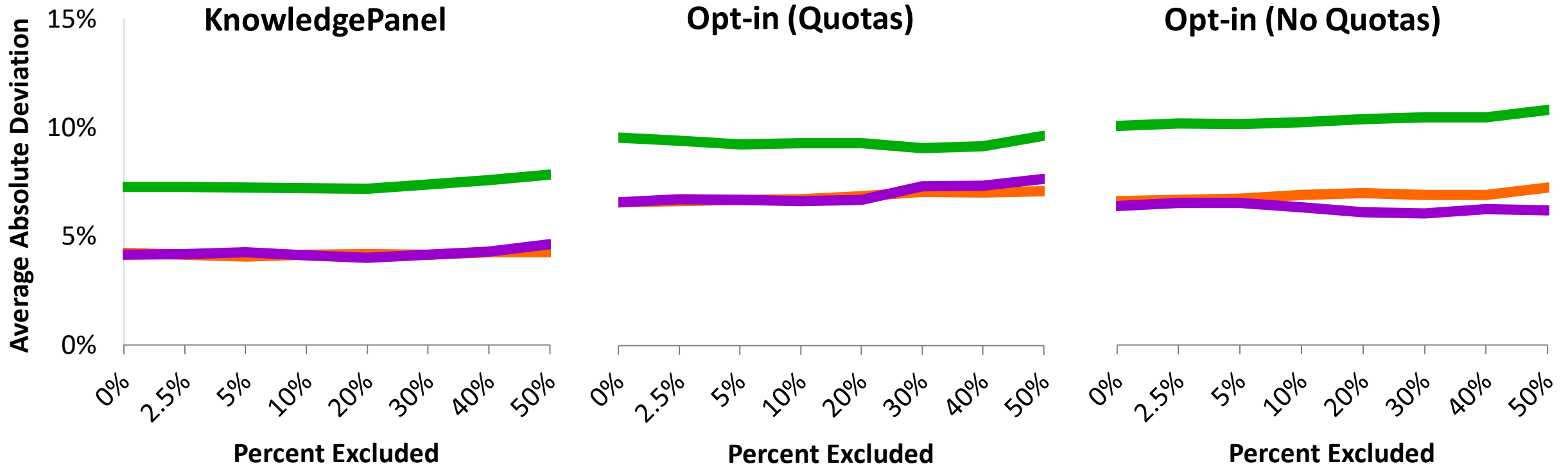
In a follow-up study using only completion speed for cleaning, we again found **no effect** on bias with increasingly rigorous exclusion criteria:



# Study Background



We also found that more data cleaning **did not reduce or increase bias within race/ethnicity subgroups**, though there may be a slight increase in bias with more extreme cleaning:





# Study Purpose

Although no improvement has been found for point estimates (i.e., proportions, means) as a result of data cleaning, we were interested in finding out **if data cleaning could affect covariance**—specifically, correlational analyses using multiple regression.

In the current study, we sought to examine how regression models could be affected by varying degrees of data cleaning.

# Method

**In October 2020, we conducted parallel studies using two online sample sources:**

- **Ipsos KnowledgePanel: N = 3,344**
  - **The most well-documented, probability-based, online panel in the U.S. recruited primarily through address-based sampling**
- **Two non-probability samples:**
  - **Opt-in using quotas for gender by age, race/ethnicity, and education to obtain a demographically balanced sample: N = 2,677**
  - **Opt-in without quotas: N = 3,293**

# Study Design



## Data cleaning method:

- We used **completion speed** as the primary criterion for cleaning.
- We created groups within each sample type that eliminated 0%, then the fastest 2.5%, 5%, 10%, 20%, 30%, 40%, and 50% of each sample.

**We then ran two regression models for each dataset under the varying levels of data exclusion due to speeding.**

# Analytic Design – Model 1



**Model 1** – Dependent variable: Life satisfaction (1=Not satisfied; 5=Completely satisfied); Predictors:

- Positive emotions
- Negative emotions
- Quality of healthcare
- Quality of places to live
- Quality of education
- Quality of jobs available
- Self-rating of health

# Analytic Design – Model 2

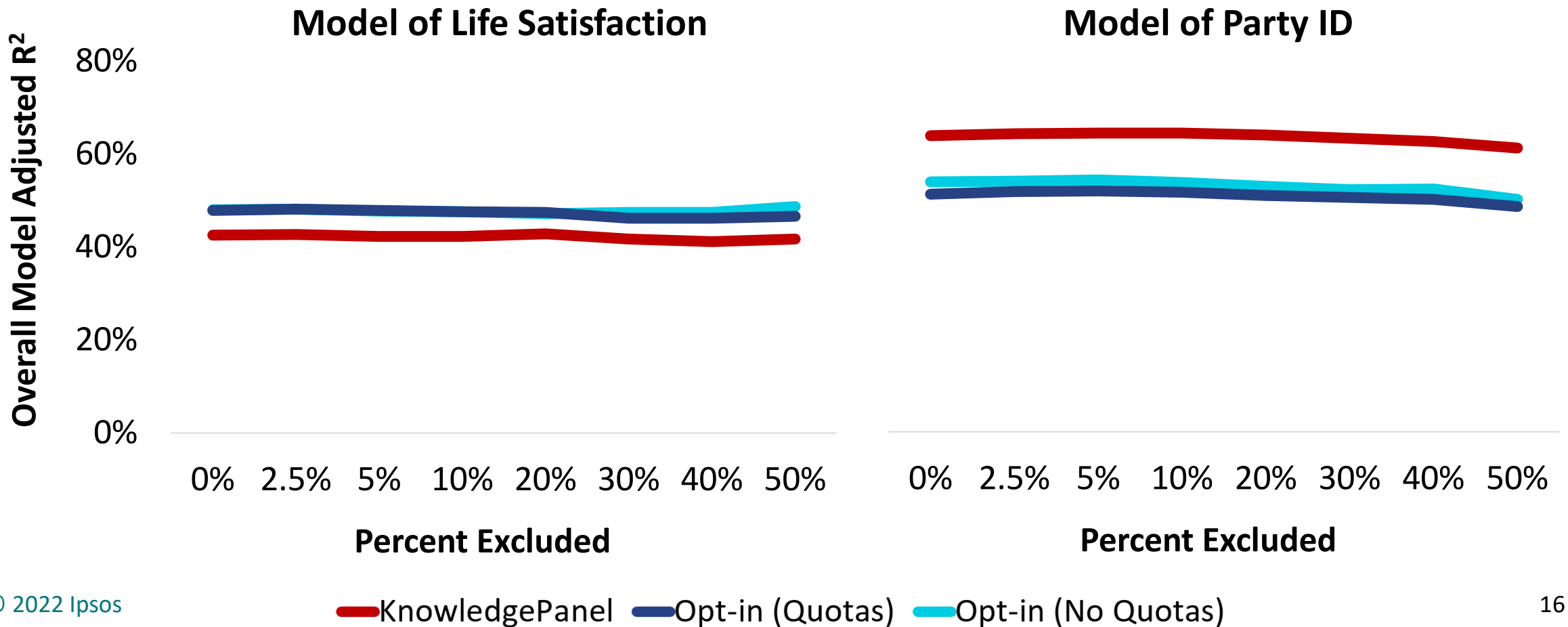
**Model 2** – Dependent variable: Political party identification (1=Strong Republican; 7=Strong Democrat); Predictors:

- **Protect gun ownership**
- **Government should do more for environment**
- **Government spending too much for Black persons**
- **Abortion should be illegal**
- **Government should provide healthcare for all**
- **Government should reduce the wealth gap**
- **Government should increase military spending**
- **Support for Black Lives Matter**
- **Allow illegal immigrants to be citizens**

# Results

# Results – Overall Model Adjusted R<sup>2</sup>

We did not find any differences or improvement in the amount of variance predicted (Adjusted R<sup>2</sup>) as more cases were deleted.



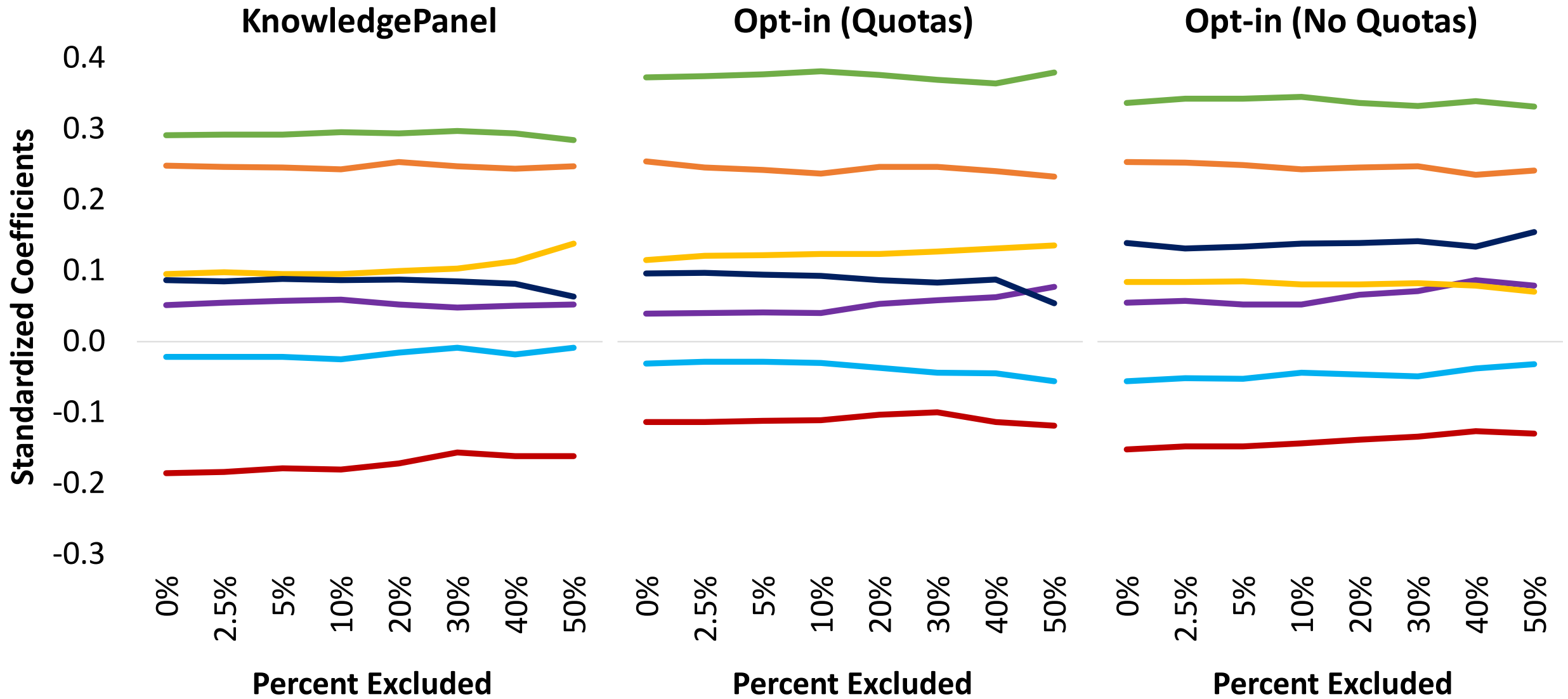


# Results – Beta Coefficients

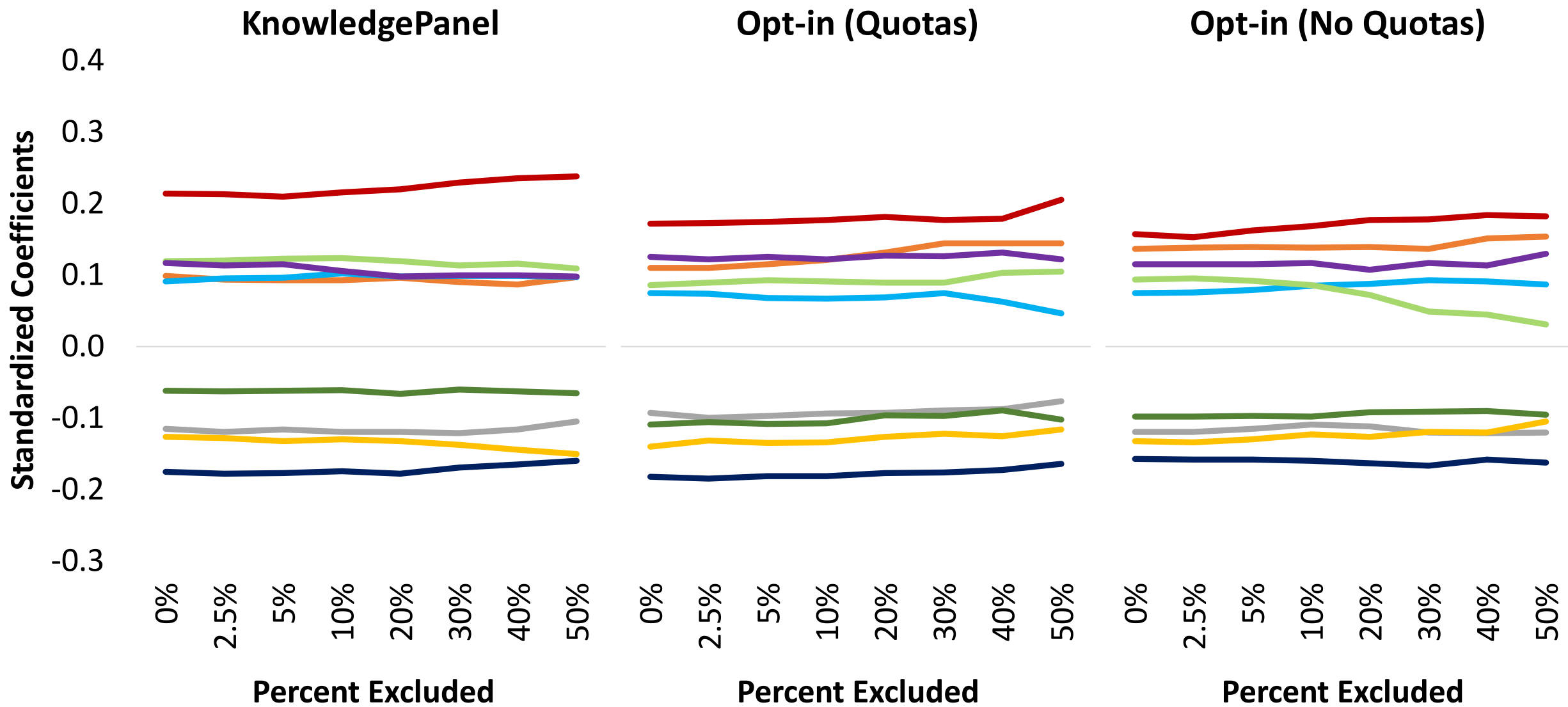
While the overall  $R^2$  may not have changed much with increased data cleaning, it is possible that as more cases are deleted, the predictor coefficients in the form of the betas **could become more unstable** and show divergence with increased cleaning.

However, for both models, **we did not see any systematic changes in betas** as increased cleaning was performed, though some betas became more unstable with extreme levels of data cleaning (around 30% deletion or higher).

# Results – Beta Coefficients (Model 1: Life Satisfaction)



# Results – Beta Coefficients (Model 2: Party ID)



# Discussion

# Conclusions and Discussion

If data cleaning eliminated ‘noise’ in the data from sub-optimal response, we would expect that at least some cleaning would improve the correlations between variables, when correlations existed between the variables. However, **we did not find any evidence to support this.**

Similar to our findings regarding no reduction of bias from standard benchmarks, **we did not find that data cleaning improves model validity** in terms of improving the overall model predictive utility.

# Conclusions and Discussion



Why are correlational models not improved, no matter how many respondents we eliminated?

- The fastest 1-2%, or the most egregious sub-optimal respondents, do provide somewhat different responses than other respondents; however, **eliminating them doesn't change the overall point estimates, variances, or covariances** (especially if the fastest are generally random responses or are similar to other respondents' responses; Thomas, 2014).
- Beyond the fastest 2%, other faster respondents do not significantly differ from slower respondents. Therefore, **cleaning out these faster respondents eliminates people who are just like those who take longer to respond**, leading to little to no change in the estimates (though you do lose statistical power due to loss of respondents and increases in weight variance).

**Thank you!**

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# Appendix: Coefficient Legends



## Model 1: Life Satisfaction

- Positive emotions
- Negative emotions
- Quality of healthcare
- Quality of places to live
- Quality of education
- Quality of jobs available
- Self-rating of health

## Model 2: Party ID

- Protect gun ownership
- Government should do more for environment
- Government spending too much for Black persons
- Abortion should be illegal
- Government should provide healthcare for all
- Government should reduce the wealth gap
- Government should increase military spending
- Support for Black Lives Matter
- Allow illegal immigrants to be citizens