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# Beyond the Breaking Point? Survey Satisficing in Conjoint Experiments

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## Abstract

Recent years have seen a renaissance of conjoint survey designs within social science. To date, however, researchers have lacked guidance on how many attributes they can include within conjoint profiles before survey satisficing leads to unacceptable declines in response quality. This paper addresses that question using pre-registered, two-stage experiments examining choices among hypothetical candidates for U.S. Senate or hotel rooms. In each experiment, we use the first stage to identify attributes which are perceived to be uncorrelated with the attribute of interest, so that their effects are not masked by those of the core attributes. In the second stage, we randomly assign respondents to conjoint designs with varying numbers of those filler attributes. We report the results of these experiments implemented via Amazon's Mechanical Turk and Survey Sampling International. They demonstrate that our core quantities of interest are generally stable, with relatively modest increases in survey satisficing when respondents face large numbers of attributes.

**Key Words:** conjoint analysis, survey experiments, survey satisficing, response bias

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# 1 Introduction

In conjoint survey experiments, respondents are asked to evaluate hypothetical profiles comprised of multiple attributes. Such designs allow researchers to evaluate trade-offs, and so have been used to understand decision-making in fields including marketing (Green & Rao 1971), economics (Adamowicz et al. 1998), and sociology (Jasso & Rossi 1977). In recent years, the increasing use of computers to administer surveys has helped fuel an increase in conjoint experiments, especially in political science (Hainmueller et al. 2014).<sup>1</sup>

Despite this newfound interest, researchers have paid little attention to questions about how to optimally design conjoint surveys given well-known challenges in survey research. According to studies on survey-taking, tasks that involve high levels of cognitive effort are more likely to induce respondents to satisfice, meaning that they adapt by using cognitive shortcuts (Krosnick 1999). Survey satisficing manifests itself in various behaviors that diminish response quality: satisficing respondents are more likely to rush through surveys, ignore or skip instructions, choose response options based on their placement, and use other effort-saving heuristics (Berinsky et al. 2014). Conjoint experiments often present respondents with extensive information, making concerns about satisficing particularly acute.

Here, we draw on research on survey methodology to investigate a key question in designing conjoint experiments: how many attributes can researchers include in a given profile before survey satisficing degrades response quality? Specifically, we conduct a series of survey experiments to investigate the degree of satisficing when respondents are faced with varying numbers of attributes. Due to what we term the *masking-satisficing trade-off*, researchers cannot always minimize satisficing without potential side-effects. In typical applications of conjoint analysis, researchers are interested in estimands that represent effects of attributes on conjoint responses, such as the Average Marginal Component Effect (AMCE) (Hainmueller et al. 2014). Interpreting such estimands requires care because of their dependence on the entire set of attributes included in the experiment. For respondents, perceptions of one attribute are often linked to perceptions of others. Without information on the full set of relevant attributes, estimates of an AMCE of

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<sup>1</sup>See especially Franchino & Zucchini (2014), Abrajano et al. (2015), Carnes & Lupu (2015), Hainmueller & Hopkins (2015), Horiuchi et al. (2018), Bansak et al. (2016), Bechtel et al. (2016), Mummolo & Nall (2016), Wright et al. (2016).

interest may be *masking* the effects of other, correlated attributes (see also Dafoe et al. 2018).

Because of concerns about masking and satisficing, researchers often face a binding trade-off when designing conjoint experiments. If they include too few attributes, their quantities of interest could mask the effects of other, omitted attributes. In that case, there is a likely gap between the quantity of theoretical interest and the quantity researchers can estimate. But if researchers include too many attributes, they may encourage survey respondents to develop time-saving shortcuts that reduce the thoughtfulness of their responses. That, too, may lead the empirically observable quantities to diverge from those of theoretical interest.

The relationship between masking and satisficing poses an empirical challenge as well. How can we identify the change in satisficing across the varying number of attributes while holding the degree of masking—and thus the underlying causal quantities estimated from the experiments—constant? If we were to randomly assign respondents to different numbers of meaningful attributes, we would risk conflating the effects of masking and satisficing, as any change in response patterns could be a product of the number of attributes or the changed information provided by the additional attributes. To overcome this challenge, we develop a novel, two-stage research design which enables us to isolate the effect of survey satisficing empirically, and we deploy our pre-registered design in two substantive domains. Specifically, we consider how American survey respondents—recruited via Amazon’s Mechanical Turk (MT) or Survey Sampling International (SSI)—choose between hypothetical candidates for the U.S. Senate (Study 1) and hotel stay packages (Study 2).

In the studies’ first stages, we identify attributes which are unassociated with the core attributes of interest by asking respondents to guess those attributes’ values conditional on the core attribute values. For example, partisan affiliation is a core attribute of interest in study 1. Accordingly, we first provide respondents with basic information about hypothetical candidates’ party affiliation and other attributes of interest and then ask them to guess about several additional attributes, such as the name of the candidate’s elementary school. By doing so, we can identify “filler attributes” about which the core attributes provide no information—either for the full sample or for various subsamples—and thus whose effects are unlikely to be masked by the effects of the core attributes. In the second stage, we then randomly assign survey respondents to varying numbers of filler attributes. By design, the core attributes of interest are not predictive of these filler attributes, meaning that changes in the core attributes’ effects are primarily due to the increased

cognitive burden from the filler attributes.

Overall, our results demonstrate the robustness of conjoint experiments even for a large number of attributes, and so prove encouraging for their future use. There is a detectable but modest decline in overall predictive power as the number of filler attributes increases, one that is slightly more pronounced for SSI respondents. Even with as many as 35 filler attributes, respondents recruited through MT and SSI provide meaningful responses, making steady use of core attributes such as the candidate’s policy positions and views from the hotel room.

With these populations at least, conjoint designs are surprisingly robust to the inclusion of many filler attributes. With respect to the number of attributes, the “breaking points” of conjoint survey experiments appear to be outside the range of current practice. Beyond conjoint designs specifically, these results also speak to questions about the use of opt-in samples in survey research as well as effort and attention in survey-taking generally (Yeager et al. 2011, Berinsky et al. 2012, Mullinix et al. 2016), points to which we return in the conclusion.

## 2 Task Difficulty and the Masking-Satisficing Trade-off

Although conjoint experiments are a variant of survey research, researchers have yet to incorporate insights from research on survey methodology (e.g. Sudman et al. 1996, Krosnick 1999, Groves et al. 2011) when considering optimal conjoint designs. In this section, we explain the masking-satisficing trade-off before developing expectations about how respondents are likely to approach conjoint experiments given prior research on survey design.

The trade-off between masking and task difficulty presents a key challenge. An important strength of conjoint designs is their capacity to include a variety of attributes simultaneously so as to examine their relative importance. Including many attributes can also help to limit the potential problem of masking (Hainmueller et al. 2014). The more attributes one includes within a conjoint task, the less likely it is that responses to the attribute(s) of interest will be partially driven by their perceived correlation with other, excluded attributes. Yet by including large numbers of attributes, researchers also increase the difficulty of the task, and thus risk inducing survey satisficing (Krosnick 1999). Our discussion below highlights this important but under-scrutinized dilemma.

## 2.1 Masking

Masking can occur if people’s perceptions of an attribute of interest are correlated with their perceptions about other attributes that are not included in the conjoint. For example, imagine that a researcher is interested in the role of partisanship in explaining vote choice, and she employs a fully randomized conjoint design that includes the party of the candidate as one attribute in the conjoint table. Given the assumptions detailed in Hainmueller et al. (2014), she can recover a valid causal estimate for the AMCE of party. Yet this AMCE is defined with respect to the other attributes that appeared alongside partisanship, and so can change as those attributes do (Hainmueller et al. 2014). For example, if voters use partisanship partly as a proxy for issue positions, the AMCE for partisanship is likely to be smaller when the conjoint tables include extensive information about candidates’ issue positions.

More generally, masking occurs when respondents perceive a correlation between an included attribute A and an excluded but influential attribute B. When B is excluded respondents may use A as a proxy for B, but if B is included they might instead decide using B and render A irrelevant. As a result, the AMCEs of A differ between designs where B is excluded or included.<sup>2</sup> It is important to recognize that masking is distinct from omitted variable bias in that an estimate of an effect might be masking another while remaining a valid causal estimate. In the presence of masking, it is not that the researcher is getting an incorrect answer so much as she is asking a different question. If B is omitted, researchers get a valid estimate of the AMCE of A defined as the causal effect of A conditional on the design excluding B. If B is included, researchers still recover a valid estimate A’s AMCE, but that AMCE has a different meaning because it is now defined as the causal effect of A conditional on the design including B. This variability in the AMCEs stems from the conditional nature of these causal effects: the AMCEs are, by definition, functions of the whole set of attributes included in the design as well as their joint assignment distribution (Hainmueller et al. 2014). In Appendix A.1.1 we provide a formal definition of masking.

## 2.2 The Masking-Satisficing Trade-off

Researchers using conjoint therefore have to decide on what AMCEs they are interested in and choose the other included attributes accordingly. Now assume a set-up where a researcher has

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<sup>2</sup>See also Dafoe et al. (2018) for an alternative formulation of a related phenomenon.

one or multiple core attributes that they care about and the goal is to isolate the effects of these core attributes from effects of other attributes that are potentially perceived to be associated with the core attributes. In this set-up the researcher has an incentive to include a large number of potentially associated attributes in the conjoint table to limit the possibility of masking.

To fix ideas, Figure 1 illustrates a sample conjoint task from Study 1. In it, respondents choose between two hypothetical Senate candidates. Imagine the researcher is interested to isolate the effect of party from other attributes that are perceived to be correlated with party. If voters place considerable weight on candidates' gay marriage stances, they may use partisanship to approximate those stances when they are absent. Accordingly, researchers can reduce masking by providing information about candidates' issue positions. More generally, if the researcher's goal were simply to reduce masking without other constraints, she would provide full information to respondents, and so recover the precise effect of interest. In general, we should expect masking to decline as the number of attributes rises, with the extent of the decline depending on the perceived correlations among attributes.

However, as more attributes are added to the conjoint table, the task becomes more difficult for respondents. People can only hold so much information in working memory, and the upper bound is thought to be around nine pieces of information (Miller 1994). To ask respondents to process twenty pieces of information per candidate is likely to encourage them to adopt effort-saving cognitive strategies that ignore some of the information and so degrade response quality (Krosnick 1991, Mutz 2011). In other words, Including too many attributes may induce excessive survey satisficing, and so compromise the quality of survey responses. Note that excessive survey satisficing can also change the estimated AMCEs. For example, we would expect the AMCE estimates to be biased towards zero if survey satisficing means that some respondents no longer pay attention to the attribute values. For a more formal discussion, see Appendix A.1.2.

This fundamental tension is what we term the masking-satisficing trade-off: The goal to reduce masking pulls researchers to including many attributes in the conjoint, while the goal to reduce survey satisficing pulls researchers to including only a minimal number of attributes in the conjoint. But despite the importance of the masking-satisficing trade-off for the design of conjoint experiments, we know very little about just how severe this tradeoff is empirically. In particular, we do not know whether this trade-off is binding given the number of attributes researchers

commonly employ. One reason for this is that it is difficult to examine the tradeoff empirically because we need to have a design that allows us to distinguish changes in the AMCEs that results from satisficing, rather than masking. Below, we present a research design which enables us to assess these trade-offs empirically.

Figure 1: An example table from a typical conjoint experiment.

Please carefully read the descriptions of the two candidates for U.S. Senator below. (1/15)

	CANDIDATE A	CANDIDATE B
Age	42	54
First Election Eligible to Vote in	Governor	Congress
Color of Childhood Family Car	White	Red
Position on Same-Sex Marriage	Favors Same-Sex Marriage	Favors Same-Sex Marriage
Position on Health Care	Government Should Do Less	Government Should Do More
Usual Day for Grocery Shopping	Monday	Tuesday
Favorite Composer	Mozart	Mozart
Party Affiliation	Democrat	Democrat

### 3 Study Design

Here, we use a novel, two-stage study design to investigate how many attributes one can include in conjoint profiles without making respondents’ evaluations overly prone to satisficing. A major challenge in doing so is the difficulty of distinguishing satisficing from other changes due to the increased number of attributes. Indeed, the same problem that motivates our question—the potential trade-off between masking and satisficing—also presents a problem to straightforward research designs which might address it. Imagine that we are interested in the effect of candidates’ party alignments on support for those candidates. We might develop a list of attributes that are likely to influence candidate choice and then randomly assign respondents to conjoint tasks with varying numbers of attributes. Yet in such a design, respondents in different experimental



conditions will differ in multiple ways: they see different numbers of attributes *and* have different types of information. As a result, if the attribute of interest has perceived correlation with the marginal attribute, the AMCE could change due to masking rather than satisficing.

To isolate the effect of satisficing, we employ a two-stage research design. The goal of the first stage is to identify attributes whose effects are known to not be masked by those of the attributes of interest. Those “filler attributes” are then used in our second stage to identify the change in the explanatory power of the main attributes as the overall number of attributes increases.

### 3.1 The First Stage: Validating Filler Attributes

The study design begins by choosing a set of “core” attributes of interest whose effects on respondent preferences will be measured. In both studies, we designate four core attributes. As described above, we investigate the extent to which adding “filler” attributes to the conjoint design leads to satisficing and so changes the effects of the core attributes. To ensure that such a change is the result of satisficing rather than masking, the study’s first stage identifies filler attributes that have no perceived correlation with the core attributes.

Specifically, the first stage entails a survey experiment in which we ask respondents to guess about prospective filler attributes based on the core attributes’ levels. If respondents are unable to guess the values of a filler attribute based on the core attribute values, that indicates that they do not perceive a meaningful association between the attributes. Since masking occurs because of the perceived association between the attribute of interest and the omitted attribute, the filler attributes that respondents do not perceive to be associated with any of the core attributes are unlikely to cause masking and therefore suitable for use in our second stage, in which we vary the number of filler attributes. In Appendix A.1.3, we formalize the conditions under which no masking would occur and discuss how our study design relates to those conditions.<sup>3</sup>

The first-stage experiment proceeds as follows. We first present respondents with tasks like that pictured in Figure 2. In each task, we present respondents with a profile comprised of randomly selected values for the four core attributes. The order of the attributes is also randomized and

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<sup>3</sup>The effect of a core attribute A masks the effect of an omitted attribute B if (1) B is perceived to be associated with A and (2) B has a non-zero effect on the conjoint response when included in the task along with A. Here, we focus on attributes that do not satisfy the first condition, which is easier to test empirically. Most of our selected filler attributes in Study 1, however, turn out to be also likely to violate the second condition; the selected filler attributes in Study 2 violate the first but do satisfy the second condition. See Appendix A.1.3 for a more formal discussion.

Figure 2: An example task from Study 1, first stage. Respondents are asked to guess at the value of a potential filler attribute given the values of four attributes of interest.

ATTRIBUTE	CANDIDATE 1
Position on Same-Sex Marriage	Favors same-sex marriage
Party Affiliation	Democrat
Position on Health Care	Government should do more
Age	42

If you had to guess, who would you say this candidate's famous relative is?

☐ Chester Arthur  
☐ Franklin Pierce  
☐ Zachary Taylor  
☐ John Tyler

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then fixed for each respondent. Given the attribute values in the profile, respondents are asked to guess the values of other, unobserved attributes. In some cases, respondents might perceive the unobserved attributes as correlated with the observed attributes: respondents who saw a Democratic candidate might be more likely to guess that the candidate was a high school teacher than a business owner. But in other cases, there is little reason to expect a correlation, and the guesses should be unrelated to the profile attributes. For instance, whether a hypothetical candidate supports or opposes same-sex marriage tells respondents nothing about which 19th-century president is her relative. If there is no perceived association, the potentially irrelevant attribute cannot be masked by the attribute of interest. For a given, randomly generated profile, each respondent goes through all of the filler attributes in this manner in a randomized order. The task is repeated several times for each respondent, with a new set of core attribute levels in each task.

To evaluate the perceived association between each filler attribute and the core attributes—i.e.

to assess whether the core attributes were predictive of respondents’ expectations regarding the filler attributes—we employed a set of linear regressions. Specifically, each filler attribute was subjected to all possible dichotomizations given its number of levels. For a two-level attribute, only one dichotomization is possible, while for three- and four-level attributes, three and seven dichotomizations are possible, respectively. For each dichotomization, the dichotomized filler attribute was regressed on indicators for all four core attributes, resulting in a set of difference-in-means estimates.<sup>4</sup> Given the binary dependent variable specification, each difference-in-means estimate corresponds to a change in probability. For each filler attribute, we then evaluated the full set of difference-in-means estimates for all filler attribute dichotomizations and all core attribute indicator variables. Finally, we classified the attribute as “uncorrelated” if none of the difference-in-means estimates for that attribute exceeded the threshold of seven percentage points.<sup>5</sup> Although this threshold is somewhat arbitrary, it does not undermine the statistical validity of second-stage results since no data from the second stage was available when making those decisions.<sup>6</sup>

We note that these tests focus on whether the core attributes are correlated with the expected filler attributes on average. In Appendix A.6, we also conduct further (non-prespecified) tests to examine the potential for heterogeneity across respondents in the perceived associations that could give rise to more complex forms of masking. For example, we examine whether there is heterogeneity in the predictive power of the core attributes regarding the expected filler attributes across different types of respondents as stratified by party, income, gender, or age. The results from these additional tests support the notion that the uncorrelated filler attributes fail to meet the conditions required for their effects being masked by the effects of the core attributes.

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<sup>4</sup>For core attributes with more than two levels, we also calculated pairwise differences between non-reference-level effects.

<sup>5</sup>We chose the seven percentage-point threshold based on results from many simulation experiments as well as our subjective judgment as to substantive significance of the effect sizes. We initially set the threshold at five percentage points (as documented in our pre-analysis plans) but changed it to seven percentage points after collecting data from the first stage experiments, *but before any portion of the second stage experiments was conducted*.

<sup>6</sup>It should also be noted that our procedure does not take into account statistical uncertainty in the estimates, implying that some fillers’ effects might be incorrectly classified as above or below the seven-percentage-point threshold. We are not particularly concerned about this possibility because of the large sample used, and also because the statistical properties of second-stage estimates do not themselves depend on the particular threshold chosen for the first-stage test, as discussed in the main text.

### 3.2 The Second Stage: Identifying Satisficing Due to Task Difficulty

In the second stage, respondents are presented with pairs of conjoint profiles—of hypothetical political candidates in Study 1 and hypothetical hotel room packages in Study 2—and asked to evaluate them. For instance, in Study 1, respondents are shown pairs of candidates for U.S. Senate and asked to choose their preferred candidate as well as rate each individual candidate. In this second stage, our goal is to assess how respondents’ evaluations of the profiles change as the profiles contain increasing numbers of attributes.

The results of the first stage allow us to identify uncorrelated filler attributes for use in the second stage. With that identified pool of uncorrelated filler attributes, we randomly assign respondents to different numbers of filler attributes so as to vary task difficulty. The four core attributes are always included in the profiles and randomly interspersed with any filler attributes. The example in Figure 3 illustrates the case where four fillers are included in Study 1.

As the number of filler attributes increases and the conjoint task becomes more demanding, do respondents adapt by providing less thoughtful responses? Our expectation is that any increased survey satisficing will induce respondents to pay less attention to the task, and so will attenuate the predictive power of the core attributes. We employ two measures of attributes’ predictive power. First, we estimate the AMCEs of the core attributes and compare the estimates across the different numbers of filler attributes. Since our filler attributes are unassociated with the core attributes by design, adding any of those filler attributes should not change the AMCEs of the core attributes due to masking. Instead, changes in the effects of the core attributes should be the result of increased survey satisficing due to the increased number of attributes.

Second, we calculate the coefficient of determination (i.e.  $R^2$ ) from the regression of conjoint responses on the four core attributes,<sup>7</sup> and compare those  $R^2$ s across the experimental conditions. Again, because the omission of unassociated filler attributes should not change the core attributes’ AMCEs due to masking, and because  $R^2$  is a function of the regression-based estimates of the AMCEs, changes in the  $R^2$  across the experimental conditions can be attributed to changes in satisficing. Note that the population value of this  $R^2$  is equivalent to the partial coefficient of determination (i.e. partial  $R^2$ ) for the core attributes from the “global” population regression of

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<sup>7</sup>Specifically, we create dummy variables for all levels of each of the core attributes except for a reference level and regress the outcome on all the dummies.

Figure 3: An example task from Study 1, second stage. Respondents are asked to assess two hypothetical candidates for U.S. Senate.

Please carefully read the descriptions of the two candidates for U.S. Senator below. (1/15)

	CANDIDATE A	CANDIDATE B
Age	42	54
First Election Eligible to Vote in	Governor	Congress
Color of Childhood Family Car	White	Red
Position on Same-Sex Marriage	Favors Same-Sex Marriage	Favors Same-Sex Marriage
Position on Health Care	Government Should Do Less	Government Should Do More
Usual Day for Grocery Shopping	Monday	Tuesday
Favorite Composer	Mozart	Mozart
Party Affiliation	Democrat	Democrat

On a scale from 1 to 7, where 1 indicates that you definitely would NOT vote for the candidate and 7 indicates that you definitely would vote for the candidate, how would you rate each of the candidates described above?

Definitely NOT vote for

1234567

Definitely vote for

Candidate A	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Candidate B	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

Which candidate would you prefer to vote for?

Candidate A

Candidate B

Preferred Candidate	<input type="radio"/>	<input type="radio"/>
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conjoint responses on the full set of attributes when the core and filler attributes are independently randomized. This implies that the  $R^2$  can be interpreted as a summary measure of the explanatory power of all the four core attributes combined, and its change as the overall variation in satisficing due to the addition of filler attributes.

## 4 Results

We implement our two-stage design in studies of two separate domains. The first considers choices among political candidates, as respondents are asked to choose between pairs of hypothetical candidates and to rate each candidate. In political science, analyzing candidate choice has been one of the most common uses of conjoint experiments (e.g. Loewen et al. 2012, Franchino & Zucchini 2014, Hainmueller et al. 2014, Abrajano et al. 2015, Carlson 2015, Carnes & Lupu 2015, Crowder-Meyer et al. 2015). The second study asks respondents to choose between and rate hotel room packages. We choose this topic partly because it was used in a celebrated, early application of conjoint analysis (Goldberg et al. 1984).

Another key difference between Study 1 and 2 concerns the nature of the filler attributes. In Study 1, we use filler attributes that are unlikely to have independent effects on respondents' evaluations of political candidates (e.g. name of famous relative), meaning that they will not have any informational value for respondents. In contrast, Study 2 uses filler attributes that are more clearly meaningful and can plausibly drive responses in either a positive or negative direction (e.g. material in bed pillows). While the Study 1 fillers merely introduce irrelevant information that respondents must sift through, the Study 2 fillers add potentially meaningful information that respondents must weigh. Our expectation is that the latter set of filler attributes will induce more cognitive burden and lead to heightened satisficing. Specific procedures for both stages of both studies, as well as plans for our statistical analysis, were pre-registered at Political Science Registered Studies Dataverse prior to launching the study.<sup>8</sup>

### 4.1 Study 1: Political Candidates

In Study 1, we investigate how the proliferation of irrelevant attributes affects the predictive power of candidates' core attributes. The core attributes for this study are candidates' party affiliation (Republican or Democratic), position on same-sex marriage (favor or oppose), position on health care (government should do more or less), and age (42, 54 or 72). To assess prospective filler attributes, we start with a list of candidate attributes that we expect to have no perceived correlation with the core attributes and often no effect on overall evaluations. We also include a

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<sup>8</sup>Available at <https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi:10.7910/DVN/WX5UXL> and <https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi:10.7910/DVN/SDFYTU>.

number of attributes that we do expect to have varying degrees of perceived association with the core attributes to enable validity checks (e.g. ideology). The complete list of filler attributes is in Table A.1 in Appendix A.2.

The first-stage survey experiment was administered to 2,489 respondents recruited through MT on September 20, 2016. We chose MT because of its increasing popularity as a platform for conjoint experiments in the social sciences as well as its fast turnaround. While MT respondents are known to differ from population-based samples in important respects, they are an accessible, attentive population that is frequently employed in experimental research (Berinsky et al. 2012, Huff & Tingley 2014, Hauser & Schwarz 2015, Mullinix et al. 2016). For improved external validity, we also replicate the second stage of the study with SSI, another popular population for survey experiments. As detailed in Appendix A.2, our first-stage experiment identified five of the sixteen tested attributes as filler attributes that are perceived to be uncorrelated with any of the core attributes.

In the second-stage experiments, respondents were shown pairs of candidates for U.S. Senate and asked to choose their preferred candidate as well as rate each individual candidate. We randomly assign respondents to different numbers of filler attributes so as to vary task difficulty; the four core attributes of interest are always included in the profiles and are randomly ordered. The example in Figure 3 illustrates the case where four fillers are included.

We implemented this design using three MT surveys. The first took place on September 26th with 1,199 respondents; the second took place November 3rd and 4th with 2,476 respondents; and the third took place on November 21st with 422 respondents.<sup>9</sup> In all three, after the respondents answered several socio-demographic questions, they were asked to complete 15 conjoint tasks. Critically, the waves differed in the number of filler attributes employed. The first stage-two survey was conducted exactly as specified in our pre-analysis study plan: we randomly assigned respondents to 0, 1, 2, 3, 4, or 5 previously validated filler attributes. After completing the first wave and observing the results, which indicated surprising robustness even for 5 filler attributes, we decided to administer additional waves with even larger numbers of fillers. The second MT wave thus included treatment arms with 0, 1, 2, 3, 4, 5, 6, 8, 10, 12, and 15 filler attributes. The third wave included only three conditions: 5, 25, and 35 filler attributes. For these additional waves, we

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<sup>9</sup>Note that any respondent who participated in multiple waves of our survey was removed from all but the first wave in which she participated.

also employed untested filler attributes which we had good reason to believe would be perceived as unrelated to the core attributes. Appendix A.3 presents the full list of filler attributes. In the results below, we show estimates using all responses pooled from the three waves. The results that only use responses from the first, pre-registered wave are in Appendix A.3.

To quantify the extent of satisficing, we estimate the AMCEs corresponding to our four core attributes for each treatment condition for the pooled MT experiments, as illustrated in Figure 4 and Table A.3 in the Appendix. We limit the sample to those respondents who expressed an identification with or leaning toward the major parties, and we transform the party and issue-position measures such that they are indicators for concordance with the respondent’s partisan affiliation. We focus here on the forced choice outcomes, although the results for the candidate ratings are very similar (see Appendix A.3). Candidates’ partisanship proves to be a strong correlate of their choices: the AMCE associated with own-party candidates is 0.198 (SE=0.012) for those who saw no filler attributes, and it drops no lower than 0.147 (SE=0.016). In substantive terms, respondents are almost twenty percentage points more likely to opt for a candidate who shares their partisanship, an estimate which declines only slightly as the number of filler attributes grows.

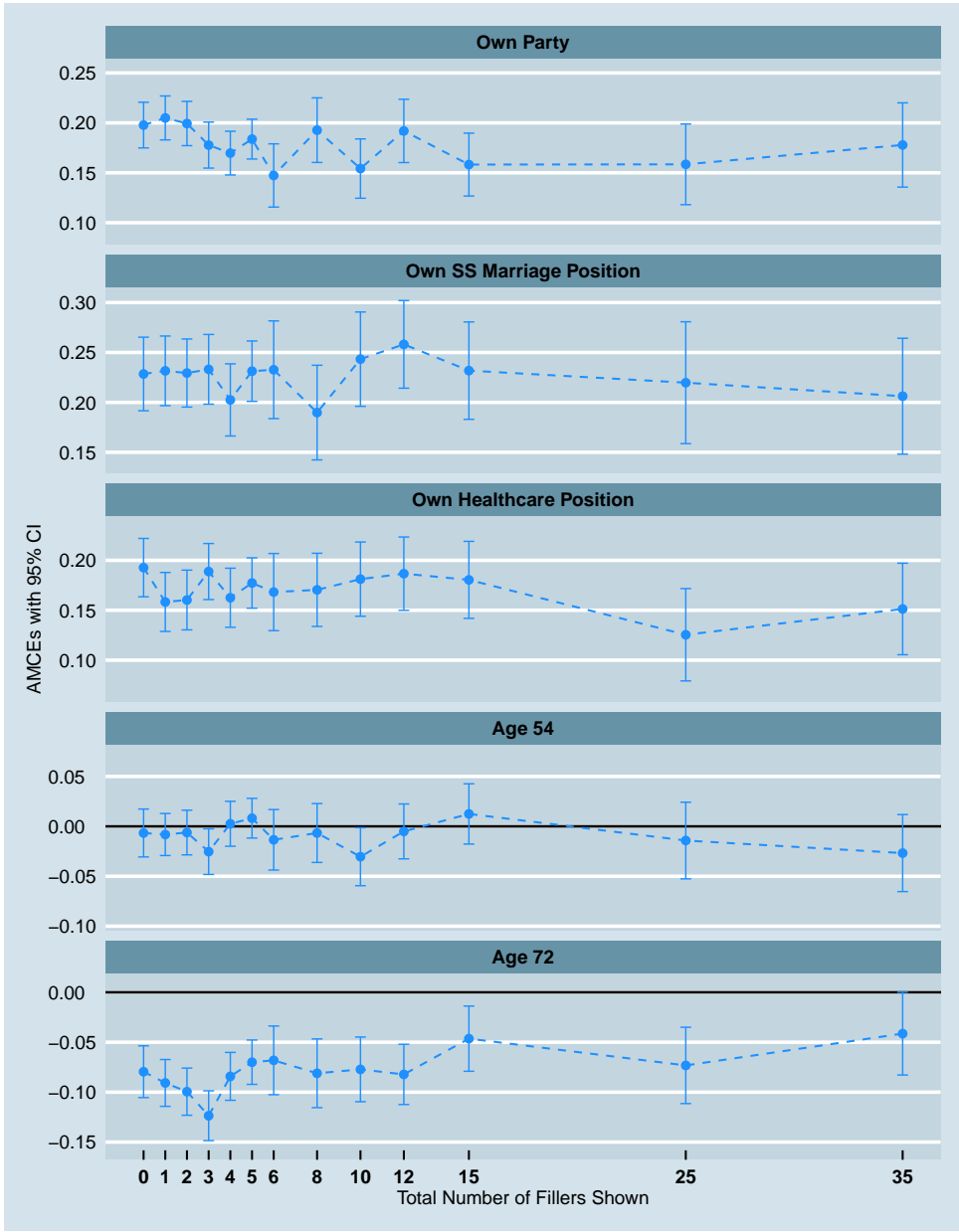
The drops in the AMCE for sharing the candidate’s same-sex marriage position or health care position are similar: they are discernible but modest, and never obscure the relationships of interest. For instance, with zero filler attributes, the effect of a candidate’s position on same-sex marriage is 0.228 (SE=0.019), an estimate that declines to no lower than 0.190 (SE=0.024). Candidates who are 72 years old are penalized, but this penalty is substantively smaller than the effects of the other core attributes (-0.080, SE=0.013 with no filler attributes), and it declines to insignificance alongside 35 filler attributes.

To consider the joint predictive power of the core attributes as the number of filler attributes rises, we calculate the partial  $R^2$  values from models in which we predict each of the forced choices as a function of the core attribute levels associated with each candidate. Figure 5 illustrates the results. Here, too, the results are consistent with a detectable but limited decrease in the core attributes’ predictive power as they are scattered among increasing numbers of filler attributes.

Next, given concerns about the extensive experience MT respondents are likely to have with surveys, we replicated our results with a survey of respondents available through SSI. These

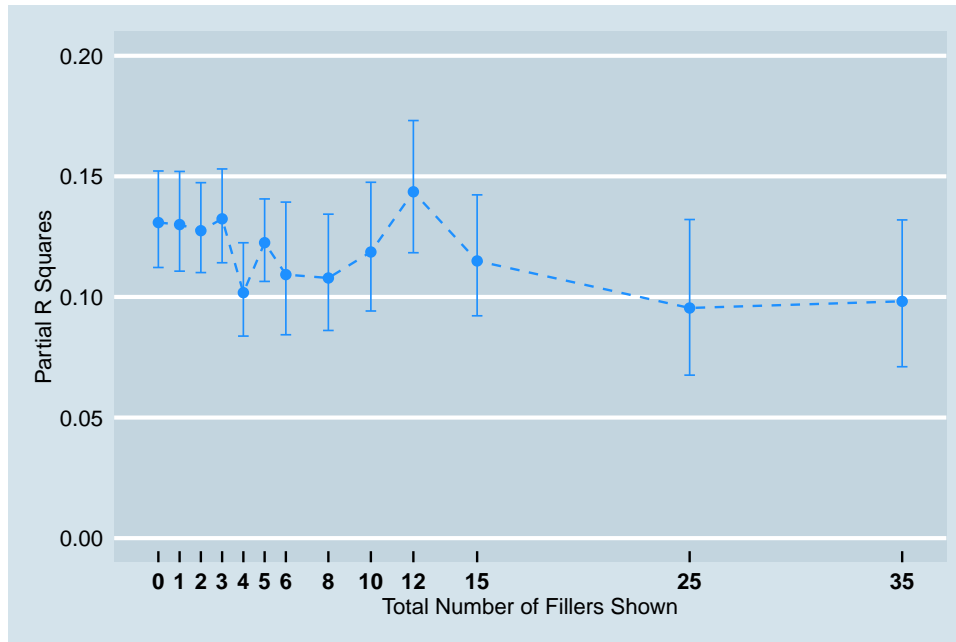


Figure 4: The AMCEs for our core attributes of interest from the three MT survey waves as the number of filler attributes increases.



respondents are also self-selected, but the volume of surveys in which they participate is markedly lower on average. Our SSI survey included 2,786 respondents, and was administered between November 30th and December 8th, 2016. We randomized the respondents to 0, 2, 4, 6, 8, 10, 15, 25, or 35 filler attributes. All respondents were randomly assigned to a number of attributes which then remained fixed throughout the survey. We pre-registered this portion of the study as

Figure 5: The partial  $R^2$  values for our core attributes with the forced-choice outcomes as function of the filler attributes, fit to the MT data.



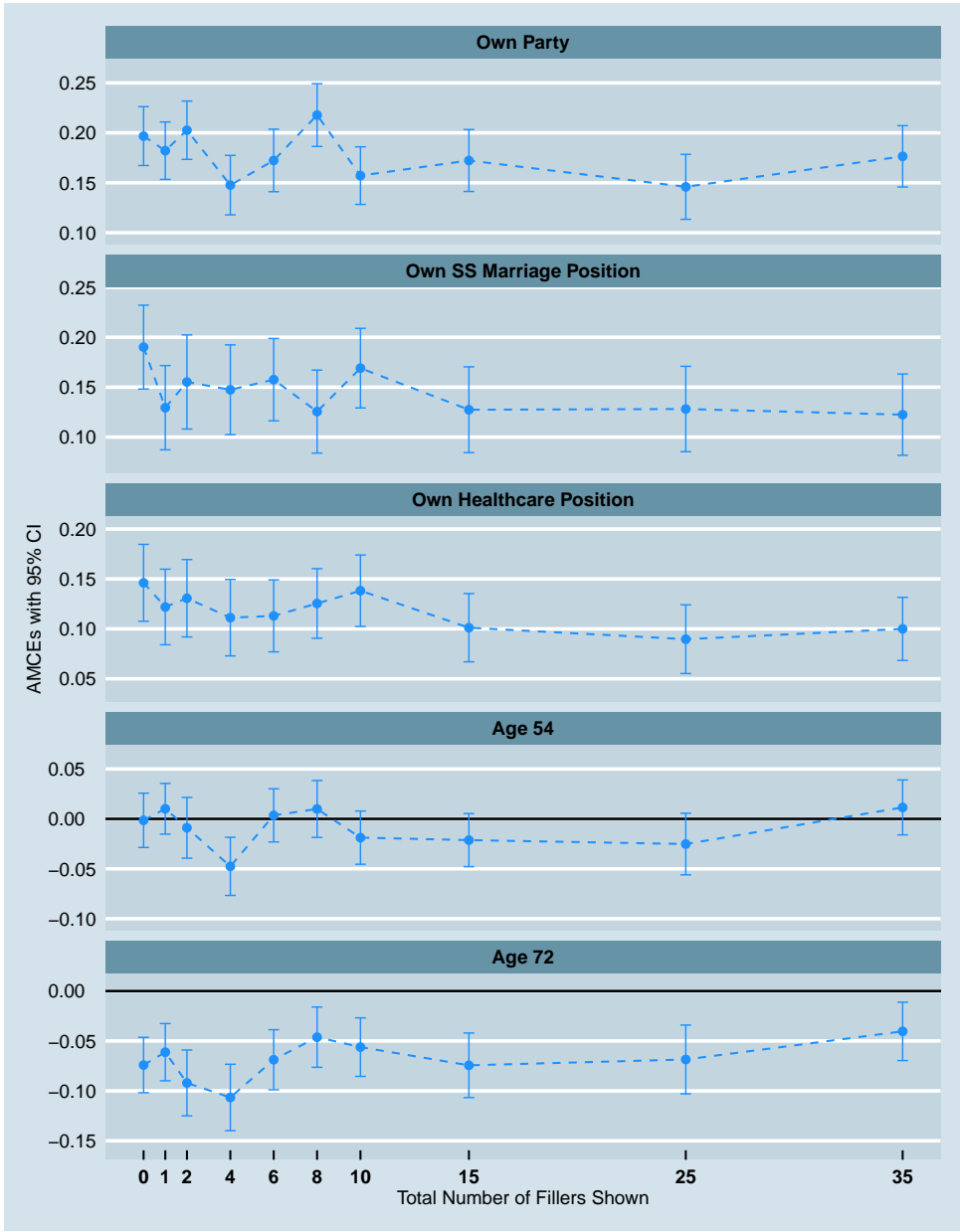
an addendum to the original pre-analysis plan before conducting any analyses.<sup>10</sup>

Figure 6 and Table A.4 in Appendix A.3 present the AMCEs for our core attributes. The results are generally quite similar. We see detectable but typically modest declines for core attributes. The effect of sharing the candidate’s party is 0.197 (SE=0.015), a figure which drops to a low of 0.146 (SE=0.017) with 25 filler attributes. Sharing the candidate’s position on same-sex marriage has an AMCE of 0.190 (SE=0.021) when no filler attributes are present and 0.122 (SE=0.021) when there are 35. Similarly, sharing the candidate’s health care position drops from 0.146 (SE=0.020) to 0.090 (SE=0.018) in the presence of 25 filler attributes.

Replicating the procedure above, we also estimated partial  $R^2$  values associated with models including our core attributes but no filler attributes. Figure 7 illustrates the results. First, it demonstrates that the partial  $R^2$  values using the SSI data are consistently lower than those recovered from the MT data. This pattern is consistent with MT respondents on average paying more attention to the task, though it could also come from any difference in preferences between the two groups of respondents. Despite this lower baseline, the trend is similar, with a detectable decline in overall predictive power that is slightly more pronounced for cases where there are large

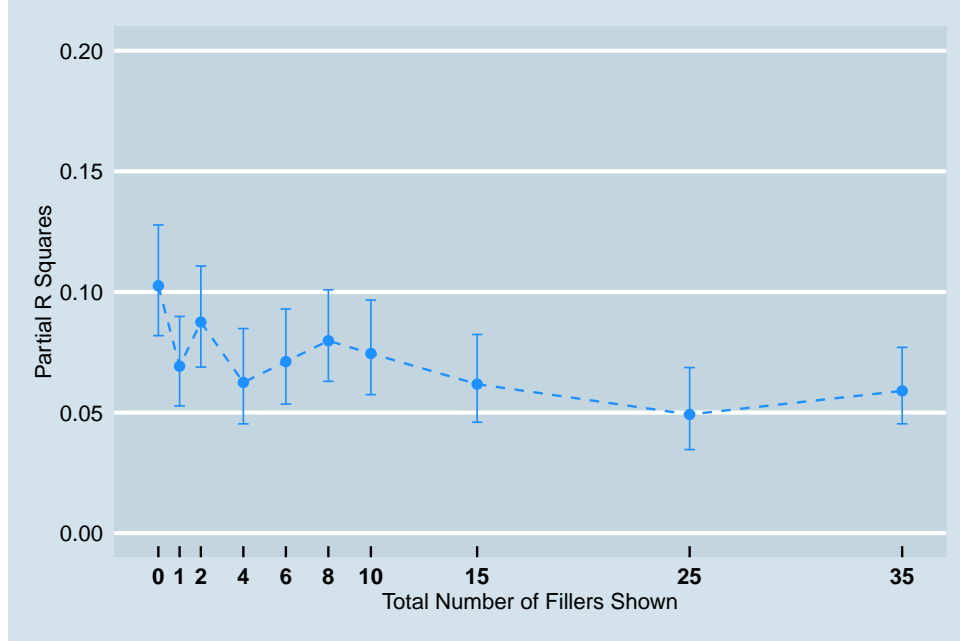
<sup>10</sup>Also available at <https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi:10.7910/DVN/WX5UXL>.

Figure 6: The AMCEs for our core attributes of interest from the SSI survey as the number of filler attributes increases.



numbers of filler attributes. Overall, however, respondents provide meaningful responses even with as many as 35 filler attributes, a number much larger than what is employed in virtually all recent studies.

Figure 7: The partial  $R^2$  values for our core attributes with the forced-choice outcomes as function of the number of filler attributes, fit to the SSI data.



## 4.2 Study 2: Hotel Rooms

In Study 2, we employ a design similar to Study 1 but investigate respondents' choice of hypothetical hotel rooms. The core attributes are the view from the room (ocean or mountain view), floor (top, club lounge, or gym and spa floor), bedroom furniture (1 king bed and 1 small couch or 1 queen bed and 1 large couch), and type of in-room wireless internet (free standard or paid high-bandwidth wireless).

Like in Study 1, we begin with a list of additional attributes that should have no perceived correlation with the core attributes, so they can be used as second-stage fillers. Unlike in Study 1, however, we choose attributes that are uncorrelated with the core attributes but likely to have their own effects on respondents' preferences. The goal behind this modification is to investigate the impact of the increased cognitive burden due to the addition of meaningful information. Studying preferences about hotel rooms facilitates the identification of such meaningful but uncorrelated attributes; in the candidate choice example, most relevant attributes are likely to be perceived as interrelated. As validity checks, we include two attributes that are likely to be associated with some of the core attributes (sailboats or trees viewable from hotel window, bedroom pillow size). Table A.8 in Appendix A.4 lists the full set of filler attributes.

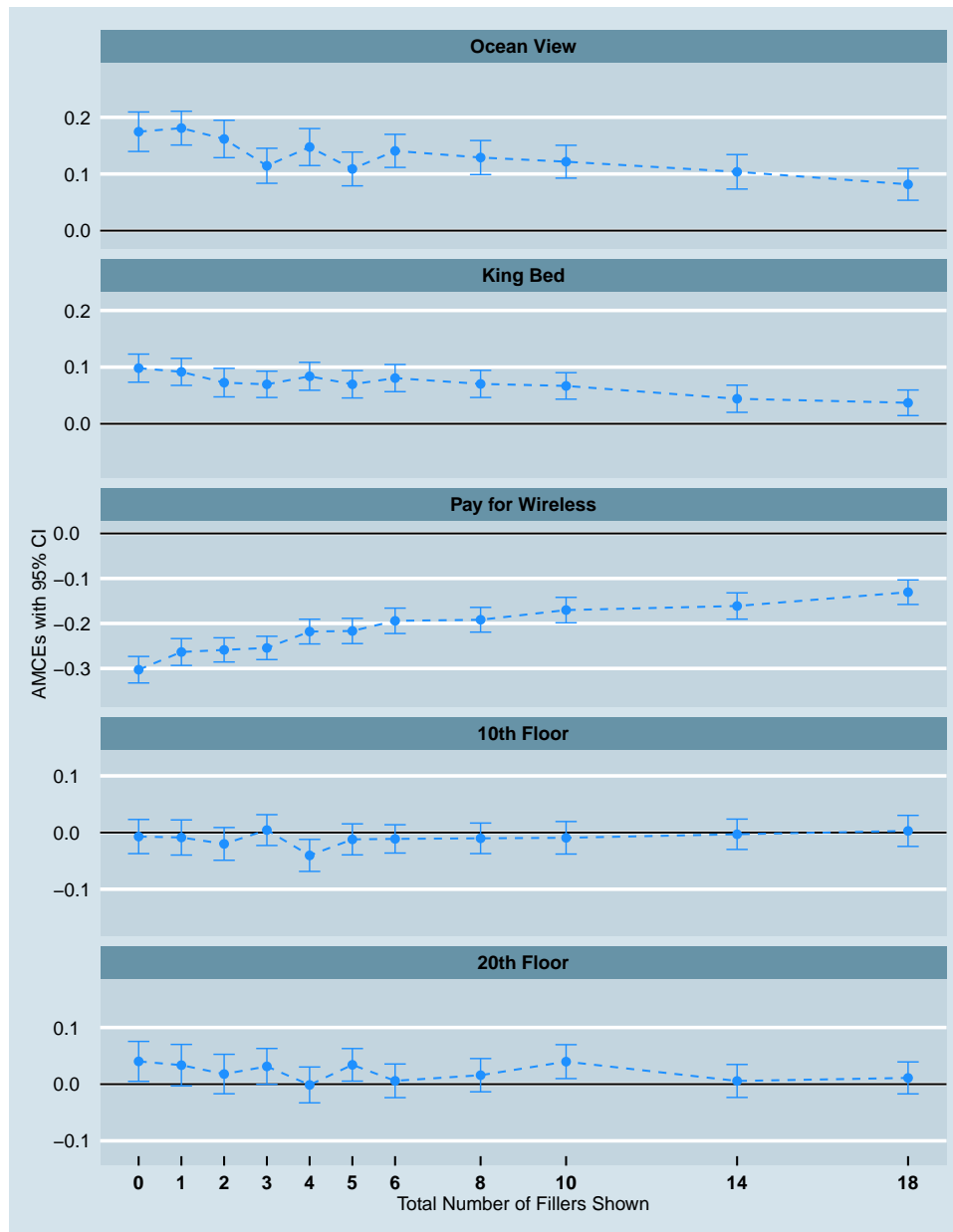
We administered the first stage to 3,291 respondents recruited through MT on February 28 - March 2, 2017 (see Appendix A.4 for details). Using the same procedure as in Study 1, we identified 18 of the 38 potential filler attributes as perceived to be uncorrelated with the core attributes. In addition, we detected strong correlations between our validity-check fillers and the core attributes, confirming that our respondents were paying attention. We then proceeded to our second-stage experiment on March 6-7, 2017, again using MT respondents ( $N = 3,307$ ). The experiment followed the same format as the corresponding experiment from Study 1. We randomly assigned respondents to 0, 1, 2, 3, 4, 5, 6, 8, 10, 14, or all of the 18 filler attributes. We then asked the respondents to complete choice and rating tasks on 15 pairs of hotel room profiles, each consisting of the four core attributes as well as a randomly chosen set of filler attributes.

Figure 9 shows the estimated AMCEs of our four core attributes across the treatment conditions. Again, we focus on the forced choice outcomes. The results for the rating outcomes are very similar and presented in Figure A.13 in Appendix A.5.<sup>11</sup> When the design includes no filler attributes, almost all of our core attributes have strong impact on respondents' preferences. The AMCE for an ocean view room is estimated at 0.175 (SE=0.018), meaning that respondents are more than 17 percentage points more likely to choose a room with an ocean view compared to a mountain view room. Respondents also prefer rooms with a king bed and a small couch to rooms with a queen bed and a large couch (AMCE=0.098, SE=0.03). The type of in-room internet is also important in respondents' choices (AMCE=-0.303, SE=0.015), implying that respondents are on average 30 percentage points less likely to choose a room with paid high-bandwidth internet compared to the otherwise identical room with free standard wireless. In contrast, floor of the room turns out to be almost irrelevant.

The core, impactful attributes remain substantively significant when we add filler attributes. However, in contrast to Study 1 where we found a largely flat line across many filler conditions, the results indicate noticeable declines in the effects of each of these attributes as the number of fillers increases. For example, the estimated AMCE for an ocean view room drops to 0.141 (SE=0.015) when 6 randomly chosen fillers are included, and it further declines to 0.082 (SE=0.014) when the profile includes 18 fillers. It is nonetheless remarkable that the attribute retains nearly half of its original effect; the estimate still implies an 8.2 percentage point increase for ocean-view rooms.

<sup>11</sup>The similarity between the results for the forced choice and rating outcomes suggest that the core attribute effect attenuation we observe is unlikely driven by ceiling/floor effects.

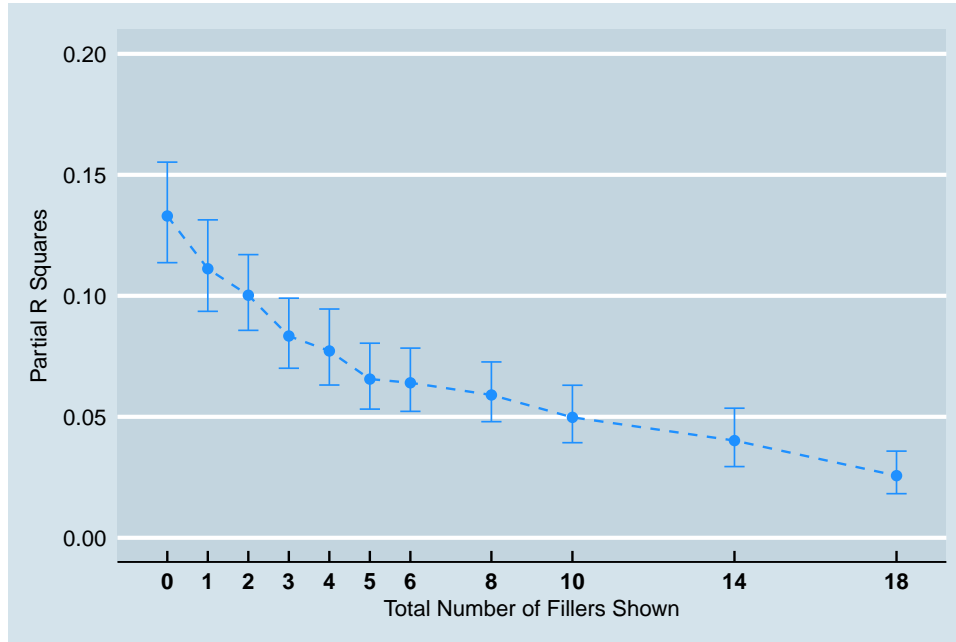
Figure 8: The AMCEs for our core attributes of interest from the hotel survey as the number of filler attributes increases.



Likewise, the estimated AMCE of a king bed and a small couch decreases to 0.037 (SE=0.012) when the number of fillers is 18. For the wireless internet attribute, the AMCE is also estimated to be slightly less than half of its original value (-0.131, SE=0.014) with 18 fillers.

Conjoint tables that include as many as 22 fillers are rarely used in practice, and thus the 18-filler condition may not be a practical benchmark. Instead, conjoint studies, at least in the fields of political science and public policy, rarely use more than 10 attributes. Thus, it is useful to

Figure 9: The partial  $R^2$  values for our core attributes with the forced-choice outcomes from the hotel study, as function of the number of filler attributes.



focus on the comparison between the experimental conditions in which 0 and 6 fillers are included. Moving from the former to the latter condition, the AMCEs each retain at least two-thirds of their initial magnitude, a demonstration of substantial robustness given that this comparison involves more than doubling the amount of meaningful information on the conjoint table.

Perhaps more importantly, the rate of attenuation of the AMCEs as additional fillers are added is virtually uniform across all of the attributes, meaning that the relative magnitudes of the estimated AMCEs remains unchanged across conditions. Accordingly, the qualitative conclusions one would draw about the relative effect sizes are invariant to the number of fillers included in the design. This finding is particularly notable given that a major contribution of conjoint designs is in allowing researchers to compare the relative magnitudes of effects across attributes.

## 5 Conclusion

There is an extensive body of research on how best to conduct phone surveys. It covers many issues researchers are likely to face in implementing telephone surveys, from survey length to question order. In recent years, the rapid growth of survey research conducted via computers has enabled researchers to employ increasingly complex research designs at little added cost. Yet,

research on survey methods has to date been focused on the change in sampling frames that has accompanied the shift toward online survey administration (e.g. Chang & Krosnick 2009, Yeager et al. 2011). For those administering surveys via computer, there is surprisingly little guidance about the extent to which insights developed for phone and in-person surveys hold up (but see Gooch & Vavreck 2015).

Conjoint experiments are one such design: they are easily implemented by computer, and so have seen a renaissance within political science in the past few years. In this paper, we sought to advance our understanding of response behavior in surveys administered by computer by probing one breaking point of conjoint designs. Specifically, we considered how many attributes researchers can include per profile. To include too few attributes may risk masking, while including too many may instead produce excessive satisficing.

Those who would assess this trade-off empirically face an empirical challenge. When changing the number of attributes, we also change the information that respondents have, and so shift the causal estimand. To isolate the effects of increased satisficing, this paper employs a set of pre-registered experiments using a novel, two-stage design in which we first isolated several “filler attributes” unrelated to the core attributes of interest. We then randomly assigned respondents to conjoint profiles with varying numbers of filler attributes.

Our first study used this design to estimate the effects of irrelevant filler attributes on response quality when respondents chose between hypothetical Senate candidates. Using such attributes, we found a detectable but substantively limited decline in the predictive power of our core attributes as the number of such filler attributes increased. Extraneous information does not on its own induce excessive satisficing, even when the number of such irrelevant attributes grows larger than the total number of attributes in most conjoint designs published recently.

Still, when researchers seek to include additional attributes, it is typically because those attributes are likely to be meaningful for the choice at hand. In our first study, the attributes did not have independent impacts on the outcome, making them atypical and limiting our capacity to generalize. To address that concern, our second study turned to a domain in which it was possible to identify attributes which had meaningful, independent effects on respondent choice without being correlated with the core attributes of interest: hotel rooms. In that case, respondents saw profiles which had many potentially meaningful attributes. Our second study thus allowed us



to examine satisficing in cases where respondents are potentially overwhelmed with meaningful information. Yet here, too, our central finding was the robustness of conjoint designs, as even 18 meaningful attributes did not erase the effects of our core attributes.

Our results have important implications for researchers designing conjoint studies. First, our results suggest that satisficing does not impose a serious binding constraint on the number of attributes included in a conjoint design.<sup>12</sup> Certainly, there is no single magic number of attributes which promises to guard against excessive satisficing. However, the limits on the upper number of attributes that we considered in our studies were purposefully set at levels above conventional practice. Even given this high number of filler attributes, the core attributes retained most of their effect magnitudes. More importantly, the addition of filler attributes did not affect the relative sizes of the core attribute effects. In other words, while satisficing appears to result in some attenuation, we do not find it to systematically alter the pattern of results, thereby ensuring that the broad interpretation of the results would remain unchanged. This points to the robustness of the conjoint design for investigating multidimensional preferences by comparing the relative importance of many different attributes.

Second, these results also yield concrete recommendations for researchers. Specifically, researchers should not allow concerns about satisficing to dictate their conjoint design decisions in terms of the number of attributes, assuming that the number is kept within the limits investigated in the studies presented here. Instead, researchers should prioritize other criteria in making their design choices. In particular, attribute selection and profile design choices should focus on accounting for masking in a way that fits the theoretical questions of interest, and on achieving the desired level of realism in the conjoint profiles.

We recognize that our studies were implemented using opt-in internet samples, which are likely to be different from other samples of respondents who have less experience taking surveys or face reduced incentives to pay attention. Yet the most commonly used samples for conjoint surveys today are opt-in internet samples, making our results relevant for a broad set of researchers. In addition, we recognize that the difficulty of a conjoint survey also depends on its subject matter. For example, evaluating two candidates for Senate is a familiar task, and is likely to be easier than evaluating multidimensional choices in less common domains. Future work that extends this

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<sup>12</sup>In a companion study, we investigate the extent to which increasing the number of choice tasks in a conjoint design affects response quality, and we find similar robustness to satisficing on that dimension (Bansak et al. 2018).

research to less attentive populations and/or different subject matter domains would be valuable.

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# Supplementary Materials

## A.1 Formal Discussion of the Study Design

In this appendix, we formally define the concepts of masking and satisficing based on the potential outcomes framework for causal inference. We then justify our study design based on the formalization. We clarify the assumptions required for the proposed study design to identify satisficing and then discuss possible approaches for testing the assumptions, tests which we implement in our empirical study.

### A.1.1 Masking

Suppose that we have  $L$  core attributes of interest and our goal is to estimate the causal effect of those attributes on a conjoint survey response denoted by  $Y_i$  for respondent  $i \in \{1, \dots, N\}$ . For the sake of simplicity, we assume that the attributes are all binary, such that the values of the core attributes assigned to respondent  $i$  can be fully represented by a vector of  $L$  binary indicator variables,  $D_i \equiv [D_{1i}, \dots, D_{Li}]^\top$ . Using the potential outcomes framework, we can denote the value of the outcome variable that would be realized for respondent  $i$  given a pair of conjoint profiles  $D_i = d$  by  $Y_i(d)$  or  $Y_i(d_1, \dots, d_L)$ . (Note that we make the dependence of the potential outcomes on other profiles in the same conjoint task implicit.) Following Hainmueller et al. (2014) (hereafter HHY), the AMCE for the first core attribute can be defined as

$$\tau_1 \equiv \mathbb{E}[\tau_{1i}] \equiv \mathbb{E}[Y_i(1, D_{(-1)i}) - Y_i(0, D_{(-1)i})],$$

where  $D_{(-1)i}$  represents the values of the core attributes for respondent  $i$  excluding the first attribute. The AMCEs for the other  $L - 1$  core attributes can be analogously defined. HHY show that, under the completely independent randomization of all attributes (Assumption 5, HHY), the AMCE of each of these attributes can be identified by the population ordinary least squares (OLS) regression of the observed outcome  $Y_i$  on  $D_i$ , i.e.  $L(Y_i|D_i) = \tau_0 + \tau^\top D_i$  where  $\tau = [\tau_1, \dots, \tau_L]^\top$  and  $L(\cdot|\cdot)$  is the linear projection operator.

Now, suppose that we are interested in the AMCE of  $D_i$  *conditional on the design* that includes another set of  $M$  attributes  $F_i \equiv [F_{1i}, \dots, F_{Mi}]^\top$ , which we call the filler attributes. That is, our quantity of interest is the average causal effects of the core attributes when respondents are also

given information about the filler attributes. Under the assumptions discussed below, this quantity of interest can be written as  $\beta \equiv \mathbb{E}[\beta_i]$  such that

$$Y_i(d) = \beta_0 + \beta_i^\top d + \gamma_i^\top F_i + \varepsilon_i, \quad (1)$$

where  $\mathbb{E}[\varepsilon_i] = 0$ . One obvious approach to identifying  $\beta$  is to implement a fully randomized conjoint experiment with the design of interest, i.e. include both  $D_i$  and  $F_i$  in the design with completely independent randomization. The population OLS regression of  $Y_i$  on  $D_i$  (or on  $D_i$  and  $F_i$ ) will identify  $\beta$  because the actual  $D_i$  and  $F_i$  will be uncorrelated with either  $\varepsilon_i$  or each other.

In practice, however, researchers may wish to avoid this approach because of concerns about satisficing, as we discuss in the main text. Suppose instead that we use the conjoint design with only  $D_i$  as included attributes. The values of the filler attributes for respondent  $i$  will then not be assigned by the design, but *mentally imputed* by respondents based on their perceived association between the core and filler attributes. Denote the imputed values of the filler attributes given the core attributes  $d$  by  $F_i(d)$ , such that the potential outcome is now written as  $Y_i(d) = \beta_0 + \beta_i^\top d + \gamma_i^\top F_i(d) + \varepsilon_i$ . Under the assumption discussed below, the imputed value of the filler attributes can be expressed as,

$$F_i(d) = \alpha_0 + A_i d + \omega_i, \quad (2)$$

where  $A_i$  is a  $M \times L$  matrix of parameters representing partial effects of  $D_i$  on  $F_i$ ,  $\alpha_0$  is a vector of  $M$  intercepts and  $\mathbb{E}[\omega_i] = 0$ .

*Masking* can now be defined as  $\tau - \beta$ , i.e. the difference between the AMCE of  $D_i$  conditional on the design that includes  $D_i$  only and the true causal effect of interest—the AMCE of  $D_i$  conditional on the design that includes both  $D_i$  and  $F_i$ . Under the assumptions embedded in



equations (1) and (2), masking for the first core attribute can be written as

$$\begin{aligned}
\tau_1 - \beta_1 &= \mathbb{E}[\tau_{1i} - \beta_{1i}] \\
&= \mathbb{E}[Y_i(1, D_{(-1)i}) - Y_i(0, D_{(-1)i}) - \beta_{1i}] \\
&= \mathbb{E}[(\beta_0 + \beta_{1i} + \beta_{(-1)i}^\top d_{-1} + \gamma_i^\top F_i(1, D_{(-1)i}) + \varepsilon_i) \\
&\quad - (\beta_0 + \beta_{(-1)i}^\top d_{-1} + \gamma_i^\top F_i(0, D_{(-1)i}) + \varepsilon_i) - \beta_{1i}] \\
&= \mathbb{E}[\gamma_i^\top \{F_i(1, D_{(-1)i}) - F_i(0, D_{(-1)i})\}] \\
&= \mathbb{E}[\gamma_i^\top (\alpha_0 + A_{1i} + A_{(-1)i}^\top d_{-1} + \omega_i - \alpha_0 - A_{(-1)i}^\top d_{-1} - \omega_i)] \\
&= \mathbb{E}[\gamma_i^\top A_{1i}],
\end{aligned} \tag{3}$$

and masking for the other  $L - 1$  core attributes can be derived analogously. Equation (3) implies that  $\beta$  cannot be identified under the conjoint design that includes only the core attributes unless either of the following conditions is satisfied: (1)  $\gamma_i = 0$ , i.e., the filler attributes have no effect on the outcome for any respondent, or (2)  $A_i = 0$ , i.e., the core attributes have no perceived association with the filler attributes for any respondent.

### A.1.2 Satisficing

Now, we consider the alternative identification strategy for  $\beta$ : including both  $D_i$  and  $F_i$  in the conjoint design. A practical concern for this approach is that including both  $D_i$  and  $F_i$  might cause *satisficing*, meaning that some respondents stop paying attention to the conjoint questions due to increased task difficulty. One way of formalizing the concept of satisficing under the current framework is to define it as a change in the data generating process for the observed outcome, such that it is no longer a function of the attributes. That is, respondent  $i$  is satisficing if the observed outcome  $Y_i$  does not equal the potential outcome  $Y_i(d)$  given by equation (1). We note that this is a form of a Stable Unit Treatment Value Assumption (SUTVA) violation, because  $Y_i \neq Y_i(d)$  even when  $D_i = d$ .

Satisficing generally causes attenuation bias in AMCE estimates that are otherwise unbiased. To see why, suppose that satisficing is of a form such that  $Y_i \mid D_i \stackrel{i.i.d.}{\sim} L(y)$  where  $L(y)$  is a probability distribution that does not depend on  $D_i$ , and that respondents randomly satisfice 100p percent of the time under the design with both the core and filler attributes but not under

the core-only design, where the level of satisficing  $p \in (0, 1)$ . Then, the population OLS regression of  $Y_i$  on  $D_i$  under the design including both the core and filler attributes will identify  $(1 - p)\beta$ , which is attenuated towards zero compared to  $\beta$  (i.e.  $|(1 - p)\beta| < |\beta|$ ).

### A.1.3 The Proposed Study Design

The above discussion implies that a naïve comparison of the AMCEs of the core attributes under the two designs—the core-only design and the design with both the core and filler attributes—will not isolate the amount of satisficing (i.e.,  $p$ ) because of the masking under the core-only design. A possible solution for this identification problem would entail utilizing the filler attributes that satisfy either of the no-masking conditions, i.e.  $\gamma_i = 0$  or  $A_i = 0$ . Our proposed two-stage study design focuses on the second condition. More specifically, our first-stage experiment corresponds to empirically testing an observable implication of the second condition,  $\mathbb{E}[A_i] = 0$ . Indeed, this is a sufficient condition for no masking if we assume  $\text{Cor}(\gamma_i, A_i) = 0$ , i.e., if respondents’ perceived association between  $D_i$  and  $F_i$  is uncorrelated with the effect of  $F_i$  on their conjoint responses. In other words, the tests in our first-stage experiment guarantee (with specified statistical uncertainty) that there is no masking for the core attributes caused by the filler attributes *unless* there exist respondents for whom  $A_i \neq 0$  and they weigh those filler attributes systematically differently from the rest of the respondents in their conjoint responses. We call this latter (rather pathological) scenario *complex masking*. In Appendix A.6, we present empirical evidence that complex masking is highly unlikely in our experiment.

It is also important to note that the above discussion rests on a set of simplifying assumptions about the potential outcomes. Specifically, our model for the potential outcomes (i.e. equations (1) and (2)) assumes that there are no interaction effects on the outcome: 1) among any of the core attributes; 2) among any of the filler attributes; or 3) between any core and filler attributes. These assumptions are immaterial for the purpose of identifying filler attributes that cause no masking for the core attributes based on the proposed study design. However, we also assume that there are no interaction effects among the core attributes on the filler attributes, and this assumption is potentially consequential. Put differently, filler attributes could also cause masking if certain combinations of their values are perceived to be associated with the core attributes, even if those attributes are all individually unassociated. Appendix A.6 also empirically investigates the plausibility of this assumption, suggesting that it is indeed unlikely that such

interactive association exists in respondents' perceptions.

## A.2 Details of the First Stage, Study 1

Table A.1: Filler Attributes Tested in First Stage of Study 1

Attribute	Levels
Famous relative	Franklin Pierce, Chester Arthur, John Tyler, Zachary Taylor
Elementary school	Washington School, Jefferson School, Madison School
Favorite highway	Route 71, Route 73, Route 77, Route 79
Vacation spot	Crystal Lake, Twin Lake, Spring Lake, Long Lake
Marital Status	single, married, divorced
Ideology	liberal, conservative
Position on immigration policy	deport all unauthorized immigrants who are in the country illegally, allow unauthorized immigrants to stay but do not allow them to be citizens, allow all unauthorized immigrants to become citizens
Position on gun control	protect all Americans' right to have guns, restrict ownership of some guns
Education	high school degree, college degree, college degree from Ivy League university
Annual income	\$75k, \$180k, \$290k
Prior elected office	none, governor, senator
Occupation	business owner, lawyer, high school teacher, car dealer
Gender	male, female
Military	did not serve, served
Race	white, African American, Asian American, Hispanic/Latino
Children	0, 1, 2, 3

Figure A.1 displays the results for the five filler attributes we tested that, in theory, should not be associated with the fixed attributes. The difference-in-means estimates are plotted in order of decreasing magnitude, with 95% confidence intervals constructed using standard errors that are clustered by respondent.<sup>13</sup> As the results show, the estimates for all five filler attributes are all substantively close to zero, with few estimates that are statistically significant. The estimate with the highest magnitude pertains to the marital status filler attribute, at approximately -0.055. While statistically distinguishable from zero, such a small effect is unlikely to contribute to a meaningful amount of masking, even if marital status had a sizable effect on candidate preferences.

<sup>13</sup>Because the age attribute in the first study included three levels, and hence two indicator variables, the difference between the two age indicators was also included in addition to the two age indicator variables themselves.

Figure A.1: Results from Study 1, first stage. Evidence of non-association between core attributes and filler attributes.

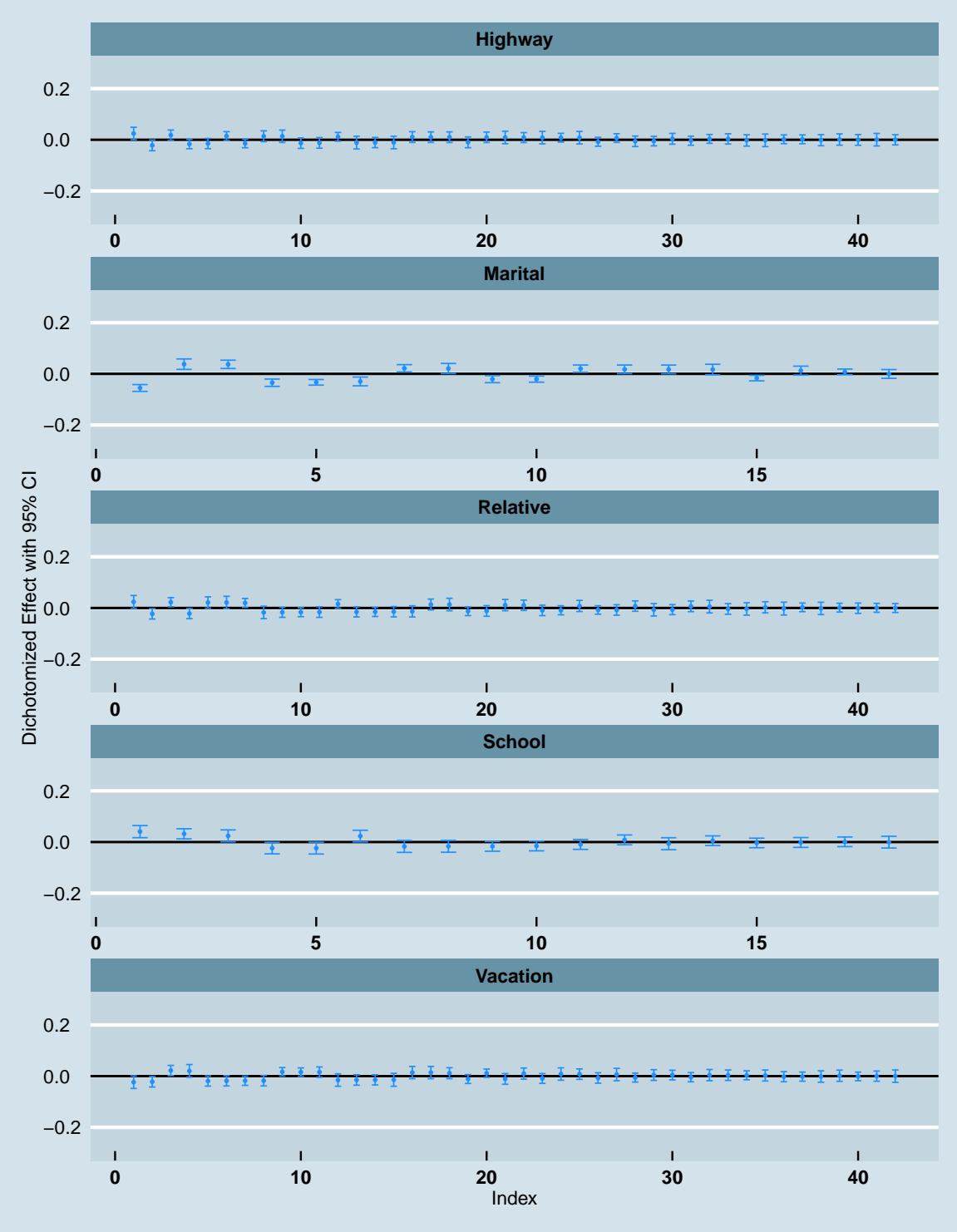
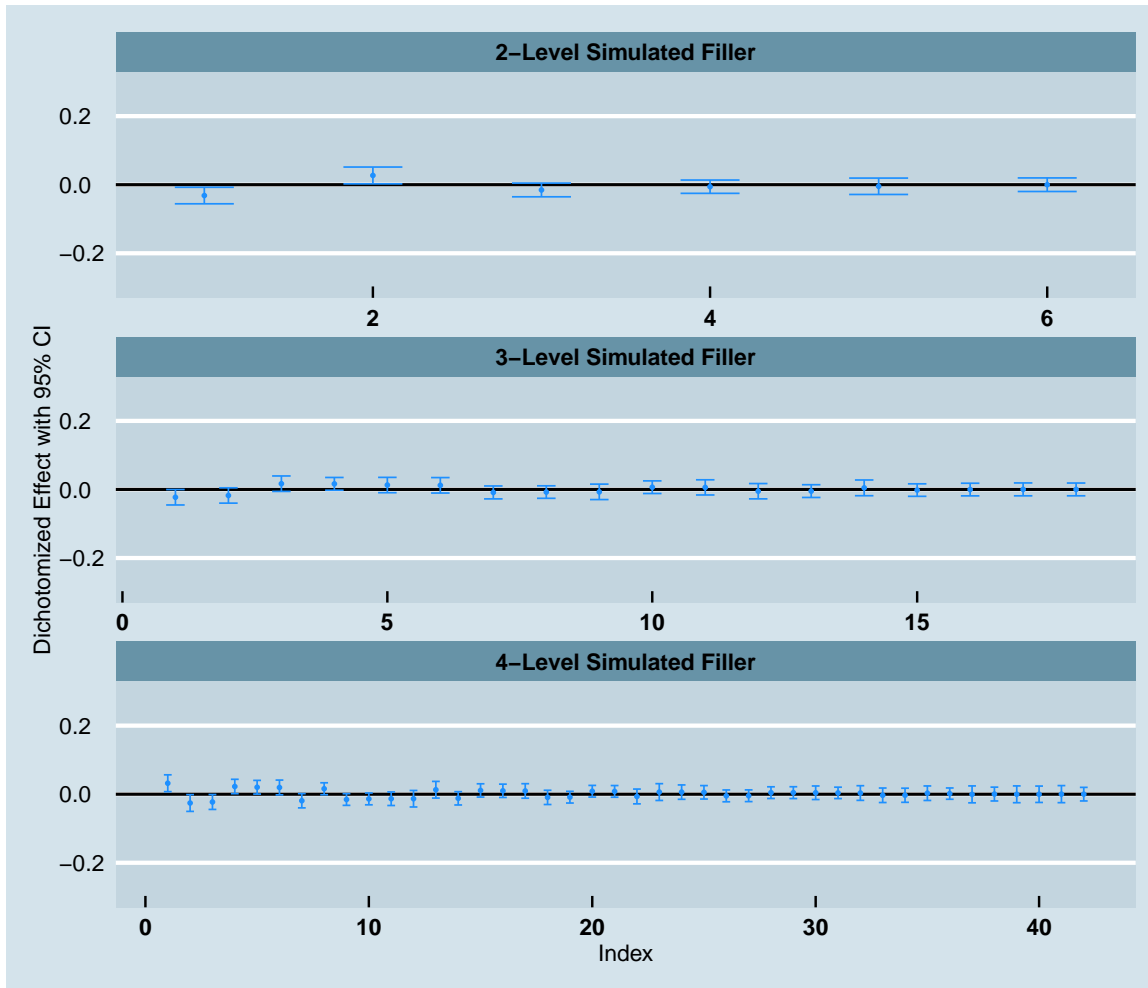


Figure A.2 shows similar plots for simulated filler attributes which have no association with the fixed attributes by construction. As can be seen, the patterns of actual estimates in Figure

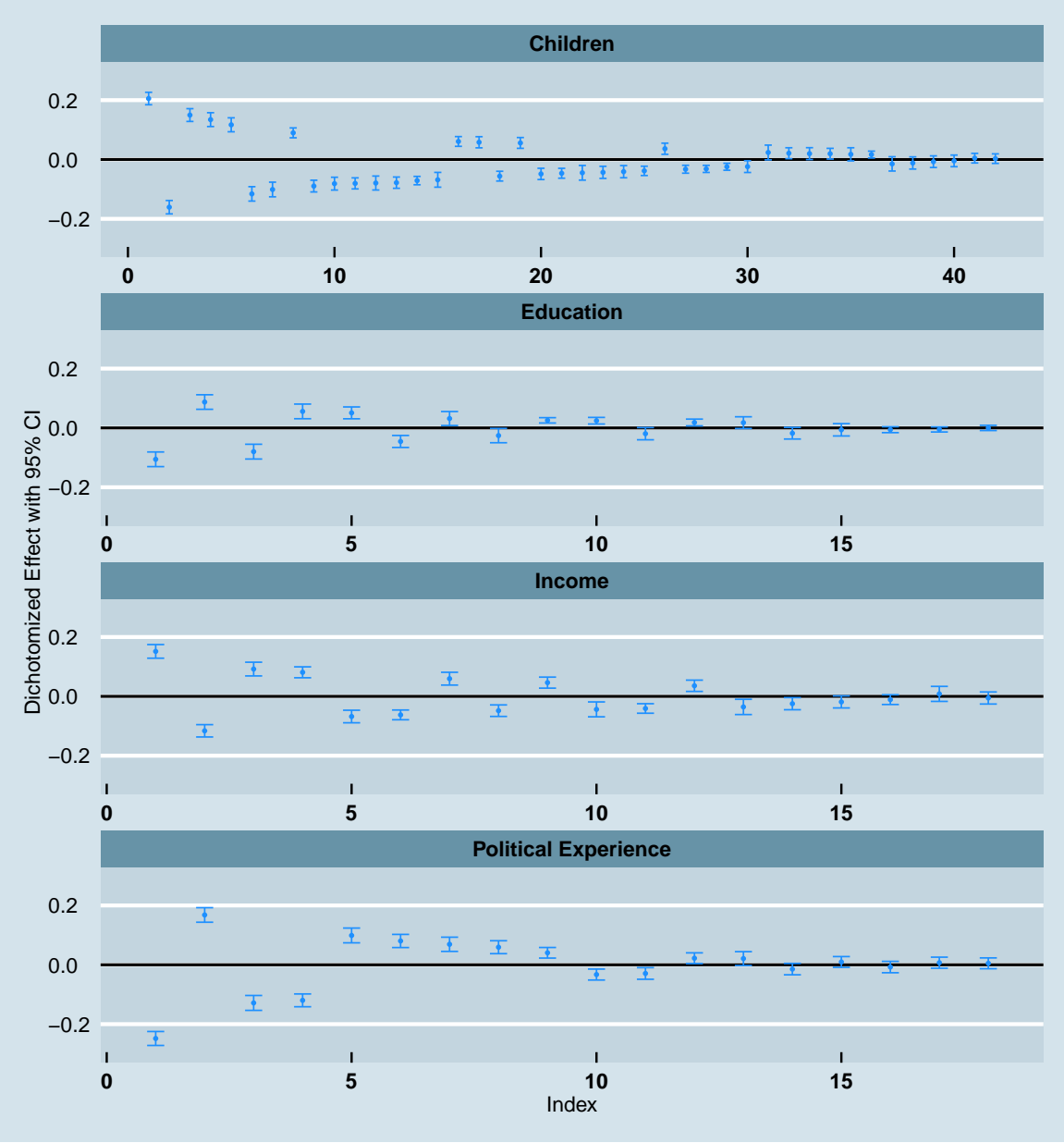
Figure A.2: Simulated Results from Study 1, first stage. Results using filler attributes that are simulated to have no association with the core attributes.



A.1 look similar to those of the simulated fillers, further illustrating the virtual non-association between the five filler attributes and the core attributes. In sum, based on the small magnitudes of the full set of difference-in-means estimates for these five filler attributes, it is not plausible that any of them could contribute to a meaningful amount of masking with respect to the core attributes. As a result, because these filler attributes do not pose the threat of masking, they can be used to isolate the possible effects of satisficing in the second stage of Study 1.

As an opposite point of comparison, Figures A.3-A.5 illustrate the results for a collection of filler attributes expected to have varying degrees of association with the core attributes. As the figures show, for each of these attributes, the estimates reach much higher magnitudes. In contrast to the five filler attributes discussed above, the filler attributes presented in Figures A.3-A.5 would

Figure A.3: Associated Fillers in Study 1, first stage. These filler attributes are associated with the Age core attribute.



be ill-suited for isolating the effects of satisficing from masking.

Figure A.4: Associated Fillers in Study 1, first stage. These filler attributes are associated with the Party and Issue Position core attributes.

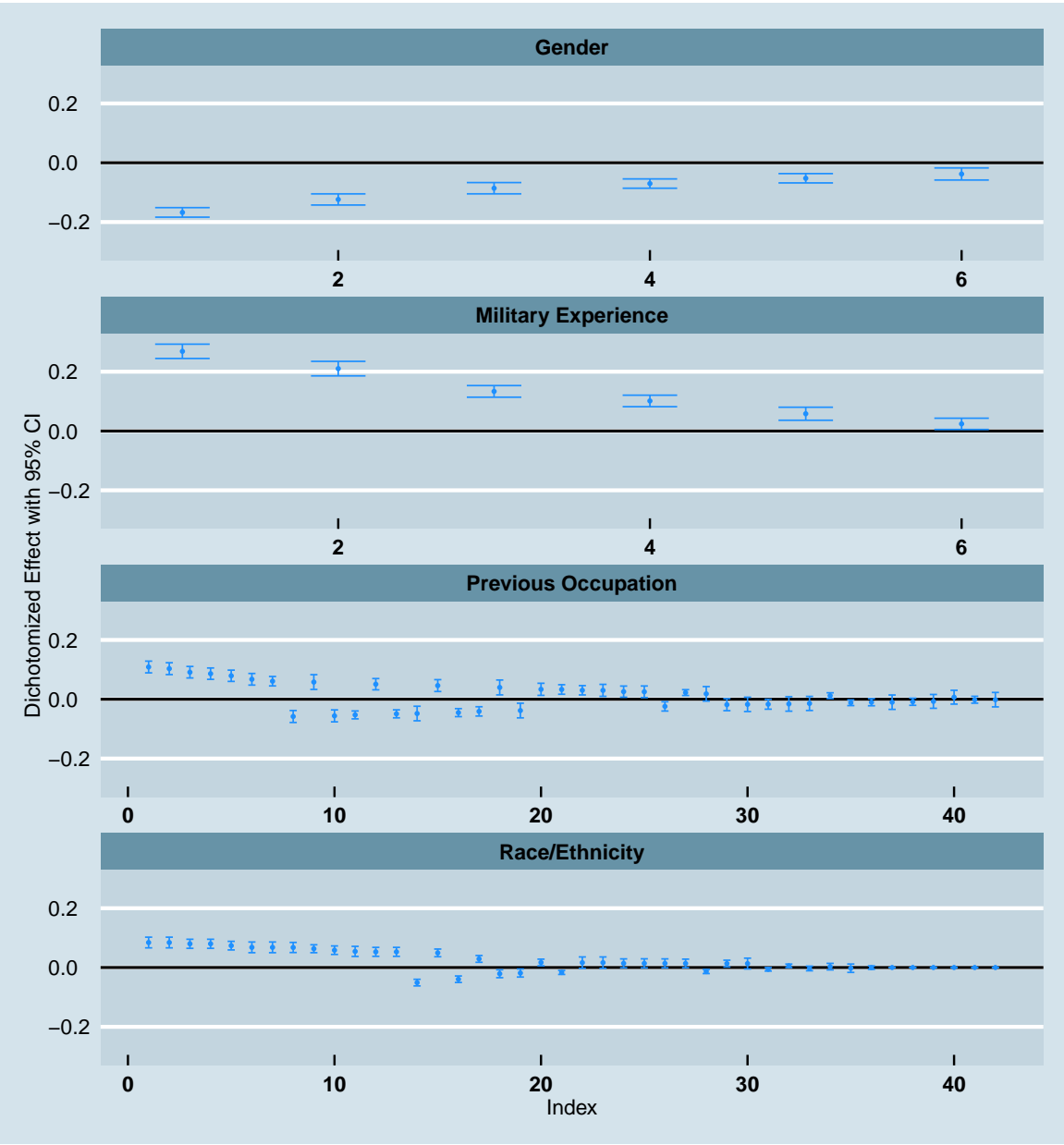
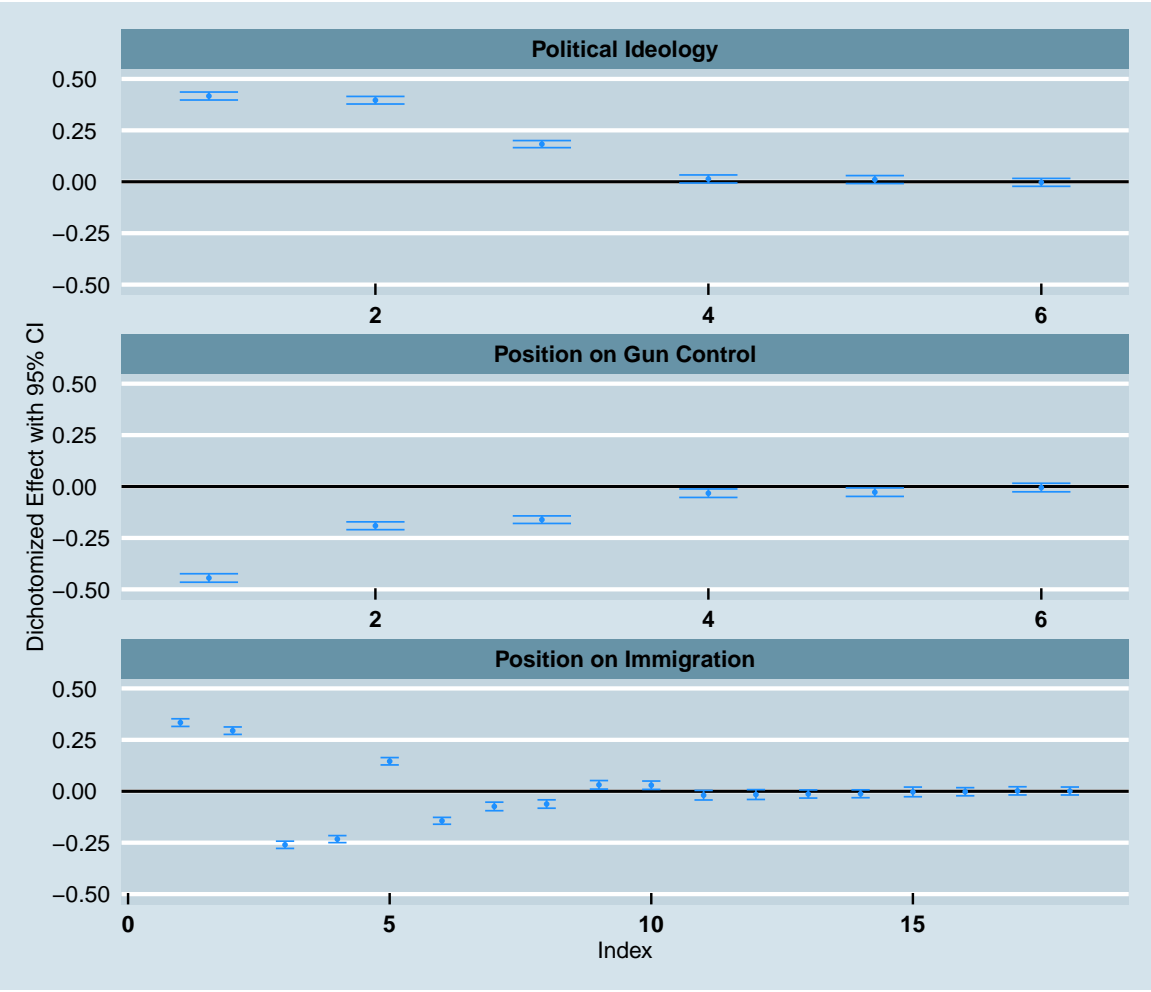


Figure A.5: Associated Fillers in Study 1, first stage. These filler attributes are associated with the Party and Issue Position core attributes.





### A.3 Details and Additional Results from the Second Stage, Study 1

Table A.2: Filler Attributes for Second-Stage Conjoint Experiments in Study 1

Attribute	Levels	Waves
Famous Relative	Franklin Pierce, Chester Arthur, John Tyler, Zachary Taylor	MT1, MT2, MT3, SSI
Elementary School	Washington School, Jefferson School, Madison School	MT1, MT2, MT3, SSI
Favorite Highway	Route 71, Route 73, Route 77, Route 79	MT1, MT2, MT3, SSI
Favorite Vacation Spot	Crystal Lake, Twin Lake, Spring Lake, Long Lake	MT1, MT2, MT3, SSI
Marital Status	Single, Married, Divorced	MT1, MT2, MT3, SSI
Family Dog's Name	Rover, Bailey, Charlie, Buddy, Duke	MT2, MT3, SSI
Favorite Ice Cream Flavor	Chocolate, Vanilla, Strawberry	MT2, MT3, SSI
First Election Eligible to Vote in	Congress, Governor, President	MT2, MT3, SSI
Age when First Voted for President	18, 19, 20, 21	MT2, MT3, SSI
Took High School Trip to Washington DC in	9th Grade, 10th Grade, 11th Grade, 12th Grade	MT2, MT3, SSI
Birthstone	Red Garnet, Emerald, Sapphire, Opal	MT2, MT3, SSI
9th Grade First-Period Class	Math, History, English, Science	MT2, MT3, SSI
Favorite Dinosaur as a Child	Triceratops, Stegosaurus, Allosaurus, Tyrannosaurus	MT2, MT3, SSI
First Book Report on	George Washington, John Adams, Thomas Jefferson, James Madison	MT2, MT3, SSI
Wedding Anniversary	May 14, June 12, September 16, October 10	MT2, MT3
Born on a	Monday, Tuesday, Wednesday, Thursday	MT3, SSI
Favorite Color	Blue, Green, Orange, Red	MT3, SSI
Born in	Odd Year, Even Year	MT3, SSI
First Name Ends in a	Vowel, Consonant	MT3, SSI
Disliked Food	Bananas, Pickles, Lettuce, Popcorn	MT3, SSI
Shares a Birthday with Family Member	Yes, No	MT3, SSI
Sixth Grade Classroom on	First Floor, Second Floor, Third Floor	MT3, SSI
Favorite Baseball Team Won World Series when	Candidate was 6, Candidate was 7, Candidate was 8, Candidate was 9	MT3, SSI
Favorite Morning Beverage	Coffee, Milk, Orange Juice, Water	MT3, SSI
Favorite Season	Winter, Spring, Summer, Autumn	MT3, SSI
Type of Tree in Home Backyard	Oak, Maple, Pine	MT3, SSI
Favorite Composer	Beethoven, Bach, Mozart	MT3, SSI
Current Home Address is on a	Street, Road, Way, Avenue	MT3, SSI
Home Front Door Faces	North, South, East, West	MT3, SSI
Color of Childhood Family Car	White, Black, Silver, Red	MT3, SSI
Best High School Sports Team was	Basketball Team, Track and Field Team, Soccer Team, Baseball Team	MT3, SSI
Prefers to Respond to E-mail in the	Morning, Afternoon, Evening	MT3, SSI
Usual Day for Grocery Shopping	Saturday, Sunday, Monday, Tuesday	MT3, SSI
Relative Fought in	World War I, World War II, Vietnam War, Korean War	MT3, SSI
Has Visited the Grand Canyon	Yes, No	MT3, SSI
Preferred Side to Sit on when Riding a Train	Left, Right	SSI

Table A.3: MTurk Sample (Pooled across Waves), DV: Preference (Forced Choice)

# Fillers	0	1	2	3	4	5	6	8	10	12	15	25	35
Own Party $\gamma$	0.198* (0.012)	0.205* (0.011)	0.199* (0.011)	0.178* (0.012)	0.170* (0.011)	0.184* (0.010)	0.147* (0.016)	0.193* (0.017)	0.154* (0.015)	0.192* (0.016)	0.158* (0.016)	0.158* (0.021)	0.178* (0.022)
SS Marriage Position $\gamma$	0.228* (0.019)	0.232* (0.018)	0.229* (0.017)	0.233* (0.018)	0.202* (0.018)	0.231* (0.015)	0.233* (0.025)	0.190* (0.024)	0.243* (0.024)	0.258* (0.022)	0.232* (0.025)	0.220* (0.031)	0.206* (0.030)
Healthcare Position $\gamma$	0.193* (0.015)	0.158* (0.015)	0.160* (0.015)	0.189* (0.014)	0.163* (0.015)	0.177* (0.013)	0.168* (0.020)	0.170* (0.019)	0.181* (0.019)	0.187* (0.019)	0.180* (0.020)	0.125* (0.024)	0.151* (0.023)
Age 54	-0.007 (0.012)	-0.008 (0.011)	-0.006 (0.011)	-0.025* (0.012)	0.003 (0.011)	0.008 (0.010)	-0.013 (0.015)	-0.007 (0.015)	-0.030* (0.015)	-0.005 (0.014)	0.012 (0.015)	-0.014 (0.020)	-0.027 (0.020)
Age 72	-0.080* (0.013)	-0.091* (0.012)	-0.100* (0.012)	-0.124* (0.013)	-0.084* (0.012)	-0.070* (0.011)	-0.068* (0.018)	-0.081* (0.018)	-0.077* (0.017)	-0.082* (0.015)	-0.046* (0.017)	-0.073* (0.019)	-0.041 (0.021)
R <sup>2</sup>	0.131	0.130	0.127	0.132	0.102	0.123	0.109	0.108	0.119	0.144	0.115	0.095	0.098
Adj. R <sup>2</sup>	0.130	0.130	0.127	0.132	0.101	0.122	0.109	0.107	0.118	0.143	0.114	0.094	0.097
Num. obs.	10800	11520	11160	11100	11460	14370	6090	6420	6030	6060	5730	3720	3540

\*  $p < 0.05$ , standard errors clustered by respondent.

$\gamma$ : coded in concordance with partisan affiliation.

All models fit with only core attributes.

Table A.4: SSI Sample, DV: Preference (Forced Choice)

# Fillers	0	1	2	4	6	8	10	15	25	35
Own Party <sup>γ</sup>	0.197* (0.015)	0.182* (0.015)	0.203* (0.015)	0.148* (0.015)	0.172* (0.016)	0.218* (0.016)	0.157* (0.015)	0.172* (0.016)	0.146* (0.017)	0.176* (0.016)
SS Marriage Position <sup>γ</sup>	0.190* (0.021)	0.129* (0.022)	0.155* (0.024)	0.147* (0.023)	0.158* (0.021)	0.126* (0.021)	0.169* (0.020)	0.127* (0.022)	0.128* (0.022)	0.122* (0.021)
Healthcare Position <sup>γ</sup>	0.146* (0.020)	0.122* (0.019)	0.131* (0.020)	0.111* (0.020)	0.113* (0.018)	0.125* (0.018)	0.138* (0.018)	0.101* (0.017)	0.090* (0.018)	0.100* (0.016)
Age 54	-0.001 (0.014)	0.010 (0.013)	-0.009 (0.016)	-0.048* (0.015)	0.004 (0.014)	0.010 (0.015)	-0.019 (0.014)	-0.021 (0.014)	-0.025 (0.016)	0.011 (0.014)
Age 72	-0.074* (0.014)	-0.061* (0.015)	-0.092* (0.017)	-0.107* (0.017)	-0.069* (0.015)	-0.046* (0.015)	-0.056* (0.015)	-0.074* (0.017)	-0.069* (0.018)	-0.040* (0.015)
R <sup>2</sup>	0.103	0.069	0.088	0.062	0.071	0.080	0.074	0.062	0.049	0.059
Adj. R <sup>2</sup>	0.102	0.069	0.087	0.062	0.070	0.079	0.074	0.061	0.048	0.058
Num. obs.	7230	7770	6720	7020	7230	7230	7290	6870	6570	7080

\* $p < 0.05$ , standard errors clustered by respondent.

<sup>γ</sup>: coded in concordance with partisan affiliation.

All models fit with only core attributes.

Figure A.6: This figure illustrates the AMCEs for our core attributes of interest from only the first MT survey wave as the number of relevant attributes increases.

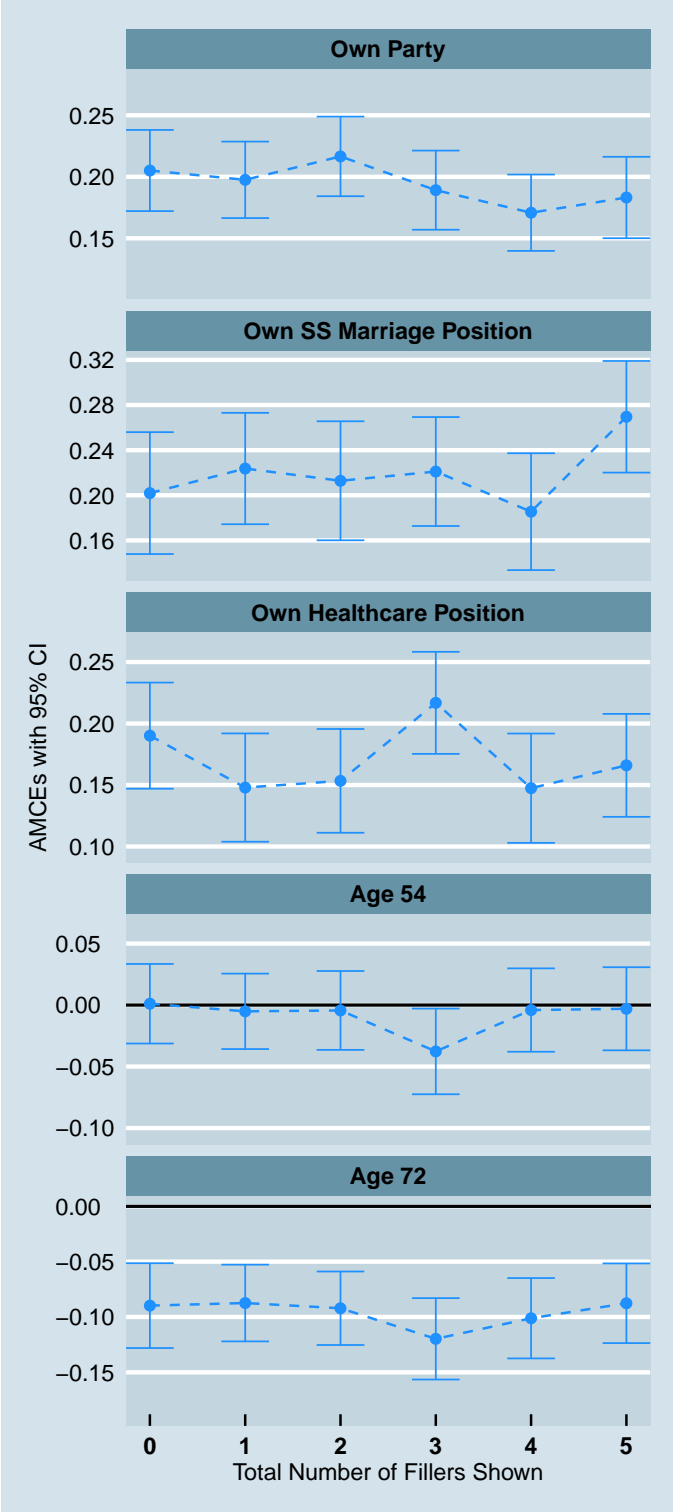


Figure A.7: This figure illustrates the partial R-squared values from models of the forced-choice outcomes using the core attributes as covariates, fit to only the first wave of the MT data.

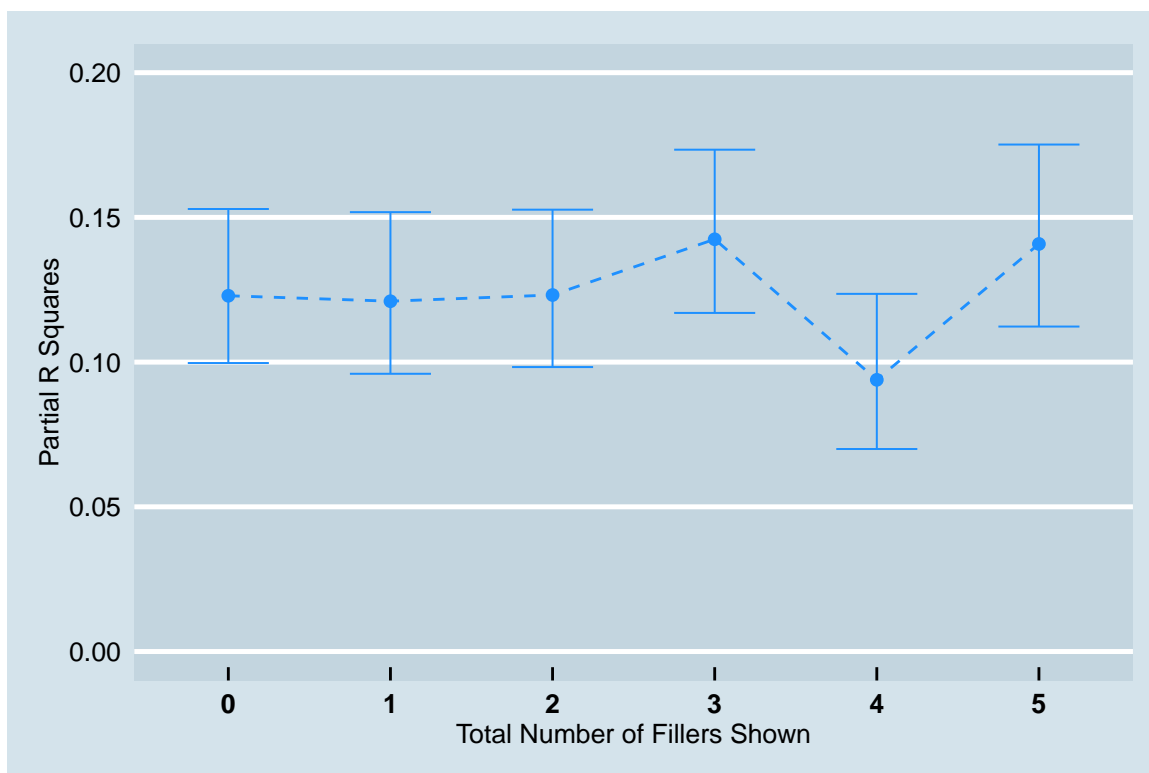


Figure A.8: This figure illustrates the AMCEs for our core attributes of interest from the three MT survey waves as the number of relevant attributes increases, using the rating dependent variable.

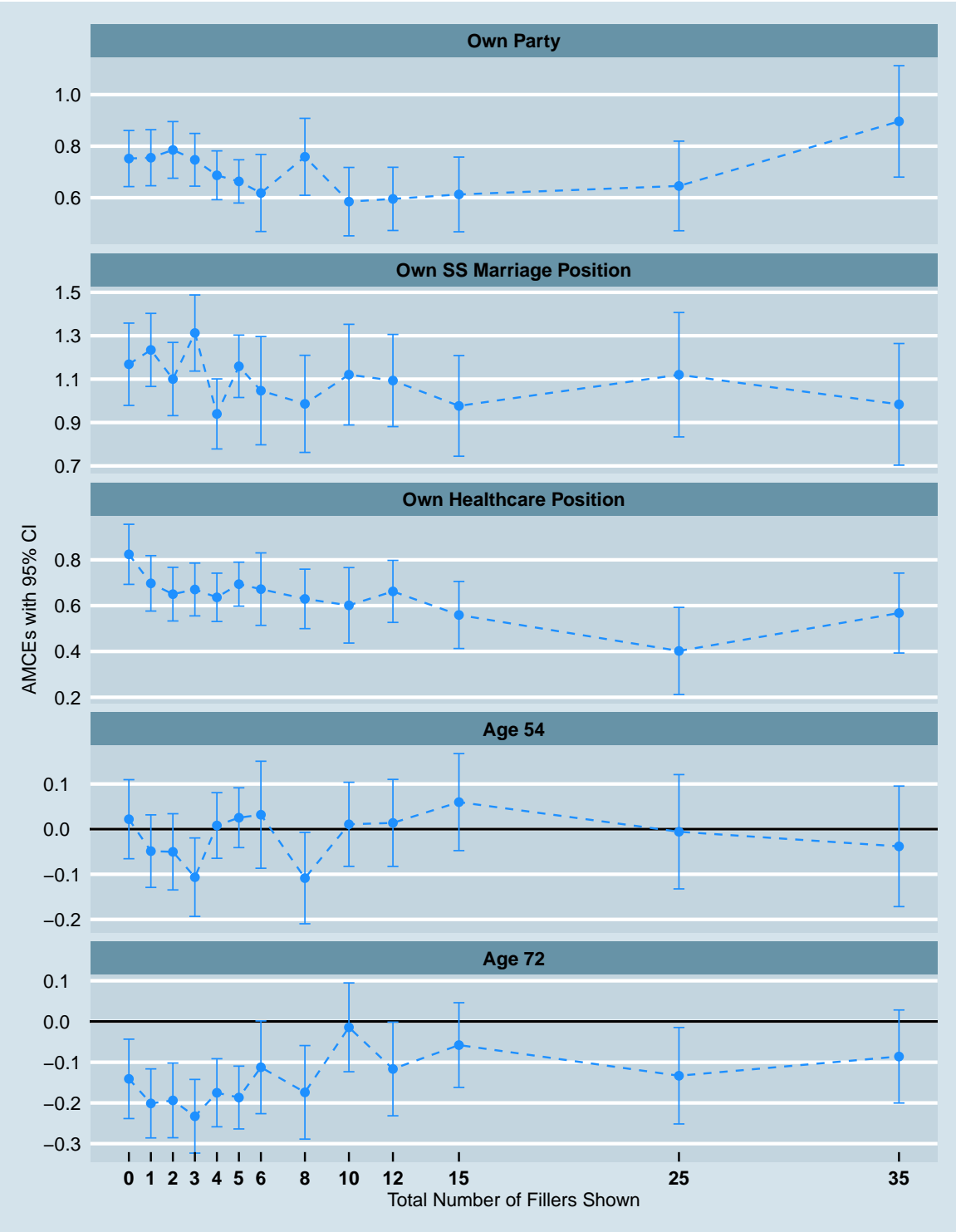
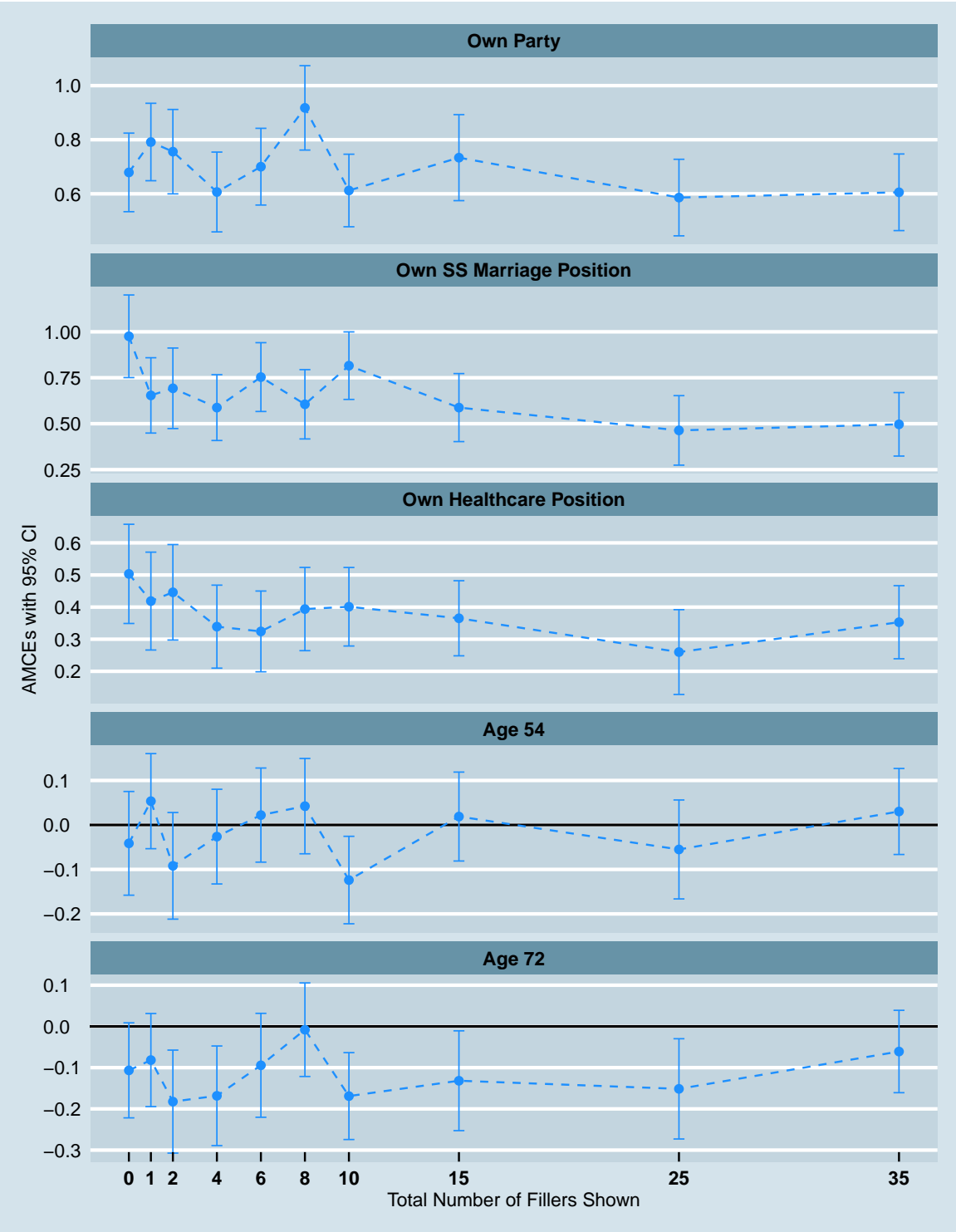


Figure A.9: This figure illustrates the AMCEs for our core attributes of interest from the SSI survey wave as the number of relevant attributes increases, using the rating dependent variable.







## A.4 Details of the First Stage, Study 2

Table A.8: Study 2 Filler Attributes

Attribute	Levels	Included in Stage 2	Abbreviated Name
Material in bed pillows	Feather, Down, Cotton, Memory Foam	Yes	Pillows
Television channels	Free cable channels, pay-per-view movie and event channels, Free Direct TV channels	Yes	Channels
Lamp lights	All fluorescent, All incandescent, Mix of fluorescent and incandescent	Yes	Lamps
Additional service provided	Free laundry, Free dry cleaning, Free bottled water, Free hot breakfast	Yes	Service
Closet options	1 walk-in closet, 2 separate reach-in closets	Yes	Closet
Hallway decor	Paintings, Photographs, Both paintings and photographs	Yes	Hallway
In-room office furniture	Large desk with desk chair but no reading lounge chair, Small desk with desk chair plus reading lounge chair	Yes	Office
In-room kitchen equipment	Refrigerator/freezer, Refrigerator/freezer and microwave, Only refrigerator	Yes	Kitchen
Wake-up calls performed by	Automated voice system, Live operator	Yes	Call
Bathroom towel options	Towels replaced daily, Towels replaced every other day, Towels not replaced during guests' stay	Yes	Towels
Bed linen options	Linens replaced daily, Linens replaced every other day, Linens not replaced during guests' stay	Yes	Linens
Proximity to elevators	Close, Far	Yes	Elevators
Mini-bar contents	Alcoholic beverages, Non-alcoholic beverages, Non-alcoholic and alcoholic beverages	Yes	Bar
Bathroom sinks	2 sinks with limited countertop space, 1 sink with extra countertop space	Yes	Sinks
Ceiling fan location	Above bed, Above couch	Yes	Fan
Default temperature (F) on thermostat	68, 70, 72, 74	Yes	Thermo
Room service menu	Same as hotel restaurant's, Different than hotel restaurant's	Yes	Menu
Complimentary chocolate on pillow	Milk chocolate, Dark chocolate, White chocolate, Mint chocolate	Yes	Chocolate
Room color scheme	Light green and blue, Light green and yellow, Beige and light grey, Sky blue and white	No	Color
Shower design	Bathtub shower with curtain, Walk-in shower with clear door, Walk-in shower with opaque door, Open walk-in shower with no door	No	Shower
Balcony options	40 sq. ft. balcony, 40 sq. ft. of extra interior space and no balcony	No	Balcony
Amount of in-room decor	Minimal decor, Moderate decor, Elaborate decor	No	Decor
Theme of in-room decor	Local artwork, Modern art, Landscape art	No	Theme
In-room coffee/tea	Drip coffee machine, Automatic espresso machine, Water heater for tea	No	Coffee
Bathroom soap and shampoo scent	Lavender, Mint, Citrus	No	Scent
Parking options	Valet parking, Self-parking in indoor garage, Self-parking in outdoor lot	No	Parking
Flooring material	Carpet, Hardwood, Tile	No	Flooring
In-room lights	Turn on automatically upon entry, Must be turned on manually	No	Lights
Hotel restaurant type	American, Italian, Chinese, Mexican	No	Food
On-site hotel car rental service	Large national chain, Small local company, None	No	Car
Television location	In front of bed, In front of couch	No	TV
Bathroom door type	Hinged door with knob, Hinged door with lever handle, Sliding door	No	Bathroom Door
Windows	Do open, Do not open	No	Windows
Valet to bring bags to room	Yes, No	No	Valet
Hours room service menu is available	8am - 11pm, 4pm - 11pm, 24 hours	No	Hours
*24/7 access to	Gym, Pool, Club lounge	No	Access
*Hotel room window has view of	Sailboats, Trees	No	Boats
*Bedroom pillow size	King size, Queen size, Standard size	No	Size

Figure A.10: Results from Study 2, first stage. Evidence of non-association between core attributes and filler attributes included in stage 2.

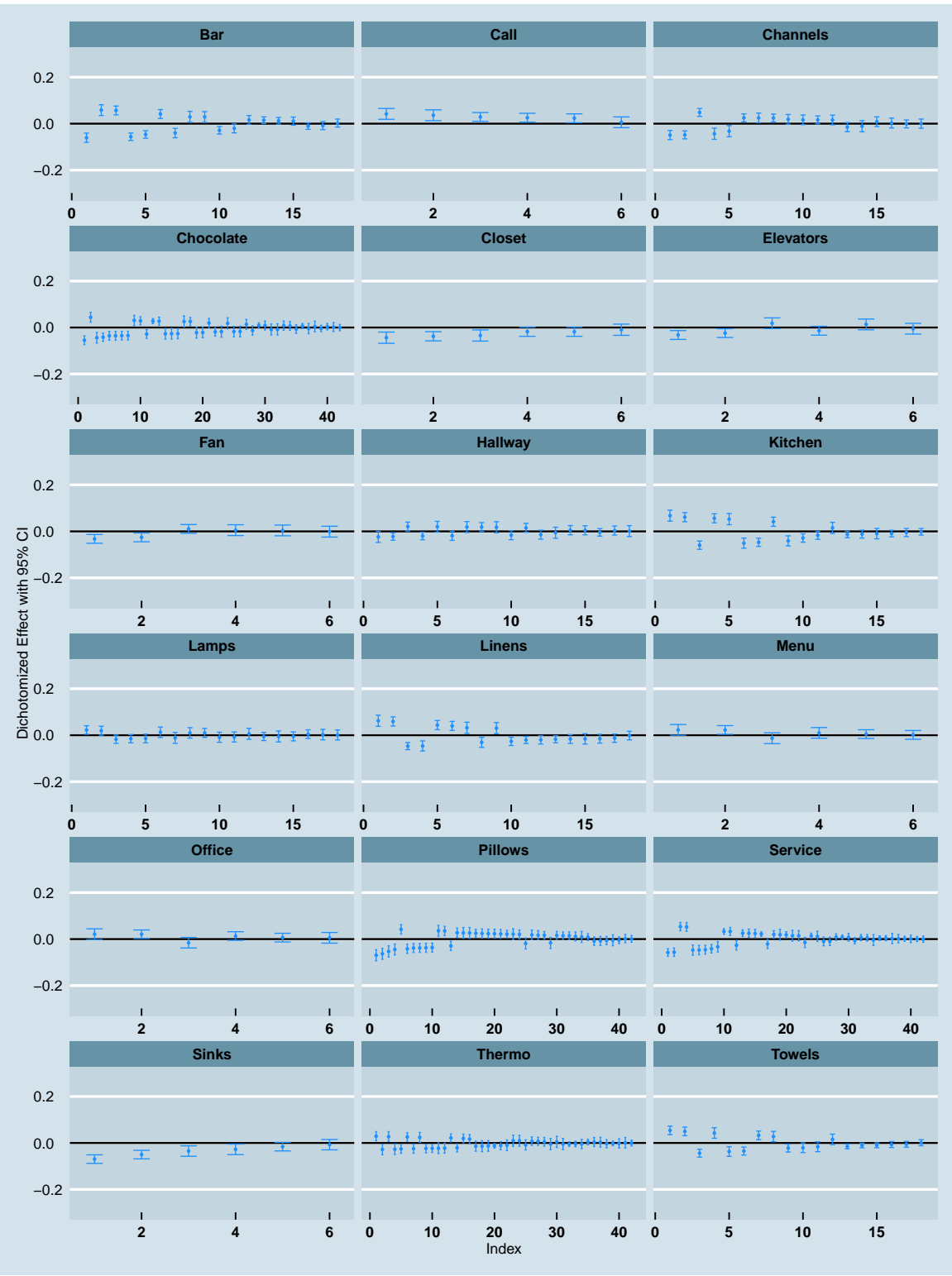


Figure A.11: Associated Filler from Study 2, first stage. These fillers were associated with core attributes.

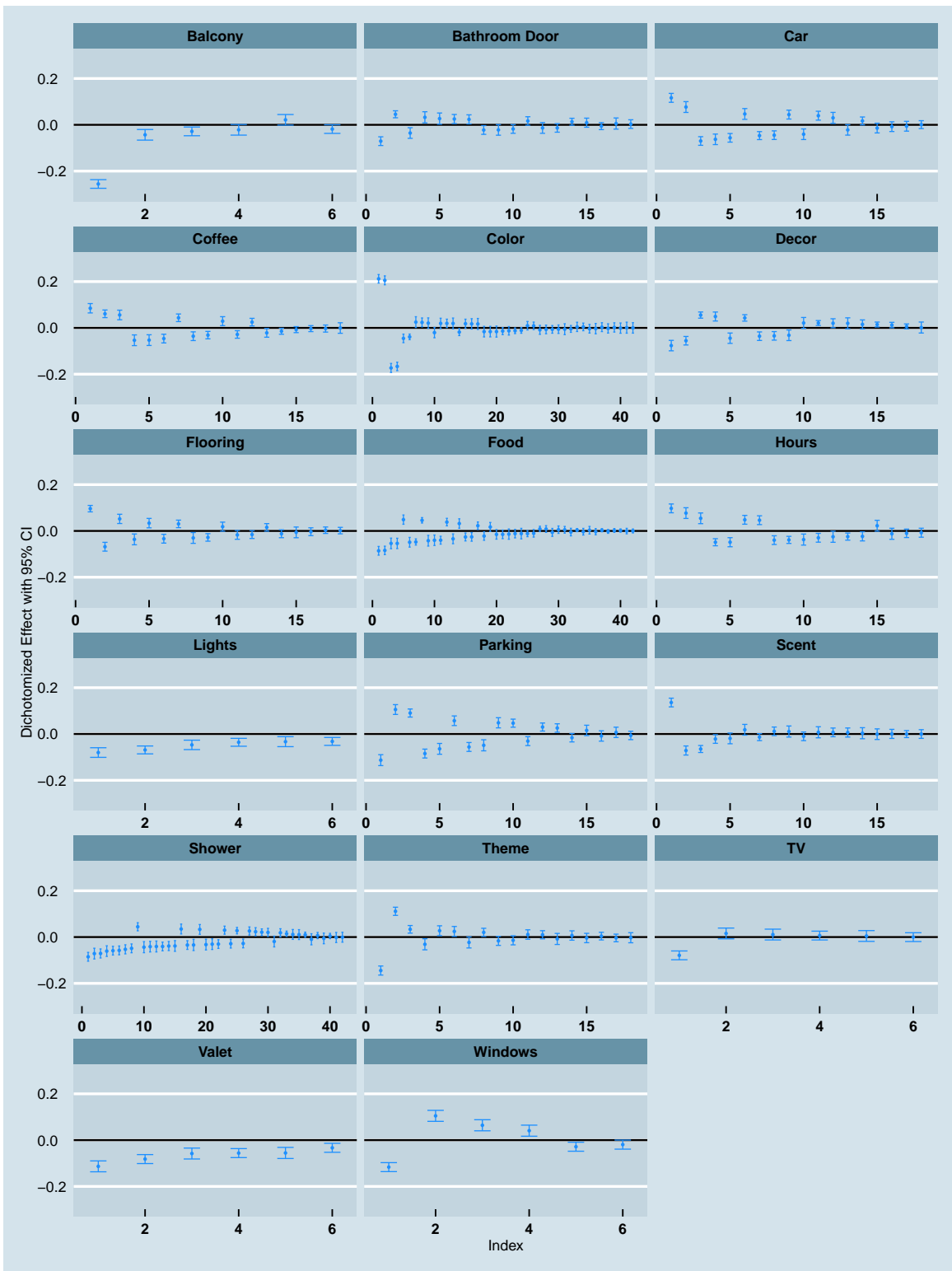
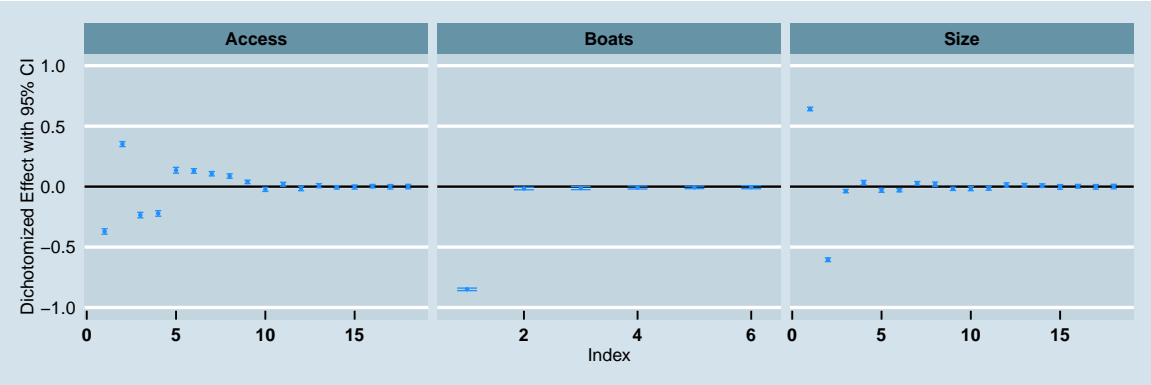


Figure A.12: Attention Check Fillers from Study 2, first stage. These fillers were designed to be associated with certain core attributes and were included as attention checks in the first stage.



## A.5 Details of the Second Stage, Study 2

Table A.9: Study 2 Stage 2 Results, DV: Preference (Forced Choice)

# Fillers	0	1	2	3	4	5	6	8	10	14	18
Ocean View	0.175* (0.018)	0.181* (0.015)	0.162* (0.017)	0.114* (0.016)	0.147* (0.017)	0.109* (0.015)	0.141* (0.015)	0.129* (0.015)	0.122* (0.015)	0.104* (0.016)	0.082* (0.014)
King Bed	0.098* (0.013)	0.092* (0.012)	0.073* (0.013)	0.070* (0.012)	0.084* (0.013)	0.070* (0.012)	0.081* (0.012)	0.070* (0.012)	0.067* (0.012)	0.044* (0.012)	0.037* (0.012)
Pay for Wireless	-0.303* (0.015)	-0.263* (0.015)	-0.259* (0.014)	-0.254* (0.013)	-0.218* (0.014)	-0.217* (0.014)	-0.194* (0.014)	-0.192* (0.014)	-0.170* (0.014)	-0.161* (0.015)	-0.131* (0.014)
10th Floor	-0.007 (0.015)	-0.009 (0.016)	-0.020 (0.015)	0.004 (0.014)	-0.040* (0.014)	-0.012 (0.014)	-0.011 (0.013)	-0.010 (0.014)	-0.009 (0.015)	-0.003 (0.014)	0.003 (0.014)
20th Floor	0.040* (0.018)	0.034 (0.019)	0.018 (0.018)	0.031 (0.016)	-0.001 (0.016)	0.034* (0.015)	0.006 (0.015)	0.016 (0.015)	0.040* (0.015)	0.006 (0.015)	0.011 (0.014)
R <sup>2</sup>	0.133	0.111	0.100	0.083	0.077	0.066	0.064	0.059	0.050	0.040	0.026
Adj. R <sup>2</sup>	0.133	0.111	0.100	0.083	0.077	0.065	0.064	0.058	0.049	0.040	0.025
Num. obs.	8940	8490	9090	9330	9030	9120	9300	8910	9030	9030	8940

\* $p < 0.05$ , standard errors clustered by respondent.

All models fit with only core attributes.

Figure A.13: This figure illustrates the AMCEs for our core attributes of interest from the second stage of study 2 as the number of relevant attributes increases, using the rating dependent variable.

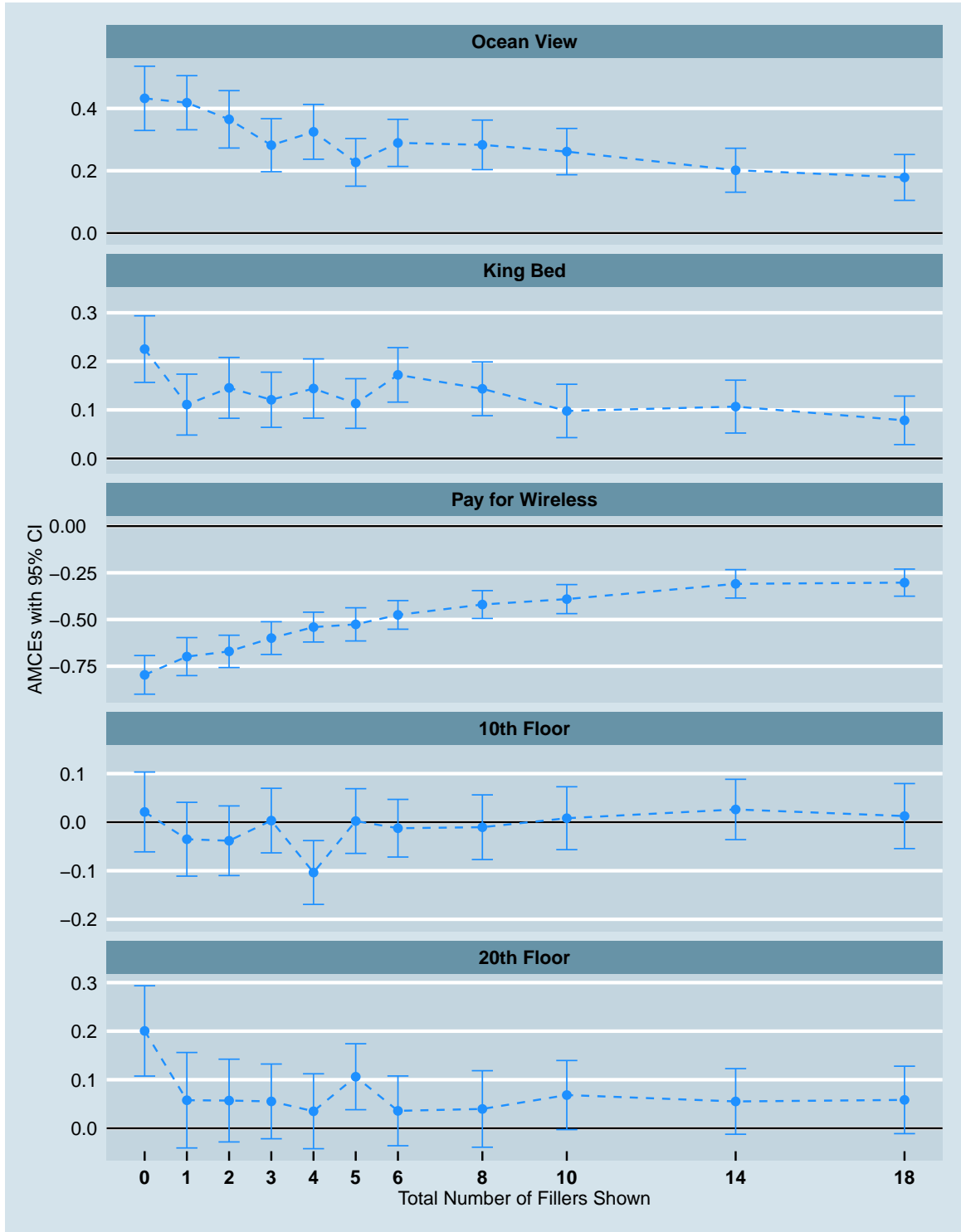




Table A.10: Study 2 Sample Sociodemographic Distributions

		Age			Education						
Gender		29/under	30-44	45-64	65+/over	Less than High School Diploma	High School Diploma / GED	Some College (no degree)	2-year College Degree	4-year College Degree	Graduate Degree
Stage 1	53%	36%	42%	19%	3%	0.3%	10%	26%	13%	38%	14%
	48%	40%	43%	16%	2%	1%	10%	25%	12%	39%	14%

Table A.11: Study 2 Sample Sociodemographic Distributions, continued

		Income										
		\$0 - \$24,999	\$25,000 - \$49,999	\$50,000	\$74,999	\$75,000	\$99,999	\$100,000	\$149,999	\$150,000	\$199,999	\$200,000+
Stage 1	17%	30%	25%	15%	10%	3%	1%					
Stage 2	17%	30%	24%	15%	10%	3%	1%					

Table A.12: Study 2 Sample Sociodemographic Distributions, continued

		Party Identification				Party Identification and/or Leaning		
		Republican	Democrat	Independent	Other	Republican	Democrat	None
Stage 1	24%	42%	30%	3%	33%	57%	11%	
Stage 2	24%	43%	30%	3%	31%	57%	12%	

## A.6 Testing Possibility of Complex Masking And Interactive Associations

Here, we present results from additional, non-prespecified tests which investigate the plausibility of the conditions under which our identification strategy is valid. First, we consider the possibility of complex masking. As we show in Appendix A.1, complex masking could occur even if filler attributes are perceived to be uncorrelated with the core attributes on average. This complex masking can occur if (1) correlations between the filler and core attributes exist for certain types of respondents and (2) if those respondents also place systematically different weights on the filler attributes when making their choices of candidates. In other words, complex masking requires systematic heterogeneity in the relationship between the fillers and the core attributes and systematic heterogeneity in the effect of the fillers on candidate choice. If the patterns of these correlations is “just right,” it could lead to a decrease in the effects of the core attributes in the second-stage experiments when the fillers are added to the model even if there is no increase in satisficing.

To investigate the possibility that complex masking might explain our results we conduct two tests:

1. Using the data from the first-stage experiments we examine whether there is systematic heterogeneity in the effects of the core attributes on the guesses about the filler attributes. In particular, we regress the reported filler attributes on the core attributes, a set of respondent characteristics (including age, income, gender, and education), and all the pairwise interactions between the core attributes and the respondent characteristics. We then conduct Wald tests against the null hypothesis that the interaction effects are jointly equal to zero. Given that respondent characteristics like age, income, gender, and education are often important in structuring preferences, a failure to reject this null provides evidence against the idea that there is systematic heterogeneity in the effects of the core attributes on the guesses of the filler attributes as required by complex masking.
2. Using the data from the second-stage experiments we examine whether there is systematic heterogeneity in the effects of the added filler attributes on candidate choice. In particular, we regress the candidate choice on the filler attributes, a set of respondent characteristics (including age, income, gender, and education), and all the pairwise interactions between

the filler attributes and the respondent characteristics. We then conduct Wald tests against the null hypothesis that the interaction effects are jointly equal to zero. Failure to reject this null provides evidence against the idea that there is systematic heterogeneity in the effects of the filler attributes on the candidate choice as required by complex masking.

In addition, we also consider the possibility that perceived associations might exist between a filler attribute and certain combinations of core attributes. That is, masking could also occur if respondents are able to guess the value of a filler attribute from a particular combination of the core attributes. For example, respondents might associate an elderly Republican candidate to a particular filler attribute even though neither age nor party alone informs them about the attribute. To investigate this possibility, we conducted a test similar to Test 1 above with respect to the pairwise interactions between the core attributes themselves.

Figure A.14 reports the tests from the first-stage experiments for the hotel study. Despite the large sample sizes we fail to reject the null that the interaction effects are jointly equal to zero. The p-values from the joint tests roughly follow a uniform distribution. Figure A.15 reports the same results for the candidate experiment and the results are similar to those from the hotel experiment. Overall these findings suggest that the effects of the core attributes on the choice of the fillers do not vary across respondents in ways that would be detected by the joint tests. This speaks against the possibility of complex masking as a potential explanation of our results.

Figures A.16 reports the test from the second-stage experiments for the hotel study. Again, we fail to reject the null that the interaction effects are jointly equal to zero for the large majority of fillers despite the large sample size. Figures A.17, A.18, and A.19 report the same results for the candidate experiment for the various samples and the results are similar to those of the hotel experiment. Overall, these findings suggest that the effects of the filler attributes on the candidate choice do not vary across respondents in ways that would be detected by the joint tests. This again inveighs against the possibility of complex masking as a potential explanation of our results.

Finally, Figures A.20 and A.21 show the results of the tests of whether the pairwise interactions of the core attributes have any perceived association with any of the filler attributes. Again, despite the large sample sizes, we fail to reject the joint null of no interaction effects, implying that such interactive association is unlikely to exist in respondents' perceptions.

Figure A.14: This figure illustrates the results from tests for the possibility of complex masking by examining whether there is systematic heterogeneity in the effects of the core attributes on the guesses of the filler attributes across respondent characteristics in the first-stage hotel experiment.

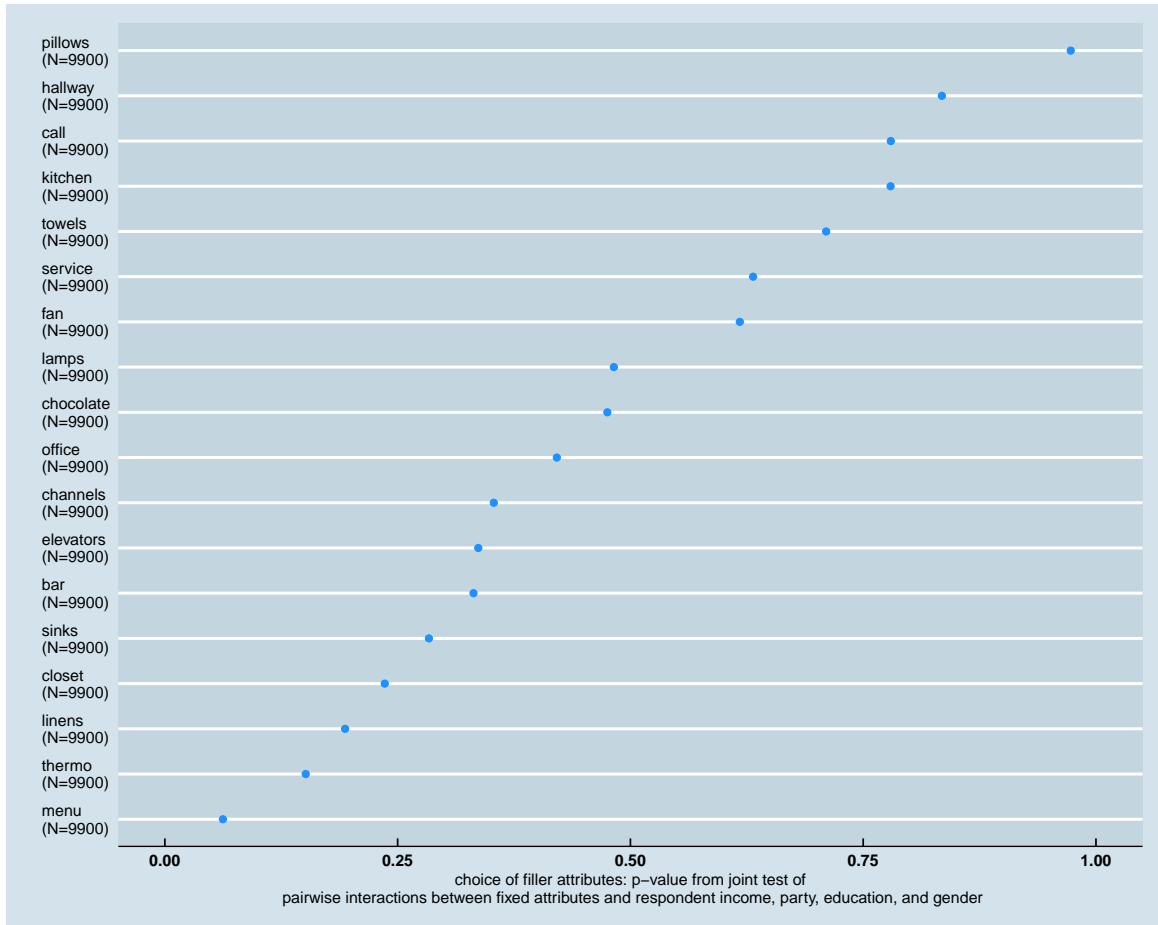


Figure A.15: This figure illustrates the results from tests for the possibility of complex masking by examining whether there is systematic heterogeneity in the effects of the core attributes on the guesses of the filler attributes across respondent characteristics in the first-stage candidate experiment.

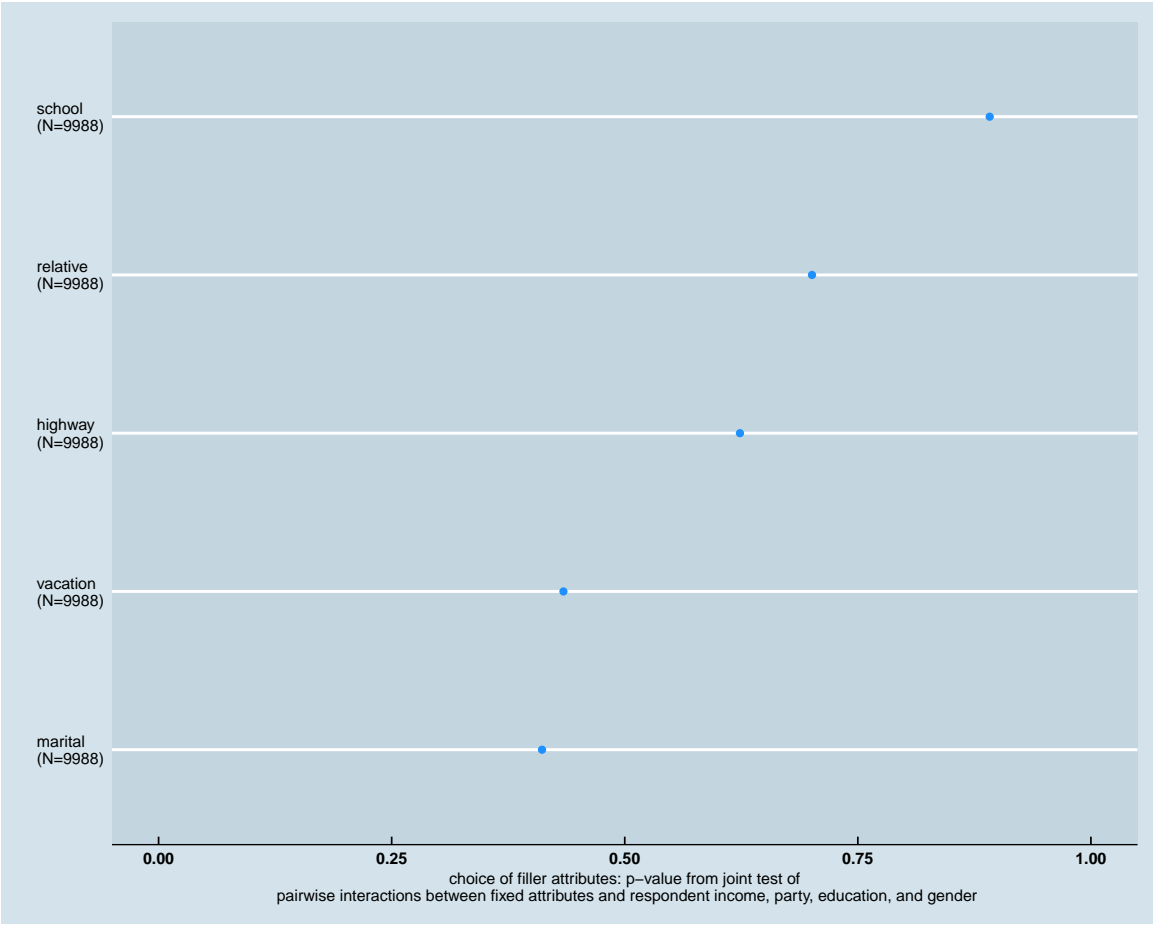


Figure A.16: This figure illustrates the results from tests for the possibility of complex masking by examining whether there is systematic heterogeneity in the effects of the fillers attributes on the candidate choice across respondent characteristics in the second-stage hotel experiment.

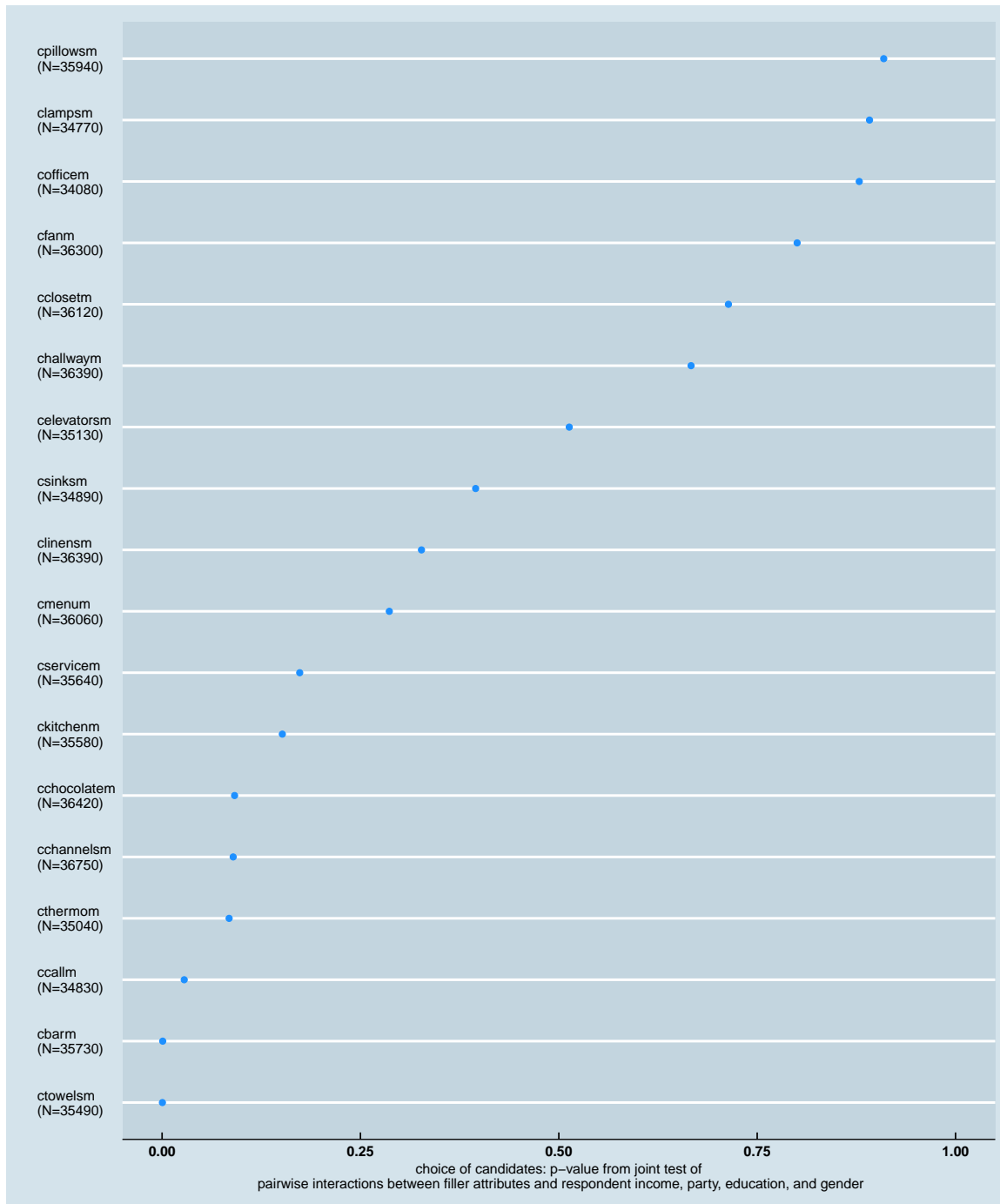


Figure A.17: This figure illustrates the results from tests for the possibility of complex masking by examining whether there is systematic heterogeneity in the effects of the fillers attributes on the candidate choice across respondent characteristics in the second-stage candidate experiment using the MT2 and MT3 samples.

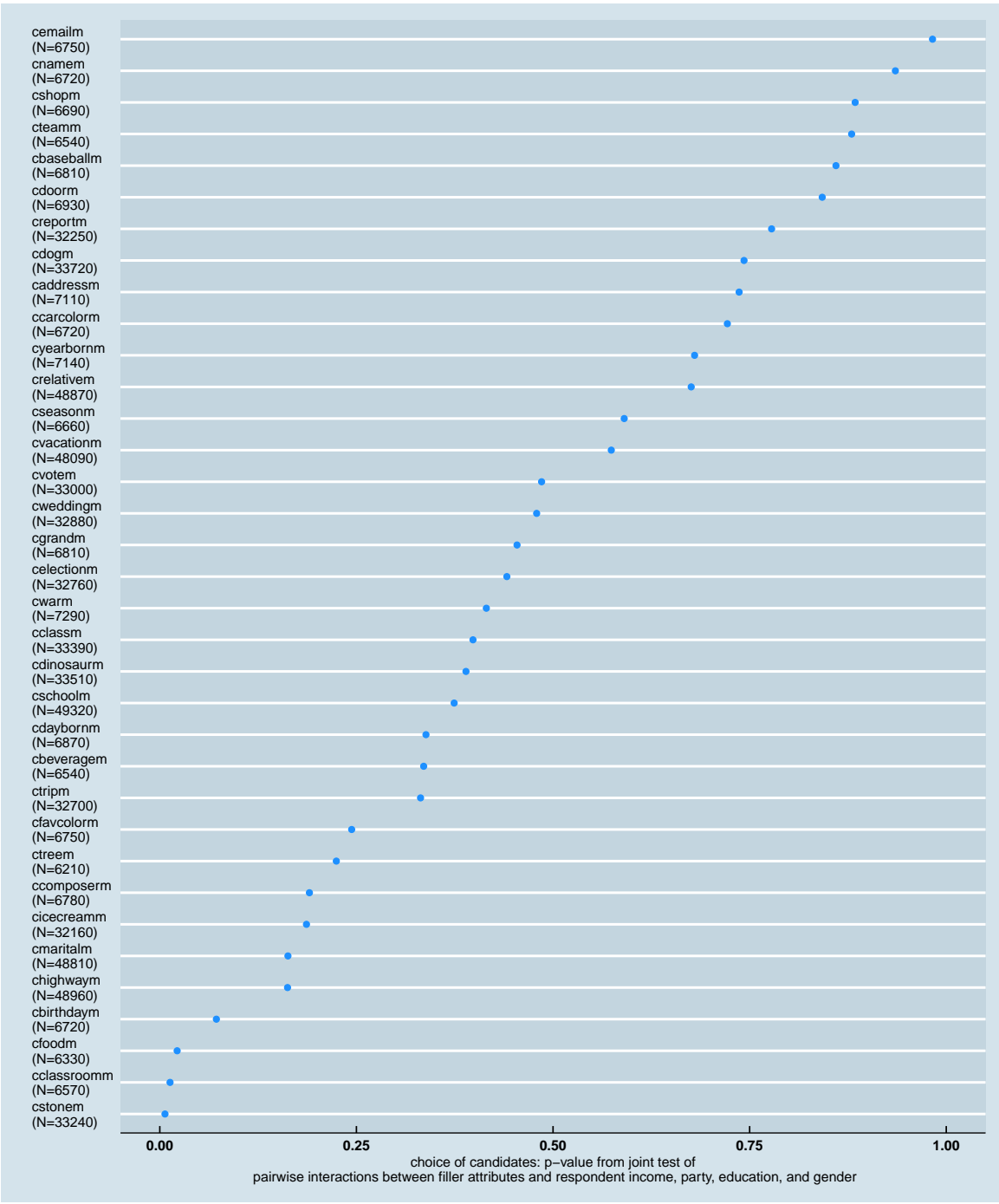


Figure A.18: This figure illustrates the results from tests for the possibility of complex masking by examining whether there is systematic heterogeneity in the effects of the fillers attributes on the candidate choice across respondent characteristics in the second-stage candidate experiment using the MT1 sample.

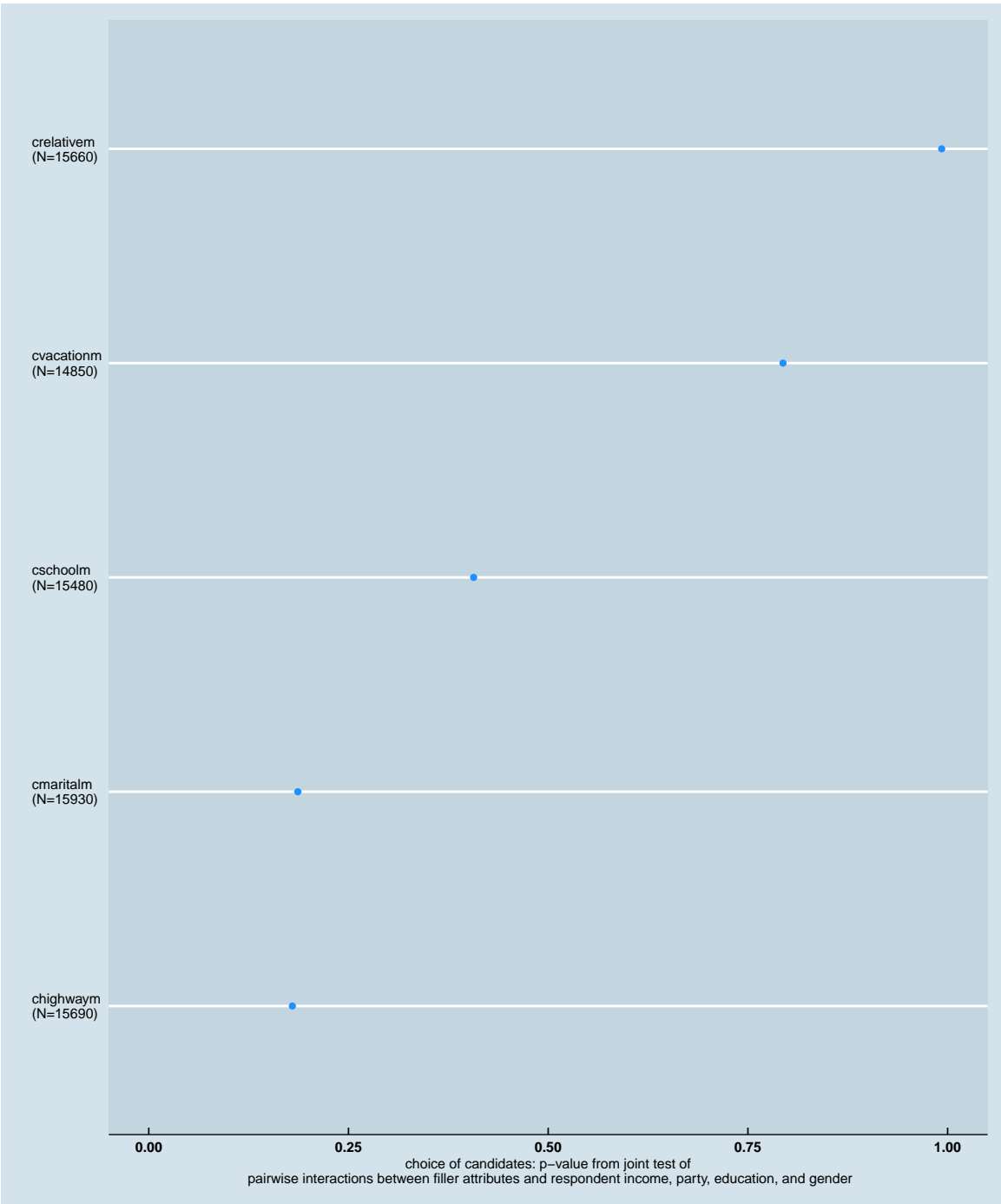




Figure A.19: This figure illustrates the results from tests for the possibility of complex masking by examining whether there is systematic heterogeneity in the effects of the fillers attributes on the candidate choice across respondent characteristics in the second-stage candidate experiment using the SSI sample.

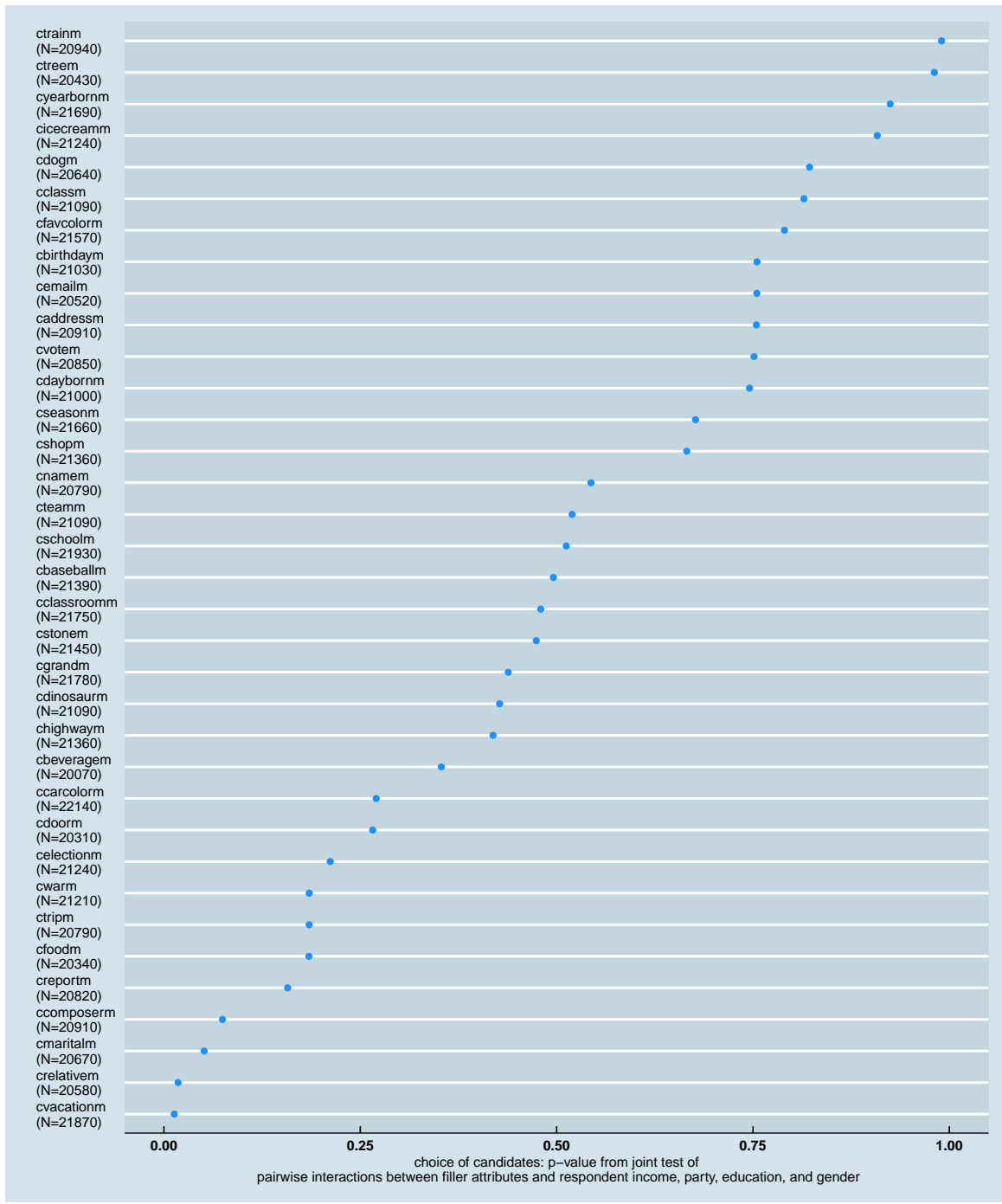


Figure A.20: This figure illustrates the results from tests for the possibility of interactive perceived association by examining whether there is systematic heterogeneity in the effects of the core attributes on the guesses of the filler attributes across values of the other core attributes in the first-stage hotel experiment.

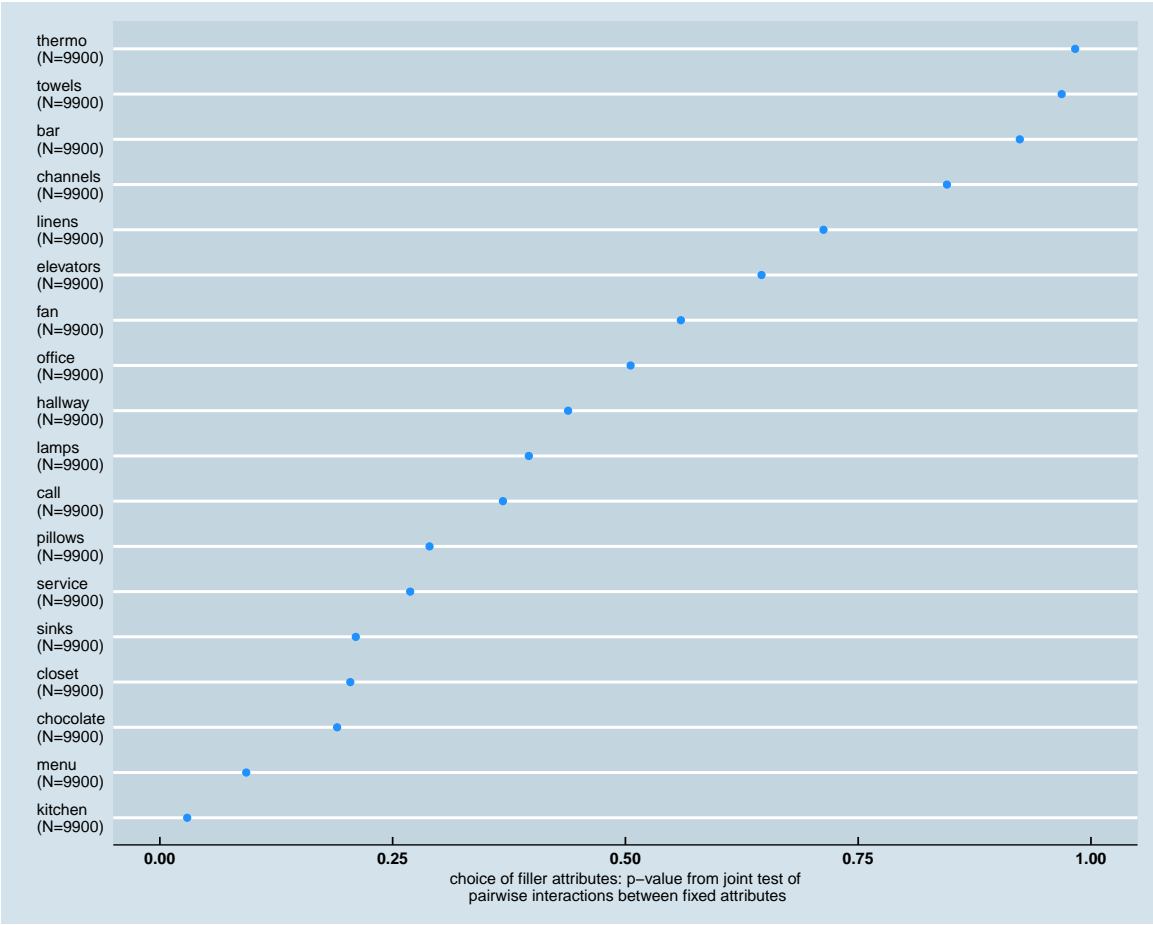


Figure A.21: This figure illustrates the results from tests for the possibility of interactive perceived association by examining whether there is systematic heterogeneity in the effects of the core attributes on the guesses of the filler attributes across values of the other core attributes in the first-stage candidate experiment.

