# Partitioning Menus to Nudge Single-item Choice 

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#### Abstract

Consumers must often choose items from a menu of options. Examples include patrons selecting entrees from a restaurant menu, employees deciding how to save for retirement from a list of 401(k) plans, or physicians choosing medical treatments from an order set. Options often need to be organized or grouped in some way, which raises the question of whether grouping menu items perturbs the options ultimately chosen by consumers. In a series of experiments, we find evidence for single-item partition dependence, where individuals are especially likely to choose an option from menu categories that are more finely partitioned (holding the total number of options constant). Unlike prior work on multi-item allocation decisions, the traditional explanation of partition dependence due to a bias towards even allocation cannot apply to single-item choice, because singular choices are not divisible. Instead, we find evidence that menu partitions influence choice because consumers view partitions as communicating information about what items are most frequently chosen (i.e., descriptive social norms). Our findings suggest that single-item partitioning can have a sizable influence on choice and behavior, and holds promise as a simple and effective tool for marketers and policymakers.


Keywords: menu design, choice architecture, partition dependence, social norms

Consumer judgment and choice is often influenced by how options are presented, ordered, framed, and described. Based on this simple but powerful insight, governments around the world have become interested in constructing behaviorally-informed "choice architecture" designed to enhance public welfare or promote other public priorities (Sunstein, 2013; Thaler \& Sunstein, 2008). Examples include policies that nudge individuals to save more for retirement, consume less energy, purchase more fuel-efficient vehicles, and increase enrollment in college (Allcott \& Rogers, 2014; Bettinger, Long, Oreopoulos, \& Sanbonmatsu, 2012; Larrick \& Soll, 2008; Madrian \& Shea, 2001). Likewise, marketers have also embraced this movement as a way to nudge consumer choice (Johnson et al., 2012).

A primary justification for nudging is that choice architecture is inevitable and inescapable marketers and policymakers, knowingly or not, design environments that will invariably affect how people choose (Thaler \& Sunstein, 2003). As such, choice architects confront choices of their own in constructing a decision environment. Some design decisions are unavoidable, such as how to frame the question being asked and how to order response options (e.g., Dayan \& Bar-Hillel, 2011); other design details are discretionary, such as designating a particular option as the default (e.g., Madrian \& Shea, 2001). For instance, any consumption decision with more than one option means choice architects must determine how to order those options (and a decision with only one option is no decision at all). However, given a list of options the choice architect is not necessarily required to set one as the default (Carroll, Choi, Laibson, Madrian, \& Metrick, 2009; Spital, 1995). Any unavoidable element of a decision environment can be thought of as a fundamental building block of choice architecture, in that all forms of choice architecture will contain it.

In this paper, we introduce a new fundamental building block of choice architecture for selection of a single-item from a menu of options (what we refer to as single-item choice). Examples of single-item choice include deciding which candidate to vote for public office, gift to purchase for a friend, college to attend, medical treatment to pursue, or mode of transportation to use when heading to work. We find evidence for single-item partition dependence, where consumers are more likely to choose from response categories that are more finely grouped or partitioned. Our findings
suggest that single-item partitioning can have a sizable influence on choice and behavior, and holds promise as a simple and effective marketing and policy tool.

## Menu Grouping and Choice

When constructing a choice menu, there is often a need to group items in order to reduce complexity or organize options (e.g., Rosch, Mervis, Gray, Johnson, \& Boyes-Braem, 1976; Tversky \& Hemenway, 1984). For instance, a wine merchant may wish to group wines by the geographic regions in which wines were produced (California, Italian, and French wines), by grape varietals (Merlot, Pinot Noir, and Malbec wines), by price points (low-priced, medium-priced, and highpriced wines), or simply by color (red and white wines). Note that menus with three or more options necessarily require a decision to be made about grouping (including no grouping at all), ${ }^{1}$ and as the number of menu options increase so too do the number of potential groupings or partitions.

While the partitioning of options may help consumers navigate the option space more efficiently, such design decisions may also serve to bias choice. Past work finds that for multi-item allocation decisions, in which a consumer divides or distributes a fixed set of resources (e.g., money), individuals are biased towards even allocation over groupings so that choices systematically vary with how the option set happens to be partitioned (e.g., Fox, Ratner, \& Lieb, 2005). To illustrate this notion, imagine the following two scenarios. In scenario A, an employee is asked to allocate earnings to a savings plan from a menu that groups options according to domestic stocks, international stocks, and bonds. In scenario B, the employee is instead asked to construct a portfolio from a menu that groups options according to stocks, domestic bonds, and international bonds. If allocations are partition dependent, then a bias towards even allocation will lead to a stock-heavy portfolio in scenario A (e.g., $1 / 3$ to domestic stocks, $1 / 3$ to international stocks, and $1 / 3$ to bonds) but will lead to a bond-heavy portfolio in scenario B (e.g., $1 / 3$ to stocks, $1 / 3$ to domestic bonds, and $1 / 3$ to international bonds). Consumers have been found to display partition dependence for allocation decisions in both laboratory and field settings, and across a diversity of domains including

[^0]choosing baskets of goods, judgments under uncertainty (where beliefs are allocated over the space of possibilities), motivation, cue weighting, personal savings versus spending, corporate investment, and parental investment (Bardolet, Fox, \& Lovallo, 2011; Fox \& Clemen, 2005; Hertwig, Davis, \& Sulloway, 2002; Martin \& Norton, 2009; Shah \& Oppenheimer, 2011; Sonnemann, Camerer, Fox, \& Langer, 2013; West, Ülkümen, Arundel, \& Fox, 2021; Wiltermuth \& Gino, 2013).

An open question is whether partition dependence also applies in the domain of single-item choice. Given that many important consumer settings involve single-item choice rather than multiitem allocation decisions, ${ }^{2}$ strategic partitioning of the menu space holds promise as an attractive tool for marketers and choice architects. However, single-item choice represents a fundamental departure from prior work because the standard explanation for partition dependence - a bias towards even allocation - cannot apply to single choices from menus, as single choices are not divisible. ${ }^{3}$ If partition dependence occurs for single-item choice, then other psychological processes besides naive diversification must be at play.

In what follows, we demonstrate that consumers do in fact display partition dependence often markedly so - for single-item choice. Along the way, we explore two mechanisms that may give rise to single-item partition dependence. The first is that menu partitions may bias the allocation of attention: consumers may spend relatively more time attending to (and elaborating upon) menu items that are unpacked (Janiszewski, Kuo, \& Tavassoli, 2013). The second is that menu partitions

[^1]communicate information about descriptive social norms: menu partitions may influence choice because they are viewed as communicating information about descriptive social norms, namely what items are frequently chosen by others. To the extent that consumers believe options frequently chosen by others represent a signal of product quality (Banerjee, 1992; Bikhchandani, Hirshleifer, \& Welch, 1992) or indicate what consumption choices are social approved by others (Bearden \& Rose, 1990), menu partitions may reveal task-relevant information. In the final portion of the paper, we discuss how these insights can be leveraged by marketers and policymakers, as well as to spur future empirical work on the theoretical underpinnings of partition dependence.

## Transparent Reporting

For all studies we determined sample size in advance of data collection. We preregistered hypotheses and analysis plans for Studies 1A, 1B, 2, and 5. For each study a small number of observations with duplicate IP addresses are excluded; the sample sizes reported below reflect the total number of participants after exclusions. The only demographic information we collected was participant age and gender, and this was always done at the end of each study. Study materials, data, code, and preregistration documents can be found at https://researchbox.org/227\&PEER_REVIEW _passcode=ZQVQIK.

## STUDY 1A: DEMONSTRATING SINGLE-ITEM PARTITION DEPENDENCE

In Study 1A, we tested single-item partition dependence for consumer decisions. We presented participants with menus in which all items from one category are individually listed or unpacked, while items from another category are clustered together. This paradigm approximates common menu partitions where a merchant lists out certain categories of goods (such as when a liquor vendor website lists out its selection of Bourbon, Scotch, and Rye whiskeys) while relegating other goods to a residual category (such as if that same website grouped all barware, bar tools, and glassware together). ${ }^{4}$ If participants display partition dependence for single-item choice, then we should see

[^2]greater market share for products from more finely partitioned categories compared to products from more coarsely partitioned categories.

## Method

We recruited a sample of 299 participants from Amazon.com's Mechanical Turk labor market (MTurk) to participate in return for a flat cash payment ( $46 \%$ male, mean age $=35$ years, age range: 19-74 years).

Participants were presented with menus of consumer goods, and indicated the item they would most prefer to receive. To encourage truthful and thoughtful responding, we notified participants at the start of the study that some of them would be selected at random to actually receive one of their chosen consumption options, and that we would follow-up with these participants in order to claim their prize. Participants made four choices in total, from menus of (1) movie DVDs, (2) books, (3) one-year magazine subscriptions, and (4) charitable contributions made in their name.

Each trial consisted of a menu of six options partitioned into two categories. The movie menu consisted of science-fiction movies and romantic comedies; the magazine menu consisted of popular science and world news magazines; the book menu consisted of behavioral science and life science books; the charity menu consisted of animal and environmental charities. For each trial, we randomly selected one category of items to be listed individually while the other category was grouped into a single listing (see Figure 1 for an example). To prevent random or thoughtless responding, participants wrote out their preference in an open text field. ${ }^{5}$ Writing out a response, rather than registering a preference by clicking on a response option, also ensures that effort costs remain constant across experimental conditions. We also note that across conditions

[^3]Figure 1: Example of Menu Partition (Study 1A)

## Animal Charities Unpacked

From the list below, choose one charitable organization to receive a $\$ 10$ donation in your name:

- Humane Society
- Animal Legal Defense Fund
- Society for the Prevention of Cruelty to Animals (SPCA)
- An environment-based charity: your choice of either the Natural Resource Defense Council, Sierra Club, or Environmental Defense Fund

From the list above, please write down one organization to receive your donation: $\qquad$

## Animal Charities Packed

From the list below, choose one charitable organization to receive a $\$ 10$ donation in your name:

- Natural Resource Defense Council
- Sierra Club
- Environmental Defense Fund
- An animal-based charity: your choice of either the Humane Society, Animal Legal Defense Fund, or the Society for the Prevention of Cruelty to Animals (SPCA)

From the list above, please write down one organization to receive your donation: $\qquad$
stated information was also held constant - regardless of the menu partition, participants were presented with the same set of items and only selected one item. To control for possible order-effects we counterbalanced (at the participant-level) the position of the grouped-category by listing it as either the first or last option in the menu.

## Analysis Strategy

To test for partition dependence, we compared choice percentages for groups of items individually listed ("unpacked" items) to those same items grouped into a single listing ("packed" items). When combining responses across choice domains, we conducted a logistic regression where the outcome variable was choosing an item from a target group (e.g., for the charity domain, $0=$ not choosing an animal-based charity, $1=$ choosing an animal-based charity) and our predictor variable was whether the menu is partitioned such that the focal group is packed or unpacked ( 0 $=$ packed, 1 = unpacked). The particular item group we designated as focal for a given domain

Table 1: Percentage of participants choosing an item from Group A (Study 1)

|  |  | Group B | Group A <br> Unpacked | Group A <br> Packed | Difference |
| :--- | :--- | :--- | :---: | :---: | :---: |
| Charities | Animal | Environmental | 85.4 | 52.9 | $32.5^{* * *}$ |
| Movies | Science Fiction | Romantic Comedies | 78.1 | 54.2 | $23.9^{*^{* * *}}$ |
| Books | Behavioral Science | Life Science | 79.1 | 31.7 | $47.4^{4^{* *}}$ |
| Magazines | Popular Science | World News | 70.0 | 28.2 | $41.8^{* * *}$ |

Notes: ${ }^{* * *} p \leq 0.001$.
does not affect the analysis, since each domain contains only two groups of items. Our model also included choice domain fixed-effects and robust standard errors clustered by participants. For all analyses in this paper using logistic regression, we report the average marginal treatment effect across experimental conditions.

## Results

We find clear evidence of single-item partition dependence. Across domains we observed a 36 percentage point increase in choosing unpacked items compared to packed items (see Table 1). In all four domains, choices reliably varied as a function of the menu partition (all $p$-values $<0.001$ ) and in two domains (books and magazines) the unpacked category captured the majority of market share. Furthermore, the size of our effect was not reliably impacted by whether the grouped option was positioned as the first or last listing on the menu ( $p=0.411$ for the interaction term between menu partition and grouped-item position).

## STUDY 1B: CHANCE GAMBLES

In Study 1B we examined whether single-item partition dependence extends to decisions under risk. We also used a different technique for constructing menu partitions. In Study 1A menu partitions were generated by individually listing out some items and clustering others; in Study 1B we presented participants with the same graphical information for all gambles but changed the borders that encompassed different gambles. Doing so leverages the gestalt principle of common region, where elements tend to be perceived as grouped together when they lie within an enclosing contour (Palmer, 1992). If participants display partition dependence for single-item

Figure 2: Example of Menu Partition (Study 1B)

choice under risk, then we should again expect to see greater market share for gambles from more finely partitioned categories compared to gambles from more coarsely partitioned categories.

## Method

We recruited a sample of 199 participants from MTurk ( $53 \%$ male, mean age $=36$ years, age range: 18-76 years). Participants were told they would be shown six gambles that varied in their degree of riskiness, and to choose the gamble they most prefer. We informed participants that five of them would be randomly selected to play their gamble for additional bonus money.

Participants were then shown six gambles, labeled A-F. The gambles were constructed to be roughly equivalent to a certain payment of $\$ 10$, based on traditional prospect theory parameters (Tversky \& Kahneman, 1992; Tversky \& Fox, 1995). We presented gambles each accompanied by a pie chart illustrating the relevant payoffs and probabilities, and randomly assigned participants to choose from one of two menu partitions. Illustrated by Figure 2, half of participants chose from a
menu where the three most risky gambles were unpacked (by encompassing each gamble separately) and the three less risky gambles were packed together (by encompassing all three gambles within a single border). The other half of participants viewed the reverse menu partition. Participants registered their preference by directly clicking on a gamble, and were allowed to choose only one gamble. As in Study 1A, we counterbalanced whether the grouped category was positioned at the top or bottom of the menu.

## Analysis Strategy

We use a two-sample test of proportions to compare the percentage of choices for one of the three riskier gambles when risky gambles were packed versus unpacked. To examine positioning effects (i.e., whether the position of the grouped category affects our results), we conduct a similar logistic regression to that used in Study 1A. Since participants only completed a single trial, we use robust standard errors rather than participant-clustered standard errors.

## Results

Participants displayed single-item partition dependence over chance gambles. Only 7\% of participants selected a riskier gamble when riskier gambles were packed together, compared to $22 \%$ when riskier gambles were unpacked $(z=2.80, p=0.005)$. While participants were generally risk averse, preferences for riskier gambles increased threefold when they were partitioned separately compared to when those same gambles were partitioned into a single grouping. Furthermore, our results were not reliably affected by whether the grouped category was positioned at the top or bottom of the menu ( $p=0.845$ for the interaction term between menu partition and grouped-item position).

## STUDY 2: DO PARTITIONS BIAS ATTENTION?

Our first two studies found strong evidence of partition dependence for single-item choice, but exactly why is unclear. One possibility is that consumers may spend relatively more time focusing and elaborating on unpacked items, which ultimately increases their appeal (Bhatnagar \& Orquin,
2022). Although a bias towards equal allocation cannot apply to single-item choice (since singular choices cannot be divided), perhaps consumers are biased in how they allocate attention to options. If the allocation of attention is partition dependent, then consumers may spend relatively more time attending to (and elaborating upon) menu items that are unpacked.

An attention-based account generates a clear and testable prediction, namely that the pattern of findings we observe in Studies 1A and 1B should reverse whenever participants are asked to choose from a menu of unpleasant options. Since participants are more likely to avoid negative stimuli that receive relatively greater attention (Janiszewski et al., 2013), the increased attention or elaboration due to unpacking a category of unpleasant options should make those options especially unappealing and less likely to be selected (for a similar logic, see Brenner, Rottenstreich, Sood, \& Bilgin, 2007). Thus, an attention-based account would predict a reversal of the partitioning effect for negative stimuli, with participants especially likely to select items from packed categories over unpacked categories. Conversely, if we continue to see a partitioning effect similar to our previous studies, then this would suggest that single-item partition dependence operates through mechanisms other than the biased allocation of attention.

## Method

We recruited a sample of 201 participants from MTurk to participate in return for a flat cash payment ( $55 \%$ male, mean age $=34$ years, age range: $19-84$ years). Participants were asked to imagine performing one of six hour-long household chores. Half of the participants responded to a menu with the indoor activities unpacked (kitchen cleaning, vacuuming, folding and washing laundry) and half responded to a menu with the outdoor activities unpacked (cleaning rain gutters, lawn-mowing, weeding). As before, we counterbalanced the position of the packed/unpacked categories across participants.

## Analysis Strategy

We used the same analysis strategy as in Study 1B.

Contrary to an attention-based account of partition dependence, we found a large partitioning effect similar to that in Study 1. Participants were more likely to choose indoor chores when those items were listed individually as opposed to when those same items were grouped together ( $82 \%$ vs. $44 \% ; z=5.01, p<0.001$ ). Unlike our previous studies, we also observe a reliable interaction between menu partition and grouped-item position ( $p=0.043$ for the interaction term): the partitioning effect was reliably larger when the packed item was placed at the bottom of the menu ( $54 \%$ marginal effect; $p<0.001$ ) compared to when it was placed at the top of the menu ( $22 \%$ marginal effect; $p=0.026$ ). Regardless of grouped-item position, the results of Study 2 suggest that menu partitions exert an influence on choice that cannot be readily explained by the biased allocation of attention.

## STUDY 3: DO MENU PARTITIONS COMMUNICATE INFORMATION?

In Study 3 we examined another explanation for single-item partition dependence, namely that partitioning the menu space communicates task-relevant information. ${ }^{6}$ For instance, Benartzi and Thaler (2001) speculated that employees engage in naive diversification when saving for retirement because they recognize their lack of financial sophistication and trust their employer has constructed a selection of funds that meets the needs of its employees. Similarly, basic conversational norms dictate that information should only be as granular as necessary (i.e., the conversational maxim of quantity; Grice, 1975), and consumers assume such conversational norms about granularity hold when confronting a menu of choices (Zhang \& Schwarz, 2012). Importantly, two logically equivalent menus (i.e., menus that contain the same set of options) can potentially communicate different information whenever consumers believe menu partitions are not constructed at random (see Prelec, Wernerfelt, \& Zettelmeyer, 1997; Sher \& McKenzie, 2006, 2014).

If menu partitions communicate information, then what information do they communicate?

[^4]We suggest that menu partitions signal information about descriptive social norms. For instance, it is plausible that marketers and policymakers alike allocate menu space to those options that are most popular, while clustering less popular options together or relegating them to a residual "other" category. Since beliefs about how other people decide is a powerful influence on one's own behavior (Bearden, Netemeyer, \& Teel, 1989; Cialdini \& Goldstein, 2004; Cialdini, Kallgren, \& Reno, 1991), menu partitions may exert their influence by structuring our beliefs about what options are relatively popular or unpopular. Stated more precisely, this account suggests that consumers act as if menu partitions abide by a "principle of maximum entropy" over the distribution of preferences in a given population (Jaynes, 1957). That is, given a set of possible ways to partition the menu space, choice architects divide the menu in a way that tries to evenly allocate preferences across options (and thus, more popular items are more finely partitioned).

In Study 3, we examine whether people infer descriptive social norms from menu partitions, and whether those beliefs affect how people choose. According to this information-based account, participants should view an item as relatively more popular when individually listed out than when grouped together. Also, to the extent that inferences about descriptive social norms causally influence consumption decisions, then beliefs about item popularity should statistically mediate menu partitioning effects.

## Method

We recruited a sample of 154 participants from MTurk ( $69 \%$ male, mean age $=28$ years, range: 18-72 years). As in Study 1, participants were asked to make choices from a menu of options, and were also asked to infer the popularity of those menu items as an empirical proxy of descriptive social norms.

Choices and inferences were performed in separate blocks. For the choice block participants were presented with four hypothetical choice menus; for each menu, half of the items were listed individually and the other half of items were clustered into a single response option. As in our previous studies, we counterbalanced the position of the packed category to be in either the first or last position. For the inference block, participants were presented with the same menu partitions

Figure 3: Example of Choice and Estimation task (Study 3)
Example choice trial

| Imagine you win an all expenses paid trip to one country of your choice. Which of the following countries would |
| :--- |
| you prefer to visit? |
| A. France |
| B. Germany |
| C. Italy |
| D. Asian country (your choice of either China, Japan, or Vietnam) |
| Which country would you choose? (Please list one country name) |

Example estimation trial

| Other respondents to this survey will be presented with the following: |
| :--- |
| Imagine you win an all expenses paid trip to one country of your choice. Which of the following countries would |
| you prefer to visit? |
| A. France |
| B. Germany |
| C. Italy |
| D. Asian country (your choice of either China, Japan, or Vietnam) <br> What percentage of other respondents of this survey would you estimate answer each of the following? (Please <br> give numbers between 0 and 100 so that your numbers sum to 100\%) <br> France <br> Germany <br> Italy <br> Asian country (your choice of either China, Japan, or Vietnam) |

they viewed in the choice block and asked to estimate the percentage of participants in the study who would choose each option, with all estimates summing to 100 (see Figure 3 for an example). We randomized the order of domains within each block, and also counterbalanced the order of the two task blocks: half of the participants completed the choice block first and inference block second, the other half completed the study in the reverse order. Counterbalancing the task blocks allowed us to compare response tendencies between the first and second blocks and rule out potential spillover effects (for instance, inferences of item popularity being influenced by prior choices, e.g. Ross, Greene, \& House, 1977).

## Analysis Strategy

We used the same analysis strategy as in Study 1A. When examining inferences about item popularity we used OLS regression instead of a logit model.

Table 2: Study 3 Results

| Domain | Group A | Group B | Choices (\%) |  |  | Judgments (mean estimate) |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  |  |  | Group A <br> Unpacked | Group A Packed | Difference | Group A <br> Unpacked | Group A Packed | Difference |
| Vacations | Europe | Asia | 71.8 | 51.3 | 20.5** | 69.8 | 54.3 | $15.5^{* * *}$ |
| Entertainment | Sports | Cultural | 62.7 | 27.8 | $34.8{ }^{* * *}$ | 77.5 | 56.5 | 21.0*** |
| Weekend trip | West Coast | East Coast | 81.3 | 51.9 | 29.4*** | 61.9 | 41.9 | 20.1 ${ }^{* * *}$ |
| Desert | Cookies | Ice Cream | 83.7 | 23.0 | $60.8^{* * *}$ | 65.0 | 30.8 | $34.2^{* * *}$ |

Notes: Descrepancies in difference scores due to rounding error. ${ }^{* *} p \leq 0.01,{ }^{* * *} p \leq 0.001$.

## Results

Table 2 provides a summary of the results. Again, we find a robust partitioning effect on choice. Across domains, we observe a 36 percentage point increase in choosing unpacked items compared to packed items ( $p<0.001$ ). In all four domains, choices reliably varied as a function of the menu partition ( $p$-values $<0.010$ ).

Consistent with an information-based account, menu partition also influenced inferences about descriptive social norms. On average, there was a 23 percentage point increase in inferred popularity for unpacked items compared to packed items ( $p<0.001$ ). In all four domains, inferences reliably varied as a function of the menu partition ( $p$-values $<0.001$ ).

As in Study 2, we find an (unexpected) interaction between menu partition and groupeditem position ( $p$-values were 0.006 and 0.024 for the interaction terms on choices and inferences, respectively). For choices, the partitioning effect was reliably larger when the packed category was placed at the bottom of the menu ( $50 \%$ marginal effect; $p<0.001$ ) compared to when it was placed at the top of the menu ( $24 \%$ marginal effect; $p<0.001$ ). For inferences, menu partitions had a larger effect on ratings of item popularity when the packed category was placed at the bottom of the menu ( $28 \%$ marginal effect; $p<0.001$ ) than when it was placed at the top of the menu $(18 \%$ marginal effect; $p<0.001$ ). Thus, like Study 2 , our effects were larger when the packed category was placed at the end of the menu, but we still find pronounced partitioning effects when placed at the top of the menu. We return to the issue of positioning effects in the general discussion.

Menu partitions strongly influenced both choices and beliefs about item popularity, and we next examine the relationship between the two. Consistent with an information-based account, the
correlation between choice and inferred popularity was positive and significant ( $r=0.41, p<0.001$ across participants and domains). The average correlation across domains and within participants was $r=0.35$; the average correlation across participants and within domains was $r=0.46$. Since a consumer's choices can affect their beliefs about how others choose (e.g., Ross et al., 1977), we also examined if block order (i.e., choosing first and then estimating item popularity, or vice versa) influenced our results. Neither choices nor inferences of item popularity were reliably affected by the order of the task blocks (for the interaction between menu partition and block order, $p$-values were 0.511 for choices and 0.602 for inferences). Furthermore, we found similar results when restricting the analysis to only the first block that participants completed, where spillover effects cannot occur (see section 2 of the Supplementary Materials).

Lastly, we examined whether beliefs about descriptive social norms statistically mediate participant choice. In other words, does the menu partitioning effect reduce in size when we statistically adjust for participants' beliefs about how frequently items are chosen by others? To examine this, we performed Sobel-Goodman mediation tests ${ }^{7}$ using bootstrapped standard errors based on 10,000 resamples clustered at the participant level, along with domain fixed effects and adjustments to the test procedure to account for potential scaling artifacts that can arise when comparing different models using binary choice data ${ }^{8}$ (Karlson, Holm, \& Breen, 2012; Preacher \& Hayes, 2008; Shrout \& Bolger, 2002). Using this procedure we find a reliable mediation effect, with inferences of item popularity mediating $51 \%$ the menu partitioning effect on choice $\left(b_{\text {indirect }}=0.92\right.$, $\mathrm{SE}=0.20,95 \% \mathrm{CI}[0.57,1.33])$. Furthermore, we find a reliable indirect effect both when restricting the analysis to participants that provided choices first ( $b_{\text {indirect }}=0.95, \mathrm{SE}=0.28,95 \% \mathrm{CI}[0.50$, $1.58]$ ), and to participants that provided inferences of item popularity first $\left(b_{\text {indirect }}=0.95, \mathrm{SE}=\right.$

[^5]$0.32,95 \%$ CI $[0.46,1.64])$.

## STUDY 4: BLOCKING INFERENCES

The results of Study 3 suggest that menu partitions influence beliefs - when confronted with a set of options, consumers tend to infer that unpacked items are more popular than packed items. The results of Study 3 also suggest that the shift in beliefs caused by the partitioning of the option set may help to explain single-item partition dependence. However, a limitation of Study 3 is that its design does not allow one to definitively conclude that the causal chain flows from menu partitions to inferences of popularity, and then from inferred popularity to participant choice. Both our putative mediator variable (descriptive social norms) and outcome variable (participant choice) were exposed to the experimental treatment (the partitioning of the menu), and so we cannot decisively rule out the reverse causal pathway - that participant choice is causally prior to beliefs about item popularity (see Imai, Tingley, \& Yamamoto, 2013; Pieters, 2017; Spencer, Zanna, \& Fong, 2005).

In Study 4 we establish causality by directly manipulating beliefs about descriptive social norms independent of menu partitions. If the information gleaned from a menu partition plays a causal role in determining choice, then partitioning effects should be attenuated whenever consumers fail to extract information provided by the menu partition. We aimed to do this by first asking participants to state their beliefs about item popularity before exposing them to the menu partition. We anticipated that having participants first state their descriptive norm beliefs would inoculate any informational effects provided by the partition, and should therefore attenuate observed partitioning effects on choice. Thus, Study 4 uses a "blockage" design (Pirlott \& MacKinnon, 2016) to test the hypothesis that menu partitions are causally mediated by beliefs about descriptive social norms.

Figure 4: Example of Choice and Estimation task (Study 4)
Example choice trial

| Imagine you win an all expenses paid trip to one country of your choice. Which of the following countries would |
| :--- |
| you prefer to visit? |
| A. France |
| B. Germany |
| C. Italy |
| D. Asian country (your choice of either China, Japan, or Vietnam) |
| Which country would you choose? (Please list one country name below) |

Example estimation trial

> Consider the two different types of vacation destinations below. Presented with these options, what proportion of people would choose an all expenses paid trip to either a European country or an Asian country? Please provide your best guess. Note that answers should sum to 100 .

European country (choice of either France, Germany, or Italy) $\qquad$
Asian country (choice of either China, Japan, or Vietnam)

## Method

We recruited a sample of 302 participants from MTurk ${ }^{9}$ ( $65 \%$ male, mean age $=29$ years, range: 18-60 years). Participants first responded to a simple attention check (Oppenheimer, Meyvis, \& Davidenko, 2009), and only those who passed the attention check were allowed to participate in the study.

Participants were presented with the same four choices as in Study 3. In addition to random assignment of menu partitions, participants were randomly assigned to either estimate the two categories comprising each choice set immediately before or after exposure to the partitioned menu (see Figure 4 for an example). Thus, some participants provided estimates of popularity for a category of items before exposure to a specific menu partitioning of those categories (estimate-first condition), while others provided popularity estimates after viewing and responding to the menu partition (partition-first condition). We expected that single-item partition dependence would be attenuated in the estimate-first condition compared to the partition-first condition.

[^6]
## Analysis Strategy

We used the same analysis strategy as in Study 3.

## Results

Table 3 provides a summary of the results. We again find a robust partitioning effect on choice. Across choice domains and conditions, we observed a 35 percentage point increase in choosing unpacked items compared to packed items ( $p<0.001$ ). In all four domains, choices reliably varied as a function of the menu partition ( $p$-values $<0.001$ ). Furthermore, the size of our effect was not reliably impacted by whether the grouped option was positioned as the first or last option on the menu ( $p=0.972$ for the interaction term between menu partition and grouped-item position).

Our primary prediction was that the partitioning effect would be attenuated (compared to our standard treatment) when participants first established their beliefs about descriptive social norms before being exposed to menu partitions. As expected, we observe a reliable attenuation effect: in the partition-first condition we observed a 41 percentage point increase in choices for unpacked items as opposed to packed items, whereas the marginal effect decreased to 29 percentage points in the estimate-first condition. This 12 percentage point decrease was reliably different from chance ( $p=0.036$ for the interaction term between task order and menu partition on choices). As shown in Table 3, the decrease in the partitioning effect is directionally consistent in all four domains.

Next, we examined inferences of item popularity (note that this was measured at the category level, rather than at the item level as in Study 3). Inferences should not be affected by the menu partition in the estimate-first condition (since participants had not yet been exposed to the menu partition), but should shift in the direction of the partition in the partition-first condition (similar to Study 3). As expected, participants who were first exposed to the menu partition rated items from the unpacked category as more popular than those from the packed category $(b=3.49, \mathrm{SE}=$ $1.36, p=0.011$ ), whereas participants who first made inferences of item popularity before viewing the menu partition did not reliably differ across conditions $(b=-0.16, \mathrm{SE}=1.39, p=0.908)$. The difference-in-differences for inferences of item popularity across task order conditions was

Table 3: Study 4 Results

| Domain | Group A | Group B | Choose, then Estimate (choice \%) |  |  | Estimate, then Choose (choice \%) |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  |  |  | Group A <br> Unpacked | Group A Packed | Difference | Group A Unpacked | Group A Packed | Difference |
| Vacations | Europe | Asia | 73.0 | 49.4 | 23.6** | 73.4 | 54.4 | 19.5* |
| Entertainment | Sports | Cultural | 76.0 | 38.7 | 37.3*** | 67.1 | 32.4 | $34.7^{* * *}$ |
| Weekend trip | West Coast | East Coast | 83.3 | 44.2 | 39.2*** | 73.0 | 56.2 | 16.8* |
| Desert | Cookies | Ice Cream | 84.4 | 20.5 | 63.9*** | 76.5 | 31.6 | $44.8{ }^{* * *}$ |

Notes: * $p \leq 0.05,{ }^{* *} p \leq 0.10,{ }^{* * *} p \leq 0.001$.
marginally significant ( $p=0.062$ for the interaction between task order and menu partition on inferred popularity).

Last, we conducted mediation tests using the same analysis strategy outlined in Study 3, but this time performed separate mediation analyses depending on whether inferences of popularity were elicited before or after choice. ${ }^{10}$ As in Study 3, inferences of item popularity reliably mediated the effect of menu partitions on choice for participants who were first exposed to the menu partition $\left(b_{\text {indirect }}=0.10, \mathrm{SE}=0.05,95 \% \mathrm{CI}[0.02,0.22]\right)$. Also as expected, inferences of popularity did not reliably mediate the partitioning effect on choice when participants first reported their estimates before exposure to the menu partitions ( $b_{\text {indirect }}=-0.01, \mathrm{SE}=0.08,95 \% \mathrm{CI}[-0.17,0.14]$ ). Thus, beliefs about descriptive social norms only mediated menu partitioning effects when participants had in fact been exposed to menu partitions, and could thus extract information from them. ${ }^{11}$

Taken together, Studies 3 and 4 suggest that menu partitions convey information about the relative popularity of menu options. Individually-listed options are viewed as more popular than options that are grouped together, and participants tended to choose the options they thought were most popular. Such a strategy may be reasonable to the extent that (a) menu partitions

[^7]accurately reflect majority preference; (b) majority preference is positively correlated with optimal consumption decisions, whether that be a product's quality or social approval from others; and (c) consumers do not have more diagnostic sources of task-relevant information available when making a decision.

## STUDY 5: MODERATION BY SOCIAL MOTIVATIONS

Studies 3 and 4 suggest that menu partitions influence beliefs about item popularity, and beliefs about item popularity influence choice. In Study 5 we test a corollary of this hypothesis, namely that menu partitioning effects should be especially pronounced for those most susceptible to social influence. We use the consumer susceptibility to interpersonal influence scale (Bearden et al., 1989), which measures the extent consumption decisions are driven by feelings of social approval from others (i.e., normative social influence) and by beliefs that other's consumption decisions are a reliable source of product quality (i.e., informational social influence). Since descriptive and injunctive social norms are often positively correlated (e.g., Brauer \& Chaurand, 2010; Eriksson, Strimling, \& Coultas, 2015; Thøgersen, 2008), we can expect that both types of interpersonal influence may be sensitive to beliefs about item popularity. For instance, those who are sensitive to normative influence may be influenced by the consumption decisions of others because majority preference is often a cue of socially acceptable behavior.

In Study 5, we use the design of Study 3 in which participants were asked to provide choices and infer the popularity of menu items, and also measure individual differences in susceptibility to interpersonal influence. If menu partitions communicate social information (i.e., what items are frequently chosen by others), then menu partitioning effects should be especially pronounced for those most susceptible to interpersonal influence. By measuring both choices and beliefs, we can also isolate where in the causal chain any potential moderation effects occur. That is, we can examine whether participants high in interpersonal influence show pronounced partitioning effects because these individuals are especially likely to infer item popularity from menu partitions (i.e, the menu partition $\longrightarrow$ descriptive norm beliefs pathway) or because these individuals give
greater weight to considerations of item popularity when making a consumption decision (i.e., the descriptive norm beliefs $\longrightarrow$ choice pathway).

## Method

We recruited a sample of 601 participants from MTurk ( $46 \%$ male, mean age $=41$ years, range: 18-83 years). The procedure was similar to that in Study 3, in which participants completed both choice and inference blocks in counterbalanced order, with four domains in each block.

After completing both choice and inference blocks, participants completed an 8-item measure of susceptibility to interpersonal influence (Bearden et al., 1989). Participants completed four items from the susceptibility to normative influence (NSI) subscale, rating their agreement with each statement on 7-point scales from strongly disagree (-3) to strongly agree (3). Example items were "it is important that others like the products and brands I buy" and "when buying products, I generally purchase those brands that I think others will approve of." We averaged the four items to create an index of NSI ( $\alpha=0.93$ ). Participants also completed four items from the susceptibility to informational influence (ISI) subscale. Example items were "to make sure I buy the right product or brand, I often observe what others are buying and using" and "I often consult other people to help choose the best alternative available from a product class." We averaged the four items to create an index of ISI ( $\alpha=0.88$ ). We also counterbalanced across subjects whether the four items from the NSI came first or second, and also randomized the order of statements within each subscale. The bivariate correlation between the two indices was 0.44 .

## Analysis Strategy

We used the same analysis strategy as in Study 3. For moderation analyses, we performed logit regression when the dependent variable was choice, and OLS regression when the dependent variable was inferences of item popularity. As with all analyses, we include domain fixed effects and cluster standard errors by participants.

Table 4: Study 5 Results

| Domain | Group A | Group B | Choices (\%) |  |  | Judgments (mean estimate) |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  |  |  | Group A Unpacked | Group A Packed | Difference | Group A Unpacked | Group A Packed | Difference |
| Vacations | Europe | Asia | 74.8 | 55.2 | 19.6*** | 77.6 | 54.1 | 23.5*** |
| Entertainment | Sports | Cultural | 63.4 | 38.1 | 25.3*** | 80.3 | 52.2 | 28.1*** |
| Weekend trip | West Coast | East Coast | 69.9 | 49.0 | 20.9*** | 63.2 | 40.2 | 23.0*** |
| Desert | Cookies | Ice Cream | 67.6 | 34.8 | $32.8^{* * *}$ | 63.0 | 32.6 | $30.4 * * *$ |

Notes: *** $p \leq 0.001$.

## Results

Before turning to our moderation analyses, we examined whether our earlier findings replicate. We again observed a reliable menu partitioning effect, with an average 25 percentage point increase in choosing unpacked items compared to packed items ( $p<0.001$ ). We also again found that menu partitions influenced beliefs about social norms, with an average 26 percentage point increase in inferred popularity for unpacked items compared to packed items ( $p<0.001$ ). Finally, we also found that inferences of item popularity fully mediated the menu partitioning effect on choice $\left(b_{\text {indirect }}=1.26, \mathrm{SE}=0.09,95 \% \mathrm{CI}[1.09,1.44]\right)$. Table 4 presents the main results (see section 5 of the Supplemental Materials for complete details).

We next examined whether menu partitioning effects were reliably moderated by NSI scores, ISI scores, or both. We report all moderation analyses in Table 5. To facilitate interpretation, we report OLS coefficients in the table but report $p$-values using logistic regression. Thus, coefficients can be interpreted as the percentage point increase in choosing from a given category of items as a linear function of an explanatory variable, and a positive coefficient for the interaction term represents the increase in menu partitioning effects as a linear function of the moderating variable. For instance, in Model 1 of Table 5 the "partition" coefficient indicates a 28.1 percentage point difference in choosing unpacked items compared to packed items (when NSI scores are set to 0 ), and that the size of this partitioning effect increases by 2.7 percentage points for every 1-point increase in NSI scores (as represented by the "partition $\times$ NSI" interaction term).

Model 1 examines whether NSI scores moderate single-item partition dependence. As shown in the table, we find a positive and marginally significant interaction term ( $p=0.060$ ), indicating that

Table 5: Study 5 Moderation Results

|  | moderation of basic effect (partition $\rightarrow$ choices) |  | ```moderation of pathway 1 (partition \(\rightarrow\) inferences)``` |  | moderation of pathway 2 (inferences $\rightarrow$ choices) |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | (1) | (2) | (3) | (4) | (5) | (6) |
| Partition | $\begin{aligned} & \hline 0.281^{* * *} \\ & (0.029) \end{aligned}$ | $\begin{aligned} & \hline 0.242^{* * *} \\ & (0.022) \end{aligned}$ | $\begin{aligned} & \hline 0.287^{* * *} \\ & (0.013) \end{aligned}$ | $\begin{aligned} & \hline 0.259^{* * *} \\ & (0.010) \end{aligned}$ | $\begin{gathered} -0.004 \\ (0.024) \end{gathered}$ | $\begin{gathered} \hline-0.004 \\ (0.024) \end{gathered}$ |
| NSI | $\begin{gathered} -0.005 \\ (0.010) \end{gathered}$ |  | $\begin{array}{r} -0.012^{*} \\ (0.005) \end{array}$ |  | $\begin{gathered} -0.012 \\ (0.014) \end{gathered}$ |  |
| Partition $\times$ NSI | $\begin{gathered} 0.027^{\dagger} \\ (0.015) \end{gathered}$ |  | $\begin{aligned} & 0.019^{* * *} \\ & (0.006) \end{aligned}$ |  |  |  |
| ISI |  | $\begin{gathered} -0.007 \\ (0.011) \end{gathered}$ |  | $\begin{array}{r} -0.008^{\dagger} \\ (0.005) \end{array}$ |  | $\begin{array}{r} -0.017 \\ (0.015) \end{array}$ |
| Partition $\times$ ISI |  | $\begin{gathered} 0.019 \\ (0.015) \end{gathered}$ |  | $\begin{gathered} 0.013^{*} \\ (0.006) \end{gathered}$ |  |  |
| Item Popularity |  |  |  |  | $\begin{aligned} & 0.977^{* * *} \\ & (0.046) \end{aligned}$ | $\begin{aligned} & 0.920^{* * *} \\ & (0.040) \end{aligned}$ |
| Item Popularity $\times$ NSI |  |  |  |  | $\begin{gathered} 0.040^{*} \\ (0.022) \end{gathered}$ |  |
| Item Popularity $\times$ ISI |  |  |  |  |  | $\begin{gathered} 0.035 \\ (0.024) \end{gathered}$ |
| Trial Fixed Effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Participants | 601 | 601 | 601 | 601 | 601 | 601 |
| Observations | 2331 | 2331 | 2404 | 2404 | 2331 | 2331 |
| $R^{2}$ | . 080 | . 078 | . 376 | . 374 | . 218 | . 216 |

Notes: OLS estimates with standard errors clustered at the participant-level. For models 1, 2, 5, and 6 the outcome variable was choosing an item from a target group (e.g., for the charity trial, $0=$ not choosing an animal-based charity, $1=$ choosing an animal-based charity). The outcome variable in models 3 and 4 was "item popularity", or the estimated percentage of other participants selecting an item from the focal group (rescaled to fall between 0 and 1). "Partition" indicates whether the menu was partitioned such that the focal group was packed or unpacked ( $0=$ packed, $1=$ unpacked). "NSI" and "ISI" represent a participant's susceptibility to normative social influence and informational social influence score, respectively. Scores on the NSI and ISI can range from -3 to 3, with higher numbers reflecting greater susceptibility. "Item popularity" is the same variable used as the outcome variable in models 3 and 4. All models include trial fixed effects. For models $1,2,5$, and 6 we use significance stars based on logit regressions. ${ }^{\dagger} p \leq 0.10$, ${ }^{*} p \leq 0.05,{ }^{* *} p \leq 0.01,{ }^{* * *} p \leq 0.001$.
menu partitioning effects grew in size for those higher in susceptibility to normative social influence. Model 2 examines whether ISI scores moderate single-item partition dependence. Although we find that partition effects grow in size as a function of ISI scores (i.e., a positive interaction term), the interaction effect was not significant ( $p=0.195$ ). Thus, menu partitioning effects were more pronounced for those most susceptible to interpersonal influence, especially normative social influence.

We next turn to where in the causal chain, from menu partitions to inferences about item popularity or from inferences about item popularity to consumption decisions, that such moderation effects occur. Models 3 and 4 examine moderation for the first part of the causal chain (i.e., the menu partition $\longrightarrow$ descriptive norm beliefs pathway). We find a reliable interaction effect for both NSI scores (Model 3: $p=0.001$ ) and for ISI scores (Model 4: $p=0.039$ ). On average, the size of the "inference gap" across menu partitions increased by 1.9 percentage points for every 1-point increase in NSI scores, and by 1.3 percentage points for every 1-point increase in ISI scores. Thus, participants high in susceptibility to interpersonal influence were especially likely to view unpacked menu items as frequently chosen by others. Models 5 and 6 examine the second part of the causal chain (i.e., the descriptive norm beliefs $\longrightarrow$ choice pathway). We find a positive reliable interaction effect between inferences of item popularity and NSI scores (Model 5: $p=0.045$ ) but no reliable interaction effect between inferences and ISI scores (Model 6: $p=0.194$ ). Thus, participants high in susceptibility to normative social influence also placed greater weight (compared to low NSI participants) on how frequently chosen an item was when making a consumption decision.

In summary, the results of Study 5 suggest that, like earlier studies, menu partitions are more likely to communicate information about item popularity, which in turn influences how participants choose. Furthermore, we find that participants most susceptible to interpersonal influence (especially normative social influence) also tend to show more pronounced menu partitioning effects. ${ }^{12}$ This appears to occur because these participants are especially likely to interpret menu partitions as a signal of item popularity, and also because they give greater weight to considerations of item popularity when selecting an item to consume.

[^8]
## GENERAL DISCUSSION

We document that single-item choice can be substantially influenced by how a set of items is partitioned or subjectively grouped. In particular, participants were more likely to choose items that were individually listed compared to when those same items were grouped together. This was true across a wide range of consumer choice settings, both hypothetical (Studies 2-5) and real (Studies 1A and 1B). The effect of partitioning the menu set was sizable, often shifting choices by 30 percentage points or more. Our findings suggest that the strategic partitioning of menus can be used as a simple and flexible tool to affect behavior change (Johnson et al., 2012). Menu partitioning can be used by marketers and policymakers to supplement more traditional forms of choice architecture, such as setting default options, or alternatively as a substitute in cases where traditional choice architecture techniques are less well-suited (e.g., Keller, Harlam, Loewenstein, \& Volpp, 2011).

Our results indicate that partitioning effects occur partly because menu partitions convey taskrelevant information. The current study contributes to a growing body of research suggesting that choice menus can influence behavior in unexpected ways through the information they communicate to the public (Krijnen, Tannenbaum, \& Fox, 2017; McKenzie, Sher, Leong, \& Müller-Trede, 2018; Tannenbaum, Valasek, Knowles, \& Ditto, 2013). For example, individuals are sensitive to how options are framed (e.g., whether a medical treatment is described as having a $90 \%$ survival rate or $10 \%$ mortality rate) partly because the framing of an option is thought to communicate information about salient reference points and, more generally, which options are endorsed by the choice architect (Keren, 2007; McKenzie \& Nelson, 2003; Sher \& McKenzie, 2006). Likewise, individuals assume that marketers provide a range of consumer options that roughly match the distribution of preferences in the population (Prelec et al., 1997; Schwarz, Hippler, Deutsch, \& Strack, 1985). Consumers clearly extract information from the structure of choice menus, and one structural property appears to be how menu items are grouped.

Since menu partitions can signal information about social norms, marketers and policymakers may wish to consider additional (and less obvious) complexities that arise when altering menu
partitions. For example, choosing an option from a packed category may suggest that such a response is relatively uncommon or atypical, and thus has the potential to induce feelings of disapproval, stigma, or embarrassment (Krishna, Herd, \& Aydınoğlu, 2019). Conversely, items that are individually listed may unwittingly communicate to consumers that those options are more popular than they actually are. Furthermore, if consumers view menu partitions as a strategic persuasion attempt by the marketer, then consumers may engage in reactive behaviors as a way of reasserting their agency and autonomy (Brehm, 1966; Friestad \& Wright, 1994).

## Positioning Effects

In all studies, we not only varied menu partitions (i.e., whether a category of items was packed or unpacked), but also orthogonally varied the position of the packed category to be placed at the top or bottom of the menu. In a subset of studies (Studies 2 and 3), we found a statistically significant interaction between the two factors, in which partitioning effects were larger when the packed category was placed at the bottom of the menu rather than at the top of the menu. One possibility, consistent with the data from Study 3, is that participants infer descriptive social norms from both menu partitions and the ordering of items, and that the two inferences reinforce each other. That is, consumers are especially likely to infer items are less popular when they are both grouped together and placed at the end of a menu, and as a result menu partitioning effects are especially large under these conditions.

To explore this finding more thoroughly, we aggregate data across all studies. Table 6 displays, for each study, the menu partitioning effect (i.e., the percentage point difference in choice across menu partitions) when the packed category was placed at the bottom or top of the menu. The last table column also reports the difference between the two partitioning effects, with positive difference scores reflecting a larger effect when the packed category is placed at the bottom of the menu. As the table shows, the difference score was positive in four of the six studies, and the two negative difference scores were negligible in size. Using a study fixed effects meta-analysis, the combined menu partitioning effect was 32.8 percentage points when the grouped category was placed at the bottom of the menu, and 26.5 percentage points when placed at the top of the

Table 6: Menu Partitioning Effects by Packed Category Position

|  | packed category <br> placed on bottom | packed category <br> placed on top | Difference |
| :--- | :---: | :---: | :---: |
| Study 1A | $34.1(4.5)^{* * *}$ | $38.7(4.2)^{* * *}$ | $-4.5(6.2)$ |
| Study 1B | $19.0(7.3)^{* *}$ | $08.7(5.8)$ | $10.3(9.3)$ |
| Study 2 | $53.7(9.2)^{* * *}$ | $22.2(10.0)^{*}$ | $31.4(13.5)^{*}$ |
| Study 3 | $50.1(6.3)^{* * *}$ | $24.5(5.7)^{* * *}$ | $25.6(8.5)^{*}$ |
| Study 4 | $34.9(4.3)^{* * *}$ | $35.2(4.3)^{* * *}$ | $-0.3(6.0)$ |
| Study 5 | $27.3(3.0)^{* * *}$ | $21.9(3.0)^{* * *}$ | $5.4(4.3)$ |
| Combined | $32.8(0.02)^{* * *}$ | $26.5(0.02)^{* * *}$ | $6.3(0.03)^{*}$ |

Notes: Average marginal effects are estimated from the logit model specified in the results section of each study. Parentheses represent robust standard errors for Studies 1B and 2, and participant-clustered standard errors for all other studies. Combined results are estimated using study fixed-effects, with weights set proportional to the inverse variance of each study. ${ }^{*} p \leq 0.05,{ }^{* *} p \leq 0.01,{ }^{* * *} p \leq 0.001$.
menu. This 6.3 percentage point difference between menu positions was statistically reliable, ${ }^{13}$ $\left(\chi^{2}(1)=5.62, p=0.018\right)$. Thus, while menu partitioning effects were large and statistically significant regardless of menu position, they were somewhat larger when grouped items were placed at the end of the menu.

## Limitations and Future Directions

An open question is whether partitioning effects are only observed among novice decision makers, who may be uncertain how to best choose for themselves. In a related project (Tannenbaum et al., 2014), we found that partitioning the response menu had a significant effect on prescription decisions among practicing physicians. In hypothetical medical vignettes that described a patient's symptom history, physicians were less likely to prescribe treatments consistent with major clinical guidelines (e.g., over-the-counter drugs rather than antibiotics for acute respiratory infections) when "inappropriate" treatment options were unpacked. Although these effects were smaller than those observed in the current paper (on average, physicians in that sample showed an $11 \%$ partitioning effect), the findings suggest that partitioning effects can be found even among experienced decision makers in a domain with considerable consequences for public health.

[^9]An important direction for future research is in applying single-item partitioning to field settings. For instance, choice architects often wish to nudge consumers on a binary decision (such as Yes/No decisions on whether to donate to a charity, or to being vaccinated). Instead of simply asking whether an individual, say, wishes to donate or consents to being vaccinated, choice architects can more finely partition the desired response option as a way of nudging compliance. Taking the donation example, charitable organizations could provide respondents with many ways of saying Yes to donation while providing only one way of saying No (e.g., "Yes, I would like to donate $\$ 10 / \$ 20 / \$ 30 / \$ 40 / \$ 50$ dollars" vs "No, I would not like to donate"; Moon \& VanEpps, 2020). To increase vaccination rates, public health officials could individually list out the different types of vaccines available for inoculating against a particular virus (e.g., "I consent to receiving the [Pfizer vaccine/Moderna/Johnson \& Johnson] vaccine" vs "I do not consent to vaccination"). Our results suggest that to the extent that individuals display single-item partition dependence, interventions such as these are likely to help increase participation rates. Consistent with this account, recent research has found that quantity-integrated selling formats, under which consumers simultaneously consider whether and how much to buy, often increase consumption rates compared to selling formats where purchasing and quantity decisions are resolved separately (Duke \& Amir, 2021; Tavassoli \& Visentin, 2021). One reason why this may occur is because quantity-integrated formats more finely partition the ways that consumers can say Yes to consumption.

Another avenue for future research is whether menu partitions communicate additional types of information besides information about descriptive social norms. One natural candidate is whether menu partitions also communicate information about injuctive norms, since descriptive and injuctive norms often travel together (e.g., Brauer \& Chaurand, 2010; Eriksson et al., 2015; Thøgersen, 2008). For instance, the default option in a choice set is often viewed as the recommended or endorsed by the choice architect (McKenzie, Liersch, \& Finkelstein, 2006; Tannenbaum \& Ditto, 2021), and perhaps items that are packed or grouped together are viewed by consumers as an indication that the marketer views these items as less suitable for most consumers. Similarly, one may speculate that packing or clustering a set of options may signal to consumers that those options
are relatively similar to each other, compared to unpacked items in the choice set (e.g., Murphy \& Brownell, 1985). To the extent that perceptions of similarity reduce attractiveness for all items (perhaps by inducing within-cluster comparisons; Brenner, Rottenstreich, \& Sood, 1999), it is possible that menu partitioning effects also operate through this channel. However, we note that while other types of menu-based inferences may contribute to partitioning effects, such additional mechanisms are unlikely to account for our complete set of results. As an example, the results of Study 4 (in which we directly intervened on beliefs about descriptive social norms) cannot be readily explained by perceptions of similarity or within-cluster comparisons due to variations in menu partitioning. Future work should explore other possible mechanisms, and the relative role of such psychological processes in explaining partitioning effects depending on the characteristics of the choice environment.

## References

Allcott, H., \& Rogers, T. (2014). The short-run and long-run effects of behavioral interventions: Experimental evidence from energy conservation. American Economic Review, 104(10), 3003-37.

Banerjee, A. V. (1992). A simple model of herd behavior. Quarterly Journal of Economics, 107(3), 797-817.

Bardolet, D., Fox, C. R., \& Lovallo, D. (2011). Corporate capital allocation: A behavioral perspective. Strategic Management Journal, 32(13), 1465-1483.

Bearden, W. O., Netemeyer, R. G., \& Teel, J. E. (1989). Measurement of consumer susceptibility to interpersonal influence. Journal of Consumer Research, 15(4), 473-481.

Bearden, W. O., \& Rose, R. L. (1990). Attention to social comparison information: An individual difference factor affecting consumer conformity. Journal of Consumer Research, 16(4), 461-471.

Benartzi, S., \& Thaler, R. H. (2001). Naive diversification strategies in defined contribution saving plans. American Economic Review, 91(1), 79-98.

Bettinger, E. P., Long, B. T., Oreopoulos, P., \& Sanbonmatsu, L. (2012). The role of application assistance and information in college decisions: Results from the H\&R Block FAFSA experiment. Quarterly Journal of Economics, 127(3), 1205-1242.

Bhatnagar, R., \& Orquin, J. L. (2022). A meta-analysis on the effect of visual attention on choice. Journal of Experimental Psychology: General, 151(10), 2342-2395.

Bikhchandani, S., Hirshleifer, D., \& Welch, I. (1992). A theory of fads, fashion, custom, and cultural change as informational cascades. Journal of Political Economy, 100(5), 992-1026.

Brauer, M., \& Chaurand, N. (2010). Descriptive norms, prescriptive norms, and social control: An intercultural comparison of people's reactions to uncivil behaviors. European Journal of Social Psychology, 40(3), 490-499.

Brehm, J. W. (1966). A Theory of Psychological Reactance. Oxford, United Kingdom: Academic Press.

Brenner, L., Rottenstreich, Y., \& Sood, S. (1999). Comparison, grouping, and preference. Psychological Science, 10(3), 225-229.

Brenner, L., Rottenstreich, Y., Sood, S., \& Bilgin, B. (2007). On the psychology of loss aversion: Possession, valence, and reversals of the endowment effect. Journal of Consumer Research, 34(3), 369-376.

Carroll, G. D., Choi, J. J., Laibson, D. I., Madrian, B., \& Metrick, A. (2009). Optimal defaults and active decisions. Quarterly Journal of Economics, 124(4), 1639-1674.

Cialdini, R. B., \& Goldstein, N. J. (2004). Social influence: Compliance and conformity. Annual Review of Psychology, 55(1), 591-621.

Cialdini, R. B., Kallgren, C. A., \& Reno, R. R. (1991). A focus theory of normative conduct: A theoretical refinement and reevaluation of the role of norms in human behavior. In M. P. Zanna (Ed.), (Vol. 24, p. 201-234). Academic Press.

Dayan, E., \& Bar-Hillel, M. (2011). Nudge to nobesity II: Menu positions influence food orders. Judgment and Decision Making, 6(4), 333-342.

Duke, K., \& Amir, O. (2021). The importance of selling formats: When integrating purchase and quantity decisions increases sales. (SSRN) doi: 10.2139/ssrn. 3099746

Efron, B. (1987). Better bootstrap confidence intervals. Journal of the American Statistical Association, 82(397), 171-185.

Ellis, A., \& Freeman, D. J. (2020). Revealing choice bracketing. (ArXiv preprint: 2006.14869)
Eriksson, K., Strimling, P., \& Coultas, J. C. (2015). Bidirectional associations between descriptive and injunctive norms. Organizational Behavior and Human Decision Processes, 129, 59-69.

Fox, C. R., \& Clemen, R. T. (2005). Subjective probability assessment in decision analysis: Partition dependence and bias toward the ignorance prior. Management Science, 51(9), 1417-1432.

Fox, C. R., Ratner, R. K., \& Lieb, D. S. (2005). How subjective grouping of options influences choice and allocation: Diversification bias and the phenomenon of partition dependence. Journal of Experimental Psychology: General, 134(4), 538-551.

Friestad, M., \& Wright, P. (1994). The persuasion knowledge model: How people cope with
persuasion attempts. The Journal of Consumer Research, 21(1), 1-31.
Grice, P. H. (1975). Logic and conversation. In P. Cole \& J. L. Morgan (Eds.), Syntax and semantics, 3: Speech acts (p. 41-58). New York: Academic Press.

Hertwig, R., Davis, J. N., \& Sulloway, F. J. (2002). Parental investment: How an equity motive can produce inequality. Psychological Bulletin, 128(5), 728-745.

Imai, K., Keele, L., \& Tingley, D. (2010). A general approach to causal mediation analysis. Psychological Methods, 15(4), 309-334.

Imai, K., Tingley, D., \& Yamamoto, T. (2013). Experimental designs for identifying causal mechanisms. Journal of the Royal Statistical Society: Series A (Statistics in Society), 176(1), 5-51.

Janiszewski, C., Kuo, A., \& Tavassoli, N. T. (2013). The influence of selective attention and inattention to products on subsequent choice. Journal of Consumer Research, 39(6), 12581274.

Jaynes, E. (1957). Information theory and statistical mechanics. Physical Review Online Archive (Prola), 106(4), 620-630.

Johnson, E. J., Shu, S. B., Dellaert, B. G., Fox, C., Goldstein, D. G., Häubl, G., ... others (2012). Beyond nudges: Tools of a choice architecture. Marketing Letters, 23(2), 487-504.

Kahneman, D., \& Tversky, A. (1982). On the study of statistical intuitions. Cognition, 11(2), 123-141.

Karlson, K. B., Holm, A., \& Breen, R. (2012). Comparing regression coefficients between samesample nested models using logit and probit: A new method. Sociological Methodology, 42(1), 286-313.

Keller, P. A., Harlam, B., Loewenstein, G., \& Volpp, K. G. (2011). Enhanced active choice: A new method to motivate behavior change. Journal of Consumer Psychology, 21(4), 376-383.

Keren, G. (2007). Framing, intentions, and trust-choice incompatibility. Organizational Behavior and Human Decision Processes, 103(2), 238-255.

Krijnen, J., Tannenbaum, D., \& Fox, C. R. (2017). Choice architecture 2.0. Behavioral Science and

Policy, 3(2), 1-18.
Krishna, A., Herd, K. B., \& Aydınoğlu, N. Z. (2019). A review of consumer embarrassment as a public and private emotion. Journal of Consumer Psychology, 29(3), 492-516.

Larrick, R., \& Soll, J. (2008). The mpg illusion. Science, 320(5883), 1593-1594.
Madrian, B. C., \& Shea, D. F. (2001). The power of suggestion: Inertia in 401(k) participation and savings behavior. Quarterly Journal of Economics, 116(4), 1149-1187.

Martin, J. M., \& Norton, M. I. (2009). Shaping online consumer choice by partitioning the web. Psychology \& Marketing, 26(10), 908-926.

McKenzie, C. R. M., Liersch, M. J., \& Finkelstein, S. R. (2006). Recommendations implicit in policy defaults. Psychological Science, 17(5), 414-420.

McKenzie, C. R. M., \& Nelson, J. D. (2003). What a speaker's choice of frame reveals: Reference points, frame selection, and framing effects. Psychonomic Bulletin and Review, 10(3), 596-602.

McKenzie, C. R. M., Sher, S., Leong, L. M., \& Müller-Trede, J. (2018). Constructed preferences, rationality, and choice architecture. Review of Behavioral Economics, 5(3-4), 337-360.

Moon, A., \& VanEpps, E. (2020). Giving suggestions: Using quantity requests to increase donations. (SSRN) doi: 10.2139/ssrn. 3080731

Muller, D., Judd, C. M., \& Yzerbyt, V. Y. (2005, Jan). When moderation is mediated and mediation is moderated. Journal of Personality and Social Psychology, 89(6), 852-863.

Murphy, G. L., \& Brownell, H. H. (1985). Category differentiation in object recognition: Typicality constraints on the basic category advantage. Journal of Experimental Psychology: Learning, Memory, and Cognition, 11(1), 70-84.

Oppenheimer, D. M., Meyvis, T., \& Davidenko, N. (2009). Instructional manipulation checks: Detecting satisficing to increase statistical power. Journal of Experimental Social Psychology, 45(4), 867-872.

Palmer, S. E. (1992). Common region: A new principle of perceptual grouping. Cognitive Psychology, 24(3), 436-447.

Pieters, R. (2017). Meaningful mediation analysis: Plausible causal inference and informative communication. Journal of Consumer Research, 44(3), 692-716.

Pirlott, A. G., \& MacKinnon, D. P. (2016). Design approaches to experimental mediation. Journal of experimental social psychology, 66, 29-38.

Preacher, K. J., \& Hayes, A. F. (2008). Asymptotic and resampling strategies for assessing and comparing indirect effects in multiple mediator models. Behavior Research Methods, 40(3), 879-891.

Prelec, D., Wernerfelt, B., \& Zettelmeyer, F. (1997). The role of inference in context effects: Inferring what you want from what is available. Journal of Consumer Research, 24(1), 118-126.

Read, D., \& Loewenstein, G. (1995). Diversification bias: Explaining the discrepancy in variety seeking between combined and separated choices. Journal of Experimental Psychology: Applied, 1(1), 34-39.

Read, D., Loewenstein, G., \& Rabin, M. (1999). Choice bracketing. Journal of Risk and Uncertainty, 19(1-3), 171-197.

Rosch, E., Mervis, C. B., Gray, W. D., Johnson, D. M., \& Boyes-Braem, P. (1976). Basic objects in natural categories. Cognitive Psychology, 8(3), 382-439.

Ross, L., Greene, D., \& House, P. (1977). The "false consensus effect": An egocentric bias in social perception and attribution processes. Journal of Experimental Social Psychology, 13(3), 279-301.

Schwarz, N., Hippler, H.-J., Deutsch, B., \& Strack, F. (1985). Response scales: Effects of category range on reported behavior and comparative judgments. Public Opinion Quarterly, 49(3), 388-395.

Shah, A. K., \& Oppenheimer, D. M. (2011). Grouping information for judgments. Journal of Experimental Psychology: General, 140(1), 1-13.

Sher, S., \& McKenzie, C. R. M. (2006). Information leakage from logically equivalent frames. Cognition, 101(3), 467-494.

Sher, S., \& McKenzie, C. R. M. (2014). Options as information: Rational reversals of evaluation and preference. Journal of Experimental Psychology: General, 143(3), 1127-1143.

Shrout, P., \& Bolger, N. (2002). Mediation in experimental and nonexperimental studies: New procedures and recommendations. Psychological Methods, 7(4), 422-445.

Simonson, I. (1990). The effect of purchase quantity and timing on variety-seeking behavior. Journal of Marketing Research, 27(2), 150-162.

Sonnemann, U., Camerer, C. F., Fox, C. R., \& Langer, T. (2013). How psychological framing affects economic market prices in the lab and field. Proceedings of the National Academy of Sciences, 110(29), 11779-11784.

Spencer, S. J., Zanna, M. P., \& Fong, G. T. (2005). Establishing a causal chain: Why experiments are often more effective than mediational analyses in examining psychological processes. Journal of Personality and Social Psychology, 89(6), 845-851.

Spital, A. (1995). Mandated choice: A plan to increase public commitment to organ donation. Journal of the American Medical Association, 273(6), 504-506.

Sunstein, C. R. (2013). Simpler: The future of government. Simon and Schuster.
Tannenbaum, D., \& Ditto, P. H. (2021). Default options and social inference. (Unpublished manuscript, University of Utah)

Tannenbaum, D., Doctor, J. N., Persell, S. D., Friedberg, M. W., Meeker, D., Friesema, E. M., ... Fox, C. R. (2014). Nudging physician prescription decisions by partitioning the order set: Results of a vignette-based study. Journal of General Internal Medicine, 30(3), 298-304.

Tannenbaum, D., Valasek, C. J., Knowles, E. D., \& Ditto, P. H. (2013). Incentivizing wellness in the workplace: Sticks (not carrots) send stigmatizing signals. Psychological Science, 24(8), 1512-1522.

Tavassoli, N. T., \& Visentin, M. (2021). To buy or how much to buy? Partition dependence in purchase-quantity decisions. Marketing Letters, 1-12.

Thaler, R. H., \& Sunstein, C. (2003). Libertarian paternalism. American Economic Review, 93(2), 175-179.

Thaler, R. H., \& Sunstein, C. R. (2008). Nudge: Improving decisions about health, wealth, and happiness. New Haven, CT: Yale University Press.

Thøgersen, J. (2008). Social norms and cooperation in real-life social dilemmas. Journal of Economic Psychology, 29(4), 458-472.

Tversky, B., \& Hemenway, K. (1984). Objects, parts, and categories. Journal of Experimental Psychology: General, 113(2), 169-193.

West, C., Ülkümen, G., Arundel, P., \& Fox, C. R. (2021). Choice architecture and budgeting for saving versus spending. (Working paper, University of Toronto)

Wiltermuth, S. S., \& Gino, F. (2013). "I'll have one of each": How separating rewards into (meaningless) categories increases motivation. Journal of Personality and Social Psychology, 104(1), 1-13.

Zhang, Y. C., \& Schwarz, N. (2012). How and why 1 year differs from 365 days: A conversational logic analysis of inferences from the granularity of quantitative expressions. Journal of Consumer Research, 39(2), 248-259.


[^0]:    ${ }^{1}$ For instance, take a simple menu composed of three options: $A, B$, and $C$. One can construct the following choice menus, where the union operator $\cup$ denotes grouping: $\{A, B, C\} ;\{A, B \cup C\} ;\{A \cup B, C\}$; or $\{A \cup C, B\}$.

[^1]:    ${ }^{2}$ Demarcating the exact boundary between single-item and multi-item (i.e., allocation) decisions is tricky because singular choices can often be viewed as part of a broader consumption stream or portfolio of choices. For instance, one can treat the decision to order dessert at a restaurant as a one-off consumption choice, or as embedded within a larger set of dieting choices over time ("If I order dessert tonight, I'll have to make up for it by having a light salad tomorrow"). The extant literature suggests consumers usually bracket too narrowly, often failing to appreciate that aggregating across decisions can lead to greater utility maximization (Ellis \& Freeman, 2020; Read, Loewenstein, \& Rabin, 1999). One implication of narrow bracketing is that many consumers will often treat decisions as singular choices, even when they could be construed otherwise.
    ${ }^{3}$ That a bias towards even allocation does not extend to single-item choice has also been noted by Read and Loewenstein (1995). They compared sequential consumption decisions (over the course of three days, participants choose a single snack to consume each day) to planned consumption decisions (participants chose in advance three snacks to be consumed over the next three days). Participants showed a strong tendency to diversify when planning consumption in advance, but tended to choose their favorite option when presented with the choices sequentially (Simonson, 1990). In explaining these findings, the authors suggested that diversification cannot occur when an item is viewed as a single distinct choice: "simultaneous choices are presented to subjects in the form of a package, and perhaps the most straightforward choice heuristic applicable to such packages is diversification. In the sequential choice condition, in contrast, subjects are presented with the choices one at a time, and the natural choice heuristic applicable to a single choice is to choose the single most preferred option" (p. 38).

[^2]:    ${ }^{4}$ We note that when options are relegated to a residual response category, they are usually also associated with increased effort costs and decreased salience. For example, websites selling consumer goods may bury unpopular items "deeper"

[^3]:    in the website (i.e., they are displayed less prominently on the website), and therefore such items often take additional time and effort to locate. In all studies, we partition menu items in a way that holds information and effort costs constant across conditions.
    ${ }^{5}$ Some participants provided unusable responses, and we excluded these responses from the analysis. The number of omitted responses ranged from 9 to 17 depending on the domain. A subset of these omitted responses were cases where participants wrote the entire grouped category instead of a single item (e.g., a participant writing "an animal-based charity" instead of specifying a specific animal-based charity). Because omitting these responses potentially biases results in favor of our hypothesis, we also examined the results when including all omitted responses and coding these observations to go against our hypothesis. All domains remain significant at $p \leq 0.001$ even when using this conservative coding scheme. We provide full details and robustness tests for Study 1A, as well as all subsequent studies, in section 1 of the Supplemental Materials.

[^4]:    ${ }^{6}$ The speculation that menu partitions may signal information has also been suggested by Kahneman and Tversky (1982), Fox et al. (2005), and Martin and Norton (2009).

[^5]:    ${ }^{7}$ The analysis above tests for mediation using the standard framework based on linear structural equation models (e.g., Preacher \& Hayes, 2008). Recently, researchers have suggested an alternative test of statistical mediation based on the potential outcomes framework to causal inference (Imai, Keele, \& Tingley, 2010). This procedure also returns a reliable mediation effect, with inferences of item popularity mediating $50 \%$ of the menu partitioning effect on choice. Another advantage of the potential outcomes approach to mediation is that it allows us to test the degree to which our results are robust to potential violations of confounding between the mediator and outcome variable (i.e., assumptions of sequential ignorability). We report the results of this sensitivity test, along with the full details for the potential outcomes mediation procedure, in section 3 of the Supplemental Materials.
    ${ }^{8}$ All bootstrapping procedures reported in this paper use bias-corrected confidence intervals (Efron, 1987).

[^6]:    ${ }^{9}$ One participant reported their age as 520 years old; we assume this was a typo, and omit this response when calculating age statistics for the sample.

[^7]:    ${ }^{10}$ As in Study 3, we can also test for mediation using the potential outcomes framework outlined by Imai et al. (2010). Similar to the results reported above, we find a reliable indirect effect through inferred popularity in the partition-first condition, but no reliable indirect effect in the estimate-first condition. Full details are provided in section 4 of the Supplemental Materials.
    ${ }^{11}$ We predicted that menu partitioning effects would be reliably mediated by inferences of item popularity, but only when participants view the menu partition first. This pattern of findings can also be tested using moderated mediation (Muller, Judd, \& Yzerbyt, 2005). Here we test the causal pathway \{menu partitioning $\longrightarrow$ descriptive norm beliefs $\longrightarrow$ choice $\}$, with block order $(0=$ estimate-first, $1=$ partition-first $)$ moderating the pathway between the independent variable and the mediator (i.e., Model 8 in Hayes, 2013). As before, we used bootstrapped standard errors based on 10,000 resamples and clustered by participants, along with domain fixed effects. This analysis returns a reliable conditional indirect effect in the predicted direction $(b=-0.15, \mathrm{SE}=0.08,95 \% \mathrm{CI}[-0.33,-0.002])$.

[^8]:    ${ }^{12}$ Another possibility for the relatively stronger predictive performance of the NSI is that the subscale contains less measurement error than the ISI subscale. Bearden et al. (1989) do in fact find greater reliability for the NSI over ISI, but the differences are small. In terms of internal reliability, they found the NSI and ISI to have alphas of 0.87 and 0.83 at time 1 , respectively, and alphas of 0.89 and 0.82 at time 2 . The NSI had a test-retest reliability of 0.79 while the ISI had a test-retest reliability of 0.75 . In our study, as noted in the methods section, also find that the internal reliability of the ISI was somewhat weaker than that of the NSI (although both measures had adequate internal reliability).

[^9]:    ${ }^{13}$ If we instead use a random-effect model for the meta-analysis, which weights studies according to both their degree of precision and as a function of the variance found across studies, we fail to find a significant difference in effect size across menu positions $\left(\chi^{2}(1)=2.25, p=0.134\right)$. The random effects model estimates a 9.9 difference across menu positions (i.e., a larger effect than the fixed effects model), but also contains more uncertainty in that estimate.

