Received: 28 July 2022 | Revised: 25 May 2023 | Accepted: 25 June 2023

DOI: 10.1002/bdm.2343

RESEARCH ARTICLE

WILEY

# Going with the crowd in volatile times: Exposure to environmental variability increases people's preference for popular options

Lishi Tan[1] | Shankha Basu[2] | Krishna Savani[3]

[1]Centre for Decision Research, Department of Management, Leeds University Business School, University of Leeds, Leeds, UK

[2]Department of Marketing, Leeds University Business School, University of Leeds, Leeds, UK

[3]Department of Management and Marketing, Faculty of Business, The Hong Kong Polytechnic University, Kowloon, Hong Kong

**Correspondence**
Krishna Savani, Department of Management and Marketing, Faculty of Business, The Hong Kong Polytechnic University, Li Ka Shing Tower M857, Hung Hom, Kowloon, Hong Kong.
Email: krishna.savani@polyu.edu.hk

**Funding information**
The Hong Kong Polytechnic University; Nanyang Technological University

## Abstract

More extreme temperature and precipitation events are defining features of climate change, and higher volatility in asset prices is a defining feature of globalization. Four experiments (two preregistered; total $N = 2086$) found that exposure to a high degree of variability in a given domain shifted people's preferences toward more popular products, that is, products rated by a larger number of consumers. This finding replicated across different experimental manipulations of variability, including graphs depicting either high or low variability in annual rainfall or temperature (Experiments 1 and 2), and in the experienced outcomes of dice rolls, which were manipulated to be perceived as having high or low variability (Experiment 3). The results generalized across different consumer choices, including services (Experiment 1) and products (Experiments 2 and 3). After exposure to higher variability, participants who received a more popular but lower rated option felt less anxious than those who received a less popular but higher rated option, indicating that choosing popular products serves to reduce the anxiety induced by higher variability (Experiment 4). This research highlights both a novel consequence of exposure to greater variability and a novel antecedent of people's preference for popular options.

KEYWORDS
choice, consumer, popularity, variability, volatility

## 1 | INTRODUCTION

As the COVID-19 pandemic emerged in early 2020, stock markets around the world exhibited unprecedented volatility (Baker et al., 2020). In March 2020, VIX, an index that measures the stock market's volatility expectations for the forthcoming 30 days, reached its highest level ever (Partington & Wearden, 2020). Now, imagine a person who viewed the S&P 500 stock index graph in March 2020 before going to www.amazon.com to buy a face mask. Two options stood out: one with 300 reviews and a mean rating of 4 and another with 200 reviews but with a mean rating of 4.5. Would viewing the graph of the S&P 500 stock index influence the person's choice of face mask on Amazon?

In the present research, we propose that exposure to different degrees of variability influences people's tendency to choose more popular options. We predict that experiencing higher degrees of variability would lead people to choose more popular alternatives, even if such alternatives have lower average ratings. A more popular option signifies a consensual choice of the majority (Andersson et al., 2009). Consistent with research suggesting that people tend to affiliate with others when they seek safety and stability (e.g., Murray & Schaller, 2012; Yamaguchi, 1998), we reason that choosing a popular option might be a way for people to affiliate with others and, hence, cope with the stress and anxiety that they experience when exposed to greater variability.

  

## 1.1 | Exposure to greater variability

Over the last few decades, people have been exposed to increasing variability in several domains. Climate change is making temperatures and precipitation more variable (Intergovernmental Panel on Climate Change, 2007). Macroeconomic indicators, such as asset prices, stock market indices, and currency exchange rates, have gradually become more volatile (CaixaBank Research, 2018). Emerging evidence suggests that experiencing high degrees of variability can affect people's attitudes and behavior. For instance, people in countries experiencing greater climatic variability are more likely to adopt a slow life history strategy by focusing their resources on prolonging life and growth and engaging less in risk-taking behavior, aggression, and violence (Van Lange et al., 2017). After being exposed to information with high degrees of variability, people are harsher when judging others who engage in unethical behaviors (Ding & Savani, 2020).

People generally prefer a world that is orderly, structured, and predictable (Landau et al., 2015). By definition, high variability in a given domain indicates less order, less structure, lower predictability, and greater risk in that domain. Experiencing such uncertainty and unpredictability can make people feel anxious and threatened. Neuroimaging studies show that unpredictability and lack of control are related to activations of the amygdala, the brain region associated with fear response (Whalen, 1998). Participants in a study who experienced an unpredictable auditory stimulus showed sustained amygdala activation, suggesting that unpredictable experiences are associated with our fear response (Herry et al., 2007). In a recent study, participants who perceived greater variability in their environment indicated feeling more anxious in their daily lives (Ding & Savani, 2020). We predict that upon experiencing higher degrees of variability, people would choose more popular products to cope with the increased anxiety and stress brought about by the high degree of perceived variability.

## 1.2 | How variability affects the choice of popular options

A way in which people cope with fear and a heightened perception of threat is through social affiliation. Priming people with social attachment can reduce threat-related activation in the amygdala (Norman et al., 2014). In another study, participants felt safer when they were part of a larger group exposed to a risk, such as a disease outbreak, than when they faced the risk alone (Yamaguchi, 1998). Similarly, exposing people to the threat of a disease outbreak reduced their willingness to break social norms (Murray & Schaller, 2012). Further, people experiencing fear are more likely to conform to others' opinions (Griskevicius et al., 2006) and are more susceptible to advertisement appeals based on the idea of social proof (e.g., "the choice of millions"; Griskevicius et al., 2009).

When choosing among consumer products, conformity can be reflected in people's preference for popular options, such as best-selling books and most-downloaded mobile apps (Bikhchandani et al., 1998; Chen, 2008; Hanson & Putler, 1996; Stern, 1995). A product's popularity can signal various attributes about the product, including its quality, novelty, and usefulness. Importantly, choosing a popular product can also reflect people's tendency to conform to the majority opinion (Mead et al., 2011; Wang et al., 2012). In fact, people often overly rely on the number of reviews a product has received, more so than other measures of the product's quality, such as the average rating provided by reviewers (Heck et al., 2020; Powell et al., 2017).

Further, popular products (e.g., those that received a large number of reviews) pose lower risk because even if they are rated lower on average, the large number of users' feedback reduces the confidence bound around the product's average rating (Powell et al., 2017). This idea is consistent with the risk homeostasis theory (Wilde, 1982, 1998), which posits that each person has their own acceptable level of risk and that they adjust their behavior to reduce any discrepancy between their perceived level of risk and their acceptable level of risk. Choosing popular products which are less risky can thus compensate for the heightened perceptions of risk induced by exposure to high environmental variability.

Taken together, the above arguments lead to the proposition that when people experience variability in their environment, they try to cope with the increased anxiety and sense of threat by conforming to the majority opinion. Popular products, by definition, reflect the majority opinion. Thus, choosing such products can serve as a coping mechanism for dealing with high variability. Consequently, we predict that when faced with choices that vary in popularity, exposure to higher variability and the consequent need for conforming to the majority opinion would lead people to put greater weight on popularity. Thus, encountering higher variability would lead people to choose options that are more popular, that is, products with a greater number of reviews. Following this idea, we predict that receiving more popular options rather than less popular ones can lead to lower anxiety after people are exposed to high variability but not after they are exposed to low variability.

# 2 | THE PRESENT RESEARCH

We test our prediction across four experiments. Experiment 1 (preregistered) manipulated perceived variability and tested whether exposure to a graph with higher (vs. lower) perceived variability in temperatures led people to choose more popular services (such as restaurants and car servicing). Past research suggests that people think that services are inherently more variable than products (Folkes & Patrick, 2003; Johnson & Nilsson, 2018). Therefore, Experiment 2 tested whether exposure to a graph with higher (vs. lower) perceived variability in rainfall led people to choose more popular products (such as clocks, lamps, and earpieces). Whereas Experiments 1 and 2 used visual cues of variability, Experiment 3 (preregistered) tested whether a direct experience with seemingly high (vs. low) variability outcomes led people to choose more popular products. Finally, Experiment 4 tested whether receiving a more versus less popular service affected the level of anxiety people experienced after being exposed to high versus low variability. If choosing popular options is a strategy people use to cope with the anxiety induced by experiencing high variability, we should observe a decreased level of anxiety for people who receive the more popular option, rather than the less popular one, after being exposed to high variability. This would provide evidence for our underlying mechanism.

Experiments 1, 2, and 4 manipulated perceived variability by giving participants the impression that the quantity depicted in graphs was more or less variable. We achieved this by adjusting *Y*-axis of the graphs. Experiment 3 manipulated the standard deviation of successive deviations while holding constant the set of dice roll outcomes that participants encountered. The details of these manipulations are described in the respective experiments' methods section.

Across all experiments, we report all participants, all experimental conditions, all exclusions, and all measures collected. We only included participants with unique IP addresses, unique geolocations, and unique IDs to ensure that only unique participants were included in the analyses (Dennis et al., 2020). Further, as all our dependent measures were adapted to the United States, we excluded all non-US citizens. These exclusion criteria were preregistered for Experiments 1 and 3. Although we used predetermined sample sizes across all studies based on a priori power analyses, we aimed to further increase the power and generalizability of the studies by ensuring that we used multiple products in the choice tasks for all studies (Baayen et al., 2008).

## 3 | EXPERIMENT 1

Experiment 1 tested whether exposure to higher degrees of variability led to a greater preference for popular options using consumer services. We predicted that participants exposed to a graph depicting greater variability in temperatures would be more likely to choose services that were more popular.

### 3.1 | Method

We preregistered the sample size, participant exclusions, and analyses for this study at https://osf.io/n62p5. All data, stimuli, and analysis code are available at https://osf.io/x4qch/.

#### 3.1.1 | Participants

As we did not have a priori basis for calculating power given the new dependent variable used in this experiment, we first posted the study for 400 participants on Amazon Mechanical Turk and obtained 373 valid responses. There was a statistically significant effect of the experimental condition on the dependent measure (see Supporting Information S1). However, a power analysis revealed that a much larger sample size was needed to obtain adequate power. Therefore, as mentioned in our preregistration plan, we conducted a power analysis using G*Power (Faul et al., 2007) with Cohen's $d = 0.23$ (from the first wave), $\alpha = .025$ (one-tailed), and power $= 80\%$. The power analysis indicated that we would need to recruit at least 596 valid responses. After applying our predetermined exclusion criteria, we posted the survey again to ensure that we will have sufficient valid participants, seeking additional 266 US residents on MTurk. Across the two waves, 701 participants completed the survey. Of these, we excluded 96 responses (44 from the low variability condition and 52 from the high variability condition) from participants who were non-US citizens or had duplicated IP addresses, geolocations, or MTurk IDs. The final sample consisted of 605 participants (322 women, 277 men, 2 others, and 4 unreported; $M_{age} = 36.98$ years, $SD = 12.22$). Given that we analyzed the data in the first wave before deciding the total sample size, the study design had a risk of inflating Type 1 error. Thus, we also report statistics corrected for Type 1 error (Lakens, 2014).

#### 3.1.2 | Procedure

We randomly assigned participants to either the high or the low variability condition. We adapted the experimental manipulation from Ding and Savani (2020, Study 2c). In both conditions, we showed participants a line graph depicting the average annual temperature in the United States from 1996 to 2016 (National Oceanic and Atmospheric Administration [NOAA], 2017). Specifically, we adjusted the range of the graph's *Y*-axis to manipulate perceived variability. In the low (high) variability condition, we used a wide (narrow) range so that the temperature appeared less (more) variable over time (see Supporting Information S1). Thus, although the data points were the same across the two graphs, the apparent variability in average annual temperature was visually higher in the high variability condition than in the low variability condition. To ensure participants spent some time studying the graphs, we asked participants three questions: (1) “In which year was the average temperature the highest? (Please type in YYYY format)”; (2) “In which year was the average temperature the lowest? (Please type in YYYY format)”; and (3) “Please summarize the main information you get from this graph in one sentence.” Finally, to check if our manipulation was successful, we asked participants: “How variable do you think is the average temperature in the US?” (7-point Likert scale ranging from *Not at all* to *Extremely*).

Next, in an ostensibly unrelated task, we measured participants' preference for more popular options by asking them to choose among five providers for each of five different services: a restaurant, a hair salon, a car servicing station, an electrician, and an event planner. To ensure ecological validity, we took these options from the service providers listed on www.yelp.com in several US cities, such as San Francisco, Boston, Atlanta, and Denver, but we edited the number of stars and customer reviews that these providers had received. For each alternative, we provided participants with the number of consumers who reviewed the service provider (range 14–1583) and the average star rating (out of 5; range 2–5) the provider received.

We ensured that all options received a minimum rating of 2 and were rated by at least 14 reviewers; that way, there was sufficient information about each option. To introduce trade-offs among the options, we ensured that for each category, the star ratings of the service providers were negatively correlated with the number of customer reviews. We presented the five alternatives for each service category on a single page and asked participants to choose one. We randomized the order of presentation of the service categories and the five alternatives within each service category. See Supporting Information S1 for all the stimuli used in this study and Appendix A for a summary.

## 3.2 | Results

### 3.2.1 | Manipulation check

An independent samples *t*-test on the manipulation check item indicated that participants in the high variability condition viewed the average annual temperature in the United States to be significantly more variable, $M = 4.50$, 95% CI [4.35, 4.66], $SD = 1.38$, than participants in the low variability condition, $M = 3.03$, 95% CI [2.88, 3.18], $SD = 1.28$, $t(603) = 13.64$, $p < .001$, Cohen's $d = 1.11$.

### 3.2.2 | Preference for popular options

We next calculated our dependent measure. For each service category, we ranked the five options by popularity such that the most popular option received a rank of 5 and the least popular option a rank of 1. We calculated participants' preference for more popular options by averaging the rank across the five service categories ($M = 2.67$, 95% CI [2.59, 2.75], $SD = 0.75$). We ran an independent samples *t*-test with the average rank of chosen option as the dependent variable and the experimental conditions as the independent variable. This analysis indicated that participants in the high variability condition preferred options that were more popular, $M = 2.84$, 95% CI [2.74, 2.93], $SD = 0.84$, than those in the low variability condition, $M = 2.67$, 95% CI [2.58, 2.76], $SD = 0.77$, $t(603) = 2.55$, $p = .011$,[1] Cohen's $d = 0.21$. We used the GroupSeq package in *R* to compute the corrected alpha level using exact Pocock (1977) bounds (Lakens, 2014). The *p*-value corrected for potential Type 1 error inflation was $p = .032$.

The analyses reported above did not take into account within-participant effects across the five trials. Further, it remains unclear if the effect documented above was driven by trials in which the options had generally high ratings. We ran two multilevel regressions treating trials as nested within participants to examine these possibilities. First, we ran a model that controlled for the average rating of all options within each trial and found that the effect of the variability condition remained statistically significant. Next, we examined if there was an interaction between the average trial rating and the experimental condition. The interaction was not significant. The detailed results of these analyses are reported in Supporting Information S1.

## 3.3 | Discussion

Experiment 1 provided evidence for our hypothesis: People who viewed a graph giving the illusion that the average annual temperature in the United States varied a lot were more likely to choose more popular service providers. The findings suggest that incidental exposure to information about variability in a domain unrelated to consumer choices can lead people to value popularity when choosing service providers.

# 4 | EXPERIMENT 2

The aim of Experiment 2 was to conceptually replicate the findings of Experiment 1 with different experimental manipulation and dependent choice context. We experimentally manipulated variability by showing graphs depicting average annual rainfall (instead of temperature, as in Experiment 1). Further, we aimed to increase the generalizability of our findings by replacing services with products, which people typically perceive as less variable than services (Folkes & Patrick, 2003; Johnson & Nilsson, 2018). We predicted that exposure to a graph showing higher variability in rainfall would lead participants to choose more popular products.

## 4.1 | Method

All data, stimuli, and analyses are available at https://osf.io/rsq4e/.

### 4.1.1 | Participants

We assumed an effect size of Cohen's $d = 0.31$ from Ding and Savani (2020, Study 2c), which used a similar manipulation. A power analysis using G*Power (Faul et al., 2007) for the difference between two independent means with $\alpha = .05$ (two-tailed) and power = 80% indicated that we would need to recruit at least 330 valid responses. To ensure that we will have sufficient valid participants after applying our predetermined exclusion criteria, we posted a survey seeking 400 US residents on MTurk. In response, 475 participants completed the survey. We excluded responses from 109 participants (55 from the high variability condition and 54 from the low variability condition) who are non-US citizens or have duplicated IP addresses, geolocations, or MTurk IDs. The final sample comprised 366 participants (218 women, 142 men, and 4 others; $M_{age} = 35.6$ years, $SD = 12.00$).

[1]We preregistered a one-tailed test because we preregistered a directional hypothesis. The one-tailed test *p*-value was .0056.

#### 4.1.2 | Procedure

We assigned participants to either the high or low variability condition. As in Experiment 1, we showed participants a line graph. However, in this study, the graph depicted the average annual rainfall in the United States from 1985 to 2015 (NOAA, 2017). As in Experiment 1, we adjusted the range of the graph's *Y*-axis to manipulate variability. To ensure participants study the graphs carefully and to strengthen the manipulation, we asked participants (1) "In which year was the average rainfall the largest? (Please type in YYYY format)" and (2) "In which year was the average rainfall the smallest? (Please type in YYYY format)." We also asked them: "Please summarize the main information you get from this graph in one sentence." Next, to check if our manipulation was successful, we asked participants: "How variable do you think was the average rainfall in the US over the past thirty years?" (7-Likert scale ranging from *Not at all* to *Extremely*).

Next, we presented participants with a choice task that was similar to that used in the previous experiment, except that we substituted services with products. We presented participants with five alternatives for each of the following product categories: dehumidifiers, lamps, earpieces, clocks, and photo frames. To ensure ecological validity, we took these options from Amazon.com's US marketplace, but we edited the number of stars and customer reviews these products actually received. For each alternative, we provided participants with the number of consumers who reviewed the product (range 14–1583) and the average star rating (out of 5; range 2–5) received.

All aspects of the product options, including the order of presentation, strictly followed the structure we used in Experiment 1. One notable distinction was that we provided an image for each product option. To minimize any influence the products' appearance might have, we selected products that looked similar. See Supporting Information S1 for all stimuli used in this study and Appendix A for a summary.

### 4.2 | Results

#### 4.2.1 | Manipulation check

An independent samples *t*-test on the manipulation check item indicated that participants in the high variability condition viewed the average rainfall in the United States to be significantly more variable, $M = 4.83$, 95% CI [4.62, 5.03], $SD = 1.43$, than participants in the low variability condition, $M = 2.94$, 95% CI [2.76, 3.12], $SD = 1.22$, $t(364) = 13.54$, $p < .001$, Cohen's $d = 1.42$.

#### 4.2.2 | Preference for popular options

We created a similar measure for participants' preference for popular options as in the previous experiment. We coded the product alternative within each category as 1 (the alternative with the lowest number of reviews) to 5 (the alternative with the highest number of reviews). We calculated participants' preference for popular options by computing the average value of their chosen alternatives across the five product categories. An independent samples *t*-test indicated that participants in the high variability condition showed greater preference for options that are popular, $M = 2.61$, 95% CI [2.51, 2.71], $SD = 0.68$, compared with those in the low variability condition, $M = 2.45$, 95% CI [2.34, 2.55], $SD = 0.70$, $t(364) = 2.22$, $p = .027$, Cohen's $d = 0.23$.

As robustness checks, we also ran multilevel analyses similar to the ones reported in Experiment 1. The results were similar to those observed in Experiment 1. These analyses once again indicated that our main finding of the effect of high variability on people's preference for popular options held even when we controlled for the average ratings of options in the trials and when we nested the trials within participants. The detailed results of these analyses are reported in Supporting Information S1.

### 4.3 | Discussion

Experiment 2 thus conceptually replicated the findings from Experiment 1: Incidental exposure to greater variability increased people's preference for more popular consumer products. This experiment also provided a more conservative test for our hypothesis, as people generally think that product quality is less variable than service quality (Folkes & Patrick, 2003; Johnson & Nilsson, 2018).

## 5 | EXPERIMENT 3

In Experiments 1 and 2, we manipulated variability using line graphs that induced visual cues of variability. In Experiment 3, we tested whether directly experiencing higher variability can also increase people's preference for more popular options. Specifically, we asked participants to roll a virtual dice 10 times. We experimentally manipulated the outcome of these throws to have higher or lower perceived variability. We predicted that participants who perceived higher variability in the outcomes of the 10 dice throws would be more likely to choose the more popular products.

### 5.1 | Method

We preregistered the sample size, participant exclusions, and analyses for this study at https://osf.io/fjs4w. All data, stimuli, and analyses, including those of the additional manipulation check study, are also available at https://osf.io/tx3e5/.

#### 5.1.1 | Participants

As this experiment used a similar dependent measure as in Experiment 1, we ran a power analysis using G*Power (Faul et al., 2007) for the difference between two independent means with Cohen's $d = 0.23$, the effect size from Experiment 1, and $\alpha = .05$ (one-tailed). We aimed for 95% power, indicating that we would need to recruit at least 804 participants. Therefore, a survey seeking 804 participants was posted on MTurk. In response, 844 participants completed the survey. We then excluded 168 responses (80 from the high variability condition and 88 from the low variability condition) from participants who were non-US citizens or had duplicated IP addresses, geolocations, or MTurk IDs. The final sample contained 676 participants (403 women, 266 men, 4 others, and 3 did not indicate their gender; $M_{age} = 36.82$ years, $SD = 11.91$).

#### 5.1.2 | Procedure

We manipulated variability using a dice roll task, which was adapted from Ding and Savani (2020, Study 3). We informed participants that the computer would roll a dice 10 times, and they would win points equivalent to the result of the dice rolls. Specifically, we told participants: "In each roll, the dice will randomly land on a number (1, 2, 3, 4, 5, or 6) and you will get point(s) corresponding to the number that the dice landed on." We randomly assigned participants to either the high or low variability condition. In the low (high) variability condition, we ensured that each dice roll outcome was followed by another outcome of a similar (different) magnitude. In the low variability condition, participants experienced the 10 dice roll outcomes in the sequence of "6, 5, 5, 6, 4, 3, 2, 1, 2, 1," whereas in the high variability condition, participants experienced the outcomes in the sequence of "6, 2, 5, 1, 5, 3, 6, 2, 4, 1." Both sequences had the same mean and standard deviation, and hence, the same overall outcome. After the dice roll task, we asked participants to complete the same product preference task as in Experiment 2.

### 5.2 | Results

#### 5.2.1 | Manipulation check

We conducted a post-test to assess whether participants indeed perceive the high and low variability conditions as intended. We recruited a separate sample of 200 participants from MTurk (87 women, 109 men, 3 others, and 1 did not indicate their gender; $M_{age} = 40.47$ years, $SD = 11.10$). We randomly assigned participants to either the high or the low variability condition and showed them the same dice roll manipulation as described above. We then asked participants how variable they thought their dice roll outcomes were (7-point Likert scale ranging from *Not at all* to *Extremely*). An independent *t*-test indicated that the participants in the high variability condition perceived the dice roll outcomes to be more variable, $M = 5.33$, 95% CI [5.07, 5.59], $SD = 1.32$, than those in the low variability condition, $M = 4.90$, 95% CI [4.66, 5.14], $SD = 1.22$, $t(198) = .38$, $p = .018$, Cohen's $d = .34$.

#### 5.2.2 | Preference for popular options

We computed a score for participants' preference for popular options, as reported in the previous experiments. We conducted an independent samples *t*-test which indicated that participants in the high variability condition showed a greater preference for popular options, $M = 2.62$, 95% CI [2.54, 2.70], $SD = 0.77$, compared with those in the low variability condition, $M = 2.50$, 95% CI [2.43, 2.58], $SD = 0.70$, $t(674) = 2.04$, $p = .042$,[2] Cohen's $d = 0.16$.

Additional multilevel models yielded similar results as those observed in Experiments 1 and 2. Participants exposed to high variability preferred more popular options even after controlling for the average ratings of the options and even when the trials were nested within participants. For the detailed results, see Supporting Information S1.

### 5.3 | Discussion

Experiment 3 provided further support for our prediction: Participants who experienced greater variability in an unrelated dice-rolling task preferred options that were more popular. The results also suggest that our finding is not limited to visual cues of variability but also experienced variability in outcomes.

## 6 | EXPERIMENT 4

In the previous experiments, we found that when people are exposed to high (vs. low) variability, they tend to prefer more popular products or services (i.e., with more reviews) even when these options are rated lower than options that are less popular (i.e., with fewer reviews). We theorized that people feel anxious when exposed to high variability (Ding & Savani, 2020), and choosing more popular options is a way to lower this anxiety. The aim of Experiment 4 was to directly test this hypothesis. As in the previous experiments, we exposed participants to either high or low variability. However, we also manipulated whether participants received the most popular (but the lowest rated) or the least popular (but the highest rated) option and measured their state anxiety. We expected that participants who are exposed to high variability would feel less anxious when they receive the most popular option compared with when they receive the least popular option.

### 6.1 | Method

All data, stimuli, and analyses are available at https://osf.io/e7a4g/.

[2]We had preregistered a one-tailed test because we preregistered a directional hypothesis. The one-tailed test *p*-value was .021.

#### 6.1.1 | Participants

As we used a new design for Experiment 4, we ran a power analysis using G*Power (Faul et al., 2007) to determine the sample size needed for a small-to-medium effect size of Cohen's $f = 0.15$ with $\alpha = .05$ and 90% power. The required sample size was 469. Rounding up this number, we posted a study seeking 500 participants on MTurk. In response, 503 participants completed the study. We excluded 64 responses (30 from the high variability condition and 34 from the low variability condition) from participants who were non-US citizens or had duplicated IP addresses, geolocations, or MTurk IDs. The final sample contained 439 participants (202 women, 232 men, 4 others, and 1 did not indicate their gender; $M_{age} = 40.71$ years, $SD = 12.27$).

#### 6.1.2 | Procedure

We used a 2 (high vs. low variability) × 2 (most popular vs. least popular service provider) between-participants design. Participants were randomly assigned to one of four cells. We used the same temperature graphs as in Experiment 1 to manipulate participants' exposure to high versus low variability and used the same manipulation check items.

Next, in an ostensibly unrelated task, we showed participants the ratings of five different electricians, purportedly obtained from Yelp.com. These were the same ratings as those used in the electrician trial from the service provider stimuli used in Experiment 1. We provided participants with the number of consumers who reviewed each electrician (range: 91–1287) and the average star rating that each electrician received (out of 5; range: 3–4). As in Experiment 1, the star ratings of the electricians were negatively correlated with the number of customer reviews, such that the electrician which received the most number of customer reviews also had the lowest average rating. Unlike our previous experiments, however, we informed participants that an electrician had been randomly selected for them. In fact, participants were randomly assigned to receive either the electrician with the most number of customer reviews (i.e., most popular) or the one with the least number of customer reviews (i.e., least popular). Although irrelevant to our analysis, we asked participants to estimate the fee per hour that their assigned electrician would charge. The aim of this question was simply to minimize any suspicion the participants might have that this task was related to the outcome variable. We then measured participants' state anxiety using the five-item short version of the Spielberger state-trait anxiety inventory (STAIS-5; Zsido et al., 2020). Specifically, we asked participants to rate how much they felt upset, frightened, nervous, jittery, and confused at that moment (7-point Likert scale ranging from *Not at all* to *Extremely*; $\alpha = .916$).

### 6.2 | Results

#### 6.2.1 | Manipulation check

An independent samples *t*-test on the manipulation check item indicated that participants in the high variability condition viewed the average annual temperature in the United States to be significantly more variable, $M = 4.44$, 95% CI [4.24, 4.64], $SD = 1.53$, than those in the low variability condition, $M = 2.83$, 95% CI [2.69, 2.98], $SD = 1.09$, $t(437) = 12.67$, $p < .001$, Cohen's $d = 1.21$.

#### 6.2.2 | State anxiety

The means, confidence intervals, and standard deviations of the outcome variable, that is, participants' state anxiety, in each condition are reported in Table 1. We conducted a two-way ANOVA with participants' anxiety score as the dependent variable and variability condition and assigned popularity condition as the two independent variables. The effect of the popularity condition on participants' state anxiety was not significant, $F(1, 435) < 0.001$, $p = .98$, $\eta^2_p < .001$. However, the main effect of the variability condition on participants' state level of anxiety was significant, such that participants exposed to high variability tend to have a higher level of state anxiety than participants exposed to low variability, $F(1, 435) = 4.76$, $p = .030$, $\eta^2_p = .011$. As predicted, we found a significant interaction effect of the variability condition and the popularity condition on participants' level of state anxiety, $F(1, 435) = 9.27$, $p = .0025$, $\eta^2_p = .021$. Given the significant interaction effect, we examined participants' anxiety scores within the high and low variability conditions. For participants exposed to high variability, those who received a more popular electrician had significantly lower state anxiety than those who received a less popular option, $F(1, 222) = 6.86$, $p = .0094$, $\eta^2_p = .030$. However, this difference was not significant for participants exposed to low variability, $F(1, 213) = 3.40$, $p = .067$, $\eta^2_p = .016$ (see Figure 1).

**TABLE 1** Cell sizes, means, standard deviations, and confidence intervals of participants' state anxiety for Experiment 4.

| | Most popular option given | | | Least popular option given | | |
|---|---|---|---|---|---|---|
| **Condition** | ***N*** | ***M (SD)*** | **95% CI** | ***N*** | ***M (SD)*** | **95% CI** |
| High variability | 113 | 1.24 (0.57) | [1.13, 1.34] | 111 | 1.51 (0.95) | [1.33, 1.69] |
| Low variability | 109 | 1.70 (1.19) | [1.48, 1.93] | 106 | 1.44 (0.93) | [1.26, 1.61] |

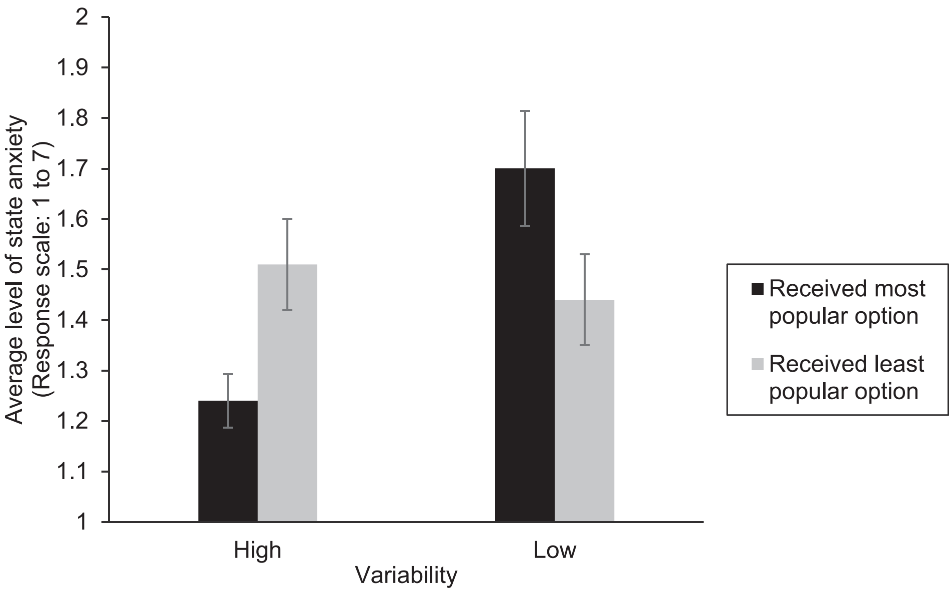


**FIGURE 1** Participants' state level of anxiety after being exposed to either high or low variability and given either a more popular or less popular electrician. Error bars indicate the standard error of the mean.

### 6.3 | Discussion

Experiment 4 provided evidence for our conceptualization that people choose popular options to cope with the anxiety induced by high variability. Participants exposed to low variability felt similarly anxious irrespective of whether they received the most popular or the least popular option. However, participants exposed to high variability felt less anxious when they received the most popular option compared with when they received the least popular option. This finding is consistent with the idea that people choose popular options after being exposed to high variability because popular options help mitigate some of the anxiety triggered by high variability.

## 7 | GENERAL DISCUSSION

Across four experiments, we found that exposure to high variability shifts people's preferences toward consumer options that are more popular. Participants who were led to believe that the average temperature (Experiment 1) or the annual rainfall (Experiment 2) was more variable preferred more popular services and products over ones that were rated more highly but were not as popular. We observed this effect when participants directly experienced high versus low variability in the outcome of repeated dice rolls (Experiment 3). Finally, we found that receiving more popular options can help lower the anxiety that people experience when exposed to high variability (Experiment 4). Thus, people choose popular options when exposed to high variability as a means to cope with the anxiety that high variability induces.

### 7.1 | Theoretical implications

These findings advance the nascent literature on the psychological consequences of exposure to variability. Past research has found that exposure to greater environmental variability decreases aggression and violence (Van Lange et al., 2017) and leads people to make harsher moral judgments (Ding & Savani, 2020). We find that exposure to environmental variability could also influence people's amoral decisions, such as consumer choices. Together with past research, our finding indicates that variability, whether observed visually or experienced directly, is likely a key construct that influences people's judgments, decisions, and behaviors across a wide range of domains.

Our research also contributes to the literature on popularity bias and the literature on conformity. Prior research in these areas has explored characteristics of the decision-maker (Bearden & Rose, 1990; Berger & Heath, 2007; Tian et al., 2001) and of products (Steinhart et al., 2014; Zaggl et al., 2019) that can lead people to conform to the majority's preferences. We contribute to this literature by documenting that even subtle environmental cues can affect people's conformist tendencies. In organizational contexts, past research suggests that following the majority opinion might increase groupthink (Bénabou, 2013), stifle creativity (Sternberg & Lubart, 1995), and hinder the adoption of innovations (Reinstaller & Sanditov, 2005). Our findings suggest that greater environmental variability might exacerbate these effects. The insights from the current research can also be used to promote prosocial behavior. For example, exposure to variability can nudge people toward more sustainable behavior if individuals believe that most others have chosen the sustainable option (e.g., Griskevicius et al., 2008).

### 7.2 | Directions for future research

Future research can extend our findings in multiple directions. First, although we have provided robust evidence for the phenomenon and ruled in our proposed mechanism, it is possible that multiple mechanisms are at play. For instance, people might believe that a product's popularity contains information about the product's quality as many people have chosen that product (Bikhchandani et al., 1992). Indeed, past research has found that people have a tendency to over-rely on products' popularity as a sign of quality even when there is a mediocre correlation between the two (Powell et al., 2017). It is possible that after experiencing variability, people might overweigh the quality information contained in the number of reviews and therefore choose popular products more often. Future research can test this idea.

In the present research, we documented an affective process underlying our phenomenon—exposure to high variability increases people's sense of anxiety, which is reduced once they choose more popular products. There could also be a parallel cognitive process—exposure to high variability increases people's sense of uncertainty about the future, which is reduced upon choosing more popular products. Choosing products with more customer reviews could reduce one's sense of uncertainty because it allows people to rely on and copy the decisions made by the majority of consumers (Morgan et al., 2015). Furthermore, consumers have greater confidence in products that are highly reviewed (Koriat, 2013), which could also help alleviate the sense of generalized uncertainty about the future that might be evoked by exposure to high variability. Another possibility is that encountering variability makes people think of the variance in the rating pattern. That is, they might think that the average rating is less stable when there are few reviews (Powell et al., 2017), as is the case in reality due to the law of large numbers; thus, participants give lower weight to the average rating given its unreliability in the high variability condition. These and other potential mechanisms can be tested in future research.

More generally, we relied on the number of reviews that products and services received to operationalize conformity to the majority's choice. Future research can examine whether our findings generalize to other operationalizations of conformity, such as in standard conformity paradigms in social psychology (e.g., Bond, 2005). Future research can also examine potential boundary conditions for this phenomenon. We theorized that variability affects the choice of popular products because such products satisfy people's need for social affiliation. However, the effect of variability might be attenuated in situations where others' choices cannot satisfy people's need for social affiliation. For instance, if a product was primarily chosen by an outgroup and is associated with the outgroup's identity (e.g., a European American choosing a salon frequented by African Americans), then choosing that product might not satisfy people's need for social affiliation. Similarly, the conspicuousness of either the product or the purchase decision could serve as another boundary condition. The effect of perceived variability may be particularly prominent with respect to products that are routinely viewed by others (e.g., mobile phones or clothing) versus those that are relatively private (e.g., home appliances); this is because conspicuous products could better fulfil people's need for social affiliation. Additionally, the conspicuousness of the decision might matter; the effect of perceived variability might be stronger if people make decisions in the presence of others, where affiliation needs might be heightened. Future research can test these boundary conditions.

All our studies involved hypothetical choices. Thus, it is possible that the current findings might not be observed with actual choices. Future research can test the effect of variability on people's preference for popular options in more consequential situations. For instance, researchers can use archival data to examine if more investors choose popular exchange-traded funds (e.g., a fund tracking the S&P500 or NASDAQ indices) versus niche exchange-traded funds (e.g., a clean energy fund or a quantum computing fund) when market volatility is higher. Another limitation of this research is that all the studies were conducted with participants from the United States. Future research could assess whether the current findings would generalize to other cultures.

Finally, across the four experiments, we found relatively small effect sizes for the phenomenon (Cohen's *d* ranging from 0.16 to 0.23 for Experiments 1 to 3, $\eta^2_p = .021$ for Experiment 4). We ensured that all the studies were adequately powered to detect these effect sizes. More importantly, recent discussions in our field suggest that small effect sizes are common, especially for experimental research, and that researchers should be skeptical of large effect sizes (Funder & Ozer, 2019). Further, research suggests that even small effect sizes in a lab setting can have large effects at a societal level (Greenwald et al., 2015). However, to verify this point, future research can conduct a field study or analyze archival data, as suggested above, to test if higher variability leads to more conformist behaviors. It is possible that although we found small effects in our experiments, the real-world impact of variability might be consequential when aggregated over thousands of choices.

In conclusion, increasing variability is a defining feature of the 21st century. Therefore, understanding the psychological consequences of exposure to variability is a pressing question for psychological science.

## ACKNOWLEDGMENTS

We thank Ee Hwee Lau, Dayana Bulchand, Sylvia Chin, Andrea Low, and Samantha Seah for their invaluable research assistance. Parts of this research were conducted when Krishna Savani was at Nanyang Technological University. This research was funded by The Hong Kong Polytechnic University and Nanyang Technological University.

## DATA AVAILABILITY STATEMENT

All data, stimuli, and analysis code are available at https://osf.io/x4qch/ (Experiment 1), https://osf.io/rsq4e/ (Experiment 2), https://osf.io/tx3e5/ (Experiment 3), https://osf.io/e7a4g/ (Experiment 4).

## ORCID

*Shankha Basu* https://orcid.org/0000-0002-4457-4247

*Krishna Savani* https://orcid.org/0000-0002-6934-1917

## REFERENCES

Andersson, M., Hedesström, T. M., & Gärling, T. (2009). Social influence on predictions of simulated stock prices. *Journal of Behavioral Decision Making*, *22*(3), 271–279. https://doi.org/10.1002/bdm.625

Baayen, R. H., Davidson, D. J., & Bates, D. M. (2008). Mixed-effects modeling with crossed random effects for subjects and items. *Journal of Memory and Language*, *59*(4), 390–412. https://doi.org/10.1016/j.jml.2007.12.005

Baker, S. R., Bloom, N., Davis, S. J., & Terry, S. J. (2020). *COVID-induced economic uncertainty (NBER working paper 26983)*. National Bureau of Economic Research.

Bearden, W. O., & Rose, R. L. (1990). Attention to social comparison information: An individual difference factor affecting consumer conformity. *Journal of Consumer Research*, *16*, 461–471. https://doi.org/10.1086/209231

Bénabou, R. (2013). Groupthink: Collective delusions in organizations and markets. *The Review of Economic Studies*, *80*, 429–462. https://doi.org/10.1093/restud/rds030

Berger, J., & Heath, C. (2007). Where consumers diverge from others: Identity signaling and product domains. *Journal of Consumer Research*, *34*, 121–134. https://doi.org/10.1086/519142

Bikhchandani, S., Hirshleifer, D., & Welch, I. (1992). A theory of fads, fashion, custom, and cultural change as informational cascades. *Journal of Political Economy*, *100*, 992–1026. https://doi.org/10.1086/261849

Bikhchandani, S., Hirshleifer, D., & Welch, I. (1998). Learning from the behavior of others: Conformity, fads, and informational cascades. *Journal of Economic Perspectives*, *12*, 151–170. https://doi.org/10.1257/jep.12.3.151

Bond, R. (2005). Group size and conformity. *Group Processes & Intergroup Relations*, *8*, 331–354. https://doi.org/10.1177/1368430205056464

CaixaBank Research. (2018). Financial markets are advancing in a more volatile environment. *CaixaBank Research*. Retrieved from https://www.caixabankresearch.com/en/economics-markets/recent-developments/financial-markets-are-advancing-more-volatile-environment

Chen, Y. F. (2008). Herd behavior in purchasing books online. *Computers in Human Behavior*, *24*, 1977–1992. https://doi.org/10.1016/j.chb.2007.08.004

Dennis, S. A., Goodson, B. M., & Pearson, C. A. (2020). Online worker fraud and evolving threats to the integrity of MTurk data: A discussion of virtual private servers and the limitations of IP-based screening procedures. *Behavioral Research in Accounting*, *32*(1), 119–134. https://doi.org/10.2308/bria-18-044

Ding, Y., & Savani, K. (2020). From variability to vulnerability: People exposed to greater variability judge wrongdoers more harshly. *Journal of Personality and Social Psychology*, *118*, 1101–1117. https://doi.org/10.1037/pspa0000185

Faul, F., Erdfelder, E., Lang, A.-G., & Buchner, A. (2007). G*Power 3: A flexible statistical power analysis program for the social, behavioral, and biomedical sciences. *Behavior Research Methods*, *39*, 175–191. https://doi.org/10.3758/BF03193146

Folkes, V. S., & Patrick, V. M. (2003). The positivity effect in perceptions of services: Seen one, seen them all? *Journal of Consumer Research*, *30*, 125–137. https://doi.org/10.1086/374693

Funder, D. C., & Ozer, D. J. (2019). Evaluating effect size in psychological research: Sense and nonsense. *Advances in Methods and Practices in Psychological Science*, *2*, 156–168. https://doi.org/10.1177/2515245919847202

Greenwald, A. G., Banaji, M. R., & Nosek, B. A. (2015). Statistically small effects of the Implicit Association Test can have societally large effects. *Journal of Personality and Social Psychology*, *108*, 553–561. https://doi.org/10.1037/pspa0000016

Griskevicius, V., Cialdini, R. B., & Goldstein, N. J. (2008). Social norms: An underestimated and underemployed lever for managing climate change. *International Journal of Sustainability Communication*, *3*, 5–13.

Griskevicius, V., Goldstein, N. J., Mortensen, C. R., Cialdini, R. B., & Kenrick, D. T. (2006). Going along versus going alone: When fundamental motives facilitate strategic (non)conformity. *Journal of Personality and Social Psychology*, *91*, 281–294. https://doi.org/10.1037/0022-3514.91.2.281

Griskevicius, V., Tybur, J. M., Gangestad, S. W., Perea, E. F., Shapiro, J. R., & Kenrick, D. T. (2009). Aggress to impress: Hostility as an evolved context-dependent strategy. *Journal of Personality and Social Psychology*, *96*, 980–994. https://doi.org/10.1037/a0013907

Hanson, W. A., & Putler, D. S. (1996). Hits and misses: Herd behavior and online product popularity. *Marketing Letters*, *7*, 297–305. https://doi.org/10.1007/BF00435537

Heck, D., Seiling, L., & Bröder, A. (2020). The love of large numbers revisited: A coherence model of the popularity bias. *Cognition*, *195*, 104069. https://doi.org/10.1016/j.cognition.2019.104069

Herry, C., Bach, D. R., Esposito, F., Salle, F. D., Perrig, W. J., Scheffler, K., Lüthi, A., & Seifritz, E. (2007). Processing of temporal unpredictability in human and animal amygdala. *Journal of Neuroscience*, *27*, 5958–5966. https://doi.org/10.1523/JNEUROSCI.5218-06.2007

Intergovernmental Panel on Climate Change. (2007). Climate change 2007: The physical science basis summary for policymakers. In *Fourth assessment report of the Intergovernmental Panel on Climate Change*. IPCC Secretariat. https://doi.org/10.1017/CBO9780511546013

Johnson, M., & Nilsson, L. (2018). The importance of reliability and customization from goods to services. *Quality Management Journal*, *10*, 8–19. https://doi.org/10.1080/10686967.2003.11919049

Koriat, A. (2013). Confidence in personal preferences. *Journal of Behavioral Decision Making*, *26*(3), 247–259. https://doi.org/10.1002/bdm.1758

Lakens, D. (2014). Performing high-powered studies efficiently with sequential analyses. *European Journal of Social Psychology*, *44*, 701–710. https://doi.org/10.1002/ejsp.2023

Landau, M. J., Kay, A. C., & Whitson, J. A. (2015). Compensatory control and the appeal of a structured world. *Psychological Bulletin*, *141*, 694–722. https://doi.org/10.1037/a0038703

Mead, N. L., Baumeister, R. F., Stillman, T. F., Rawn, C. D., & Vohs, K. D. (2011). Social exclusion causes people to spend and consume strategically in the service of affiliation. *Journal of Consumer Research*, *37*, 902–919. https://doi.org/10.1086/656667

Morgan, T. J., Laland, K. N., & Harris, P. L. (2015). The development of adaptive conformity in young children: Effects of uncertainty and consensus. *Developmental Science*, *18*(4), 511–524. https://doi.org/10.1111/desc.12231

Murray, D. R., & Schaller, M. (2012). Threat(s) and conformity deconstructed: Perceived threat of infectious disease and its implications for conformist attitudes and behavior. *European Journal of Social Psychology*, *42*, 180–188. https://doi.org/10.1002/ejsp.863

National Oceanic and Atmospheric Administration. (2017). Climate at a glance: National time series. *National Centers for Environmental Information*. Retrieved December 20, 2017, from https://www.ncdc.noaa.gov/cag/

Norman, L., Lawrence, N., Iles, A., Benattayallah, A., & Karl, A. (2014). Attachment-security priming attenuates amygdala activation to social and linguistic threat. *Social Cognitive and Affective Neuroscience*, *10*, 832–839.

Partington, R., & Wearden, G. (2020). Global stock markets post the biggest falls since the 2008 financial crisis. *The Guardian*. Retrieved from https://www.theguardian.com/business/2020/mar/09/global-stock-markets-post-biggest-falls-since-2008-financial-crisis

Pocock, S. J. (1977). Group sequential methods in the design and analysis of clinical trials. *Biometrika*, *64*, 191–199. https://doi.org/10.1093/biomet/64.2.191

Powell, D., Yu, J., DeWolf, M., & Holyoak, K. J. (2017). The love of large numbers: A popularity bias in consumer choice. *Psychological Science*, *28*, 1432–1442. https://doi.org/10.1177/0956797617711291

Reinstaller, A., & Sanditov, B. (2005). Social structure and consumption: On the diffusion of consumer good innovation. *Journal of Evolutionary Economics*, *15*, 505–531. https://doi.org/10.1007/s00191-005-0265-9

Steinhart, Y., Kamins, M., Mazursky, D., & Noy, A. (2014). Effects of product type and contextual cues on eliciting naive theories of popularity and exclusivity. *Journal of Consumer Psychology*, *24*, 472–483. https://doi.org/10.1016/j.jcps.2014.04.004

Stern, B. B. (1995). Consumer myths: Frye's taxonomy and the structural analysis of consumption text. *Journal of Consumer Research*, *22*, 165–185. https://doi.org/10.1086/209443

Sternberg, R. J., & Lubart, T. I. (1995). *Defying the crowd: Cultivating creativity in a culture of conformity*. Free Press.

Tian, K. T., Bearden, W. O., & Hunter, G. L. (2001). Consumers' need for uniqueness: Scale development and validation. *Journal of Consumer Research*, *28*, 50–66. https://doi.org/10.1086/321947

Van Lange, P. A., Rinderu, M. I., & Bushman, B. J. (2017). Aggression and violence around the world: A model of CLimate, Aggression, and Self-control in Humans (CLASH). *Behavioral and Brain Sciences*, *40*, e75. https://doi.org/10.1017/S0140525X16000406

Wang, J., Zhu, R., & Shiv, B. (2012). The lonely consumer: Loner or conformer? *Journal of Consumer Research*, *38*, 1116–1128. https://doi.org/10.1086/661552

Whalen, P. J. (1998). Fear, vigilance, and ambiguity: Initial neuroimaging studies of the human amygdala. *Current Directions in Psychological Science*, *7*, 177–188. https://doi.org/10.1111/1467-8721.ep10836912

Wilde, G. J. S. (1982). The theory of risk homeostasis: Implications for safety and health. *Risk Analysis*, *2*(4), 209–225. https://doi.org/10.1111/j.1539-6924.1982.tb01384.x

Wilde, G. J. S. (1998). Risk homeostasis theory: An overview. *Injury Prevention*, *4*(2), 89–91. https://doi.org/10.1136/ip.4.2.89

Yamaguchi, S. (1998). Biased risk perceptions among Japanese: Illusion of interdependence among risk companions. *Asian Journal of Social Psychology*, *1*, 117–131. https://doi.org/10.1111/1467-839X.00008

Zaggl, M. A., Hagenmaier, M. A., & Raasch, C. (2019). The choice between uniqueness and conformity in mass customization. *R&D Management*, *49*, 204–221. https://doi.org/10.1111/radm.12327

Zsido, A. N., Teleki, S. A., Csokasi, K., Rozsa, S., & Bandi, S. A. (2020). Development of the short version of the Spielberger state–trait anxiety inventory. *Psychiatry Research*, *291*, 113223. https://doi.org/10.1016/j.psychres.2020.113223

## SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

**How to cite this article:** Tan, L., Basu, S., & Savani, K. (2023). Going with the crowd in volatile times: Exposure to environmental variability increases people's preference for popular options. *Journal of Behavioral Decision Making*, e2343. https://doi.org/10.1002/bdm.2343

## APPENDIX A

| Categories | Option # | Experiment 1: Service providers | | Experiments 2 and 3: Products | |
|---|---|---|---|---|---|
| | | Number of stars | Number of customer reviews | Number of stars | Number of customer reviews |
| Car servicing station (service)/earpieces (product) | 1 | 3 | 17 | 3 | 17 |
| | 2 | 3 | 33 | 3 | 63 |
| | 3 | 2.5 | 162 | 2.5 | 162 |
| | 4 | 2.5 | 548 | 2.5 | 548 |
| | 5 | 2 | 880 | 2 | 880 |
| Hair salon (service)/lamp (product) | 1 | 3.5 | 14 | 3.5 | 14 |
| | 2 | 3.5 | 48 | 3.5 | 81 |
| | 3 | 3 | 301 | 3 | 301 |
| | 4 | 3 | 382 | 3 | 334 |
| | 5 | 2.5 | 457 | 2.5 | 457 |
| Electrician (service)/clock (product) | 1 | 4 | 91 | 4 | 91 |
| | 2 | 4 | 98 | 4 | 108 |
| | 3 | 3.5 | 123 | 3.5 | 123 |
| | 4 | 3.5 | 943 | 3.5 | 343 |
| | 5 | 3 | 1287 | 3 | 1287 |
| Restaurant (service)/dehumidifier (product) | 1 | 4.5 | 45 | 4.5 | 45 |
| | 2 | 4.5 | 155 | 4.5 | 155 |
| | 3 | 4 | 388 | 4 | 388 |
| | 4 | 4 | 616 | 4 | 616 |
| | 5 | 3.5 | 949 | 3.5 | 949 |
| Event planner (service)/photo frame (product) | 1 | 5 | 319 | 5 | 319 |
| | 2 | 5 | 541 | 5 | 541 |
| | 3 | 4.5 | 850 | 4.5 | 850 |
| | 4 | 4.5 | 1013 | 4.5 | 1013 |
| | 5 | 4 | 1583 | 4 | 1583 |