Original Article

Valence-Based Biases in News Selection

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Abstract: Recent work highlights individual-level variation in negativity biases in news selection. There has, however, been limited work exploring the source of this individual-level variation. This study considers predispositions in information processing as a source of difference in news selection. We explore individual differences in learning biases identified using Hot Rod, a new purpose-built online game. Asymmetries in respondents' learning of negative and positive information in Hot Rod are correlated with news selection decisions. It thus appears that valence-based differences in news consumption are at least partly a function of the same biases that govern learning and information processing more broadly.

Keywords: news consumption, negativity bias, political communication, learning

There is a wealth of research on the kinds of content that finds its way into news coverage (e.g., Bennett, 1990; Shoemaker, 1996), and correspondingly rich literatures that try to understand why individuals select certain news stories over others (e.g., Arceneaux & Johnson, 2013; Palmgreen et al., 1981; Stroud, 2008). The objective of this study was to examine the degree to which individual-level differences in news consumption reflect durable psychological differences in information processing.

The tone or valence of news coverage has been central to some of the literature on news selection. Tone or valence has also been important in psychological work on information processing and attitude formation. This overlap offers, in our view, an opportunity to examine the possibility that patterns in news consumption are not unique to news consumption, but rather reflective of the way in which different individuals respond to valenced information as they learn about and understand the world around them.

We believe that exploring this possibility is of some significance for scholars of political psychology and journalism. There are at least two reasons. First, if news selection is linked to predispositions related to information processing generally, then at least part of the variation in individuals' news preferences is stable, that is, not wholly contingent on the nature of news in the moment. This is important for those seeking to understand the nature of news preferences and consumption (e.g., Bachleda et al., 2020). Second, if news selection is linked to predispositions related to information processing generally, then the impacts of decisions by journalists, editors, and/or platforms is at least somewhat limited. Put differently, the impact of editorial/platform decisions on news consumption increases considerably if news selection is entirely unhinged, that is, disconnected from some kind of predisposition in information processing.

Accordingly, here we explored the possibility that news selection reflects, at least in part, stable predispositions in learning. We did so using Hot Rod, an online game modeled directly on BeanFest (Fazio et al., 2004), a well-established computer game that has made major contributions to our understanding of learning and weighting biases.[1] Hot Rod was designed not for the laboratory but for large-scale dissemination through standard online survey software, allowing us to explore news selection in a large nationally representative sample of Americans. The results support our expectations: players' behavior in Hot

[1] In the context of the BeanFest literature, learning biases are asymmetries in learning from negative versus positive outcomes. A negativity bias in learning reflects a propensity to learn more from negative outcomes than positive ones. Weighting biases, by contrast, reflect the degree to which individuals take negative and positive objects into account when making judgements about novel objects (i.e., attitude generalization). When making a judgement about a novel object that is equally similar to one known positive and one known negative object, a negativity bias in weighting indicates a propensity to judge the novel object negatively, that is, to weight similarity to the negative object more heavily. The emphasis in the current paper is on the learning bias, for reasons described below; but our exploration of learning will include some analysis of generalization as well, particularly in the Appendix material.

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Rod – in which players learn based on both positive and negative feedback – is associated with preferences for positive versus negative news headlines.

Background

Story selection by users is a central feature of news consumption, especially as news consumption is increasingly online. Audience interests have always been central to news selection, of course. It has, after all, always been the case that the reader decides whether they will read or skip a given newspaper story. But a reliance on "clicks" likely makes audience-generating factors especially important for news consumption as well as production. And the ability to be increasingly selective about news means that users' news content is increasingly influenced by their own preferences.

These facts have been central to the burgeoning literature on selective exposure in news consumption (e.g., Stroud, 2008), which highlights the role of cognitive dissonance (Festinger, 1962) – the discomfort felt when we encounter information that is contrary to our beliefs – as a driver of news selection. They also play a featured role in work on negativity and outlyingness in news content (e.g., Lamberson & Soroka, 2018; Shoemaker, 1996), particularly work raising concerns about the possibility that increased selectivity will lead to audience-seeking media content that is increasingly negative and sensationalistic.

That news content is predominantly negative is foundational to scholars' understanding of news media. There is well-established literature on the frequency and impacts of both negative news content (e.g., Cappella & Jamieson, 1997; Patterson, 1994) and negative political advertising (e.g., Lau et al., 1999; Valentino et al., 2011). There also is work demonstrating that humans will on average prioritize negative information over positive information, generally speaking (e.g., Baumeister et al., 2001; Rozin & Royzman, 2001) and in politics and news consumption specifically (e.g., Soroka, 2014).

A growing body of work also highlights variation around this average behavior. Even as humans may on average seek, respond to, and/or weigh negative information more heavily than positive information, there appears to be a good amount of individual-level variation. That variation is highlighted in recent work on psychophysiological reactions to news content cross-nationally (Soroka et al., 2019a); it is evident in work that links variation in negativity biases to political ideology (e.g., Oxley et al., 2008; Shook & Fazio, 2009); and it is evident in psychological work on learning and attitude formation (e.g., Fazio et al., 2004) as well.

Research that uses BeanFest to examine attitude formation alongside a range of related phenomena was especially influential for the present paper. The use of games to examine learning and/or information processing is well established. Games have been used as learning tools (Garris et al., 2002; Ke, 2011; Randel et al., 1992); they also have been used to explore psychological characteristics and mechanisms (e.g., Gobet et al., 2004; Lange et al., 2012), and to test formal models of behavior (e.g., Axelrod & Dawkins, 2006). BeanFest itself is a computer game played in the lab. Participants are presented with a series of beans and must try to learn which beans to "approach" in order to win points, based on variations in (a) how circular versus oval they are and (b) how many dots they have. After a series of practice rounds in which participants guess and receive feedback, they play a final game in which they (a) make guesses with no feedback on which beans are healthy or unhealthy and (b) are faced with a combination of practiced and novel beans. This is, to be sure, a very thin account of the game, but more details are provided in the Methods section. The most critical feature of the game for the time being is that it allows researchers to examine valence-based asymmetries in learning.

Past work makes clear that the valence-based asymmetries captured in BeanFest are correlated with a range of other attitudes, including negative cognitive style, depression, and anxiety (Shook et al., 2007). Valence-based asymmetries are associated with political ideology, whereby conservatives show larger negativity biases in learning than liberals (Shook & Fazio, 2009; in line with work finding a similar relationship using psychophysiological measures, e.g., Oxley et al., 2008; although also see Bakker et al., 2020; Fournier et al., 2020). Subsequent research has also linked asymmetries captured in BeanFest play to participants' reactions to stressful events (Pietri et al., 2012), to measures of negativity and risk (Pietri et al., 2013; Rocklage & Fazio, 2014), and the formation of social relationships (Rocklage et al., 2017). None of these phenomena is the focus of the analyses here, but we see each as evidence of the concurrent validity of measures extracted from BeanFest gameplay. In short: Quantities identified in BeanFest have been linked to a broad range of attitudes and behaviors; for this reason, we are interested in whether a similar game might be used to explore valence-based asymmetries in news consumption.

The accumulated literature using BeanFest has relied on a number of variations on the rules of BeanFest, as well as the ways in which BeanFest results are calculated, in order to better explore particular aspects of both learning and attitude generalization. But the cumulative message of the literature is relatively clear: Gameplay reveals asymmetries in the weight that participants give to negative and positive information, and those asymmetries are systematically connected with a range of measures of information processing, risk, and political and social attitudes.

Our contention is that the asymmetry in learning revealed by a game such as BeanFest will be connected with media consumption behavior as well. Note first that just as the BeanFest literature has revealed valence-based variation in learning, so too does recent work on reactions to news content. Recent studies highlight considerable variation in responsiveness to negative and positive news coverage. Soroka et al. (2019a) demonstrate wide variation in psychophysiological reactions to positive and negative network news stories within each of 17 different countries, for instance. Soroka et al. (2019b) highlight this individual-level variation within the United States in particular. And just as BeanFest results have been linked to a range of sociopolitical attitudes, so too has the tendency to prioritize positive or negative news content: Bachleda et al. (2020) examined headline-selection tasks across multiple countries and found connections between "negativity bias in news selection" and factors such as government satisfaction and economic sentiment.

Note also that the activity of news consumption is very similar to BeanFest. Indeed, the literature already considers news consumption, at least in part, as a learning exercise (e.g., Lee, 2013; McCombs & Poindexter, 1983; Shoemaker, 1996). The strength of a BeanFest-style game in this context is its ability to measure learning preferences in an environment that is entirely exogenous from current affairs news; and then to examine the possibility that these asymmetries in learning are linked to news consumption behavior.

We consider news selection as our dependent variable, and predispositions in learning as our independent variable. We hypothesize the following:

Hypothesis 1 (H1): There will be a positive association between valence-based asymmetries in news selection and valence-based asymmetries in learning.

Insofar as this is the case, we suggest that it will offer support for the claim that news consumption is driven at least in part by individual-level differences in learning.

Method

Hot Rod

Our first objective was to adjust the BeanFest game with an eye toward creating a widely deployable measure of biases in learning. We did so by developing an online video game called "Hot Rod." Hot Rod is similar to BeanFest in almost every way, but instead of beans that vary in shape and dots we use race cars that vary in rear wheel size and number of racing stripes. Just as in BeanFest, the two dimensions have 10 possible values (1 to 10). Panel A in Figure 1 shows two examples of cars with minimal and then maximal values for both wheels and stripes.

As far as online games go, Hot Rod is not especially sophisticated. Using the descriptions of variations of BeanFest in the existing literature, we built a series of game rounds that can be fielded using the Qualtrics platform (albeit with adjustments using javascript; the modules used to run Hot Rod are now freely available through the Harvard Dataverse at https://doi.org/10.7910/DVN/D7N8ZQ). We see the use of a standard survey platform as advantageous in that Hot Rod can be run in a relatively straightforward way on a platform many researchers have access to. We also see the transition from beans to race cars as advantageous insofar as it makes the game a little more interesting. There are risks in moving to objects toward which participants may already have attitudes. We believe these risks are minimal in the case of cartoon race cars, however; and, moreover, we believe the minimal risks are offset by the advantages of building an instrument that is more interesting and feels more like an online video game.

The game presents race cars to participants in five rounds – four practice rounds and a final game round. In all rounds, participants must guess whether the Challenger car will defeat the Champion. For practice rounds, participants learn whether their guesses are correct or not – after each guess, there is a screen that shows the results of the race. At the beginning of each of the practice rounds, participants are given 100 points. With each correct guess, participants gain 10 points, and with each incorrect guess, they lose 10 points. If they reach 0 points the round restarts, while if they reach 200 points, they end the round early. Panels C and D of Figure 1 show examples of the guessing screen and the results screen from the four practice rounds.

Rounds 1 and 3 use the same set of 12 cars in random order; Rounds 2 and 4 use a different set of 16 cars in random order. Not all of the 100 possible wheel and stripe combinations are used, as can be seen in Panel B of Figure 1. The panel maps out the cars that will win (solid shapes) or lose (hollow shapes), as well as the cars shown in the first, second, third, fourth, and game rounds. The map itself is exactly the same as is typically used in BeanFest, although the number of cars/beans presented in each round differs slightly (across BeanFest versions, and here). Note that learning the right combinations of wheels and stripes is difficult – there are not-straightforward combinations of the two that will win or lose. And participants must make their decisions in 10 s, after which time they are presented with the results screen (and no change in their points).

In the final game round, participants are told that they will no longer receive feedback – they must simply make their guesses with no results screen or points tally until the end of the game. This round features 40 cars, as indicated in Figure 1B. Note that half of these cars are ones that have been seen in prior rounds, and others are novel – proximate/similar to prior cars, but marginally different. (Novel cars are central to a measure of attitude generalization, i.e., they capture participants' ability to generalize from what they have learned in prior rounds (see Footnote 1)). As in the practice rounds, game-round cars are presented in random order. Each car now times out after only 5 s, after which the game moves on to the next car. The final score is given as a proportion of the 40 cars guessed correctly, where missed cars are counted as incorrect responses.

Given results in prior work (esp. Fazio et al., 2004; Shook et al., 2007), we focus on the *full-feedback* variant of our game, in which participants learn about cars regardless of whether they guess *win* or *lose*.[2] And we rely on a single measure common in the BeanFest literature: a learning bias based on the number of game-round correct guesses, by positive or negative valence (winning vs. losing cars). We discuss this measure in more detail in the Results section.

Survey

The data we relied on are based on an online sample of US respondents, collected in two waves by YouGov. YouGov uses a sample matching procedure to derive representative samples from nonrandomly selected pools of online respondents.[3] The response rate was 24.1%; demographic details for respondents who completed the survey are provided in Appendix Table A1.

All respondents play the Hot Rod game, after which they complete a series of survey questions fielded in the same Qualtrics platform. The survey begins with headline-selection tasks that make up our measure of negativity biases in news selection (NBNS). The measure has been designed and tested elsewhere (Bachleda et al., 2020), and is relatively straightforward: In each of five questions, participants are asked to indicate which of four headlines they would like most to read. In each case, there are two positive and two negative headlines, in random order. Selections are made across five topics – the economy, the environment, health, politics, and foreign affairs – also in random order.

The question wording and headlines are as follows.

> Imagine that you are going to read a news story in order to learn something interesting, important or useful about the ECONOMY. You have FOUR headlines from which to make ONE selection. Which of the following would you read?: Experts Deeply Worried about Rising Cost of Living; Inflation Figures Released: Outlook Is Positive; Employment Up From Last Month; Has Employment Already Peaked? Future Prospects Worsen.
>
> . . . ENVIRONMENT. . . Which of the following would you read?: Scientists Offer Warnings About Depleted Ozone Layer; Monthly Trend Suggests Improvement in Global Warming; Report Suggests Rising Concerns About Rising Temperatures; Successful Reforestation Offers Signs of Hope.
>
> . . . POLITICS. . . Which of the following would you read?: Support for Government at All-Time Low; Assistance in Sight for Congressional Leadership; Congress Fumbles Again; Parties Succeed in Rebuilding Bases of Support.
>
> . . . HEALTH CARE. . . Which of the following would you read?: Easy Ways to Improve Heart Health; Why Are Heart Attacks on the Rise?; Doctors' Healthy Eating Tips; Meals That Can Harm Your Health.
>
> . . . FOREIGN AFFAIRS. . . Which of the following would you read?: Global Trade Summit Widely Criticized; Foreign Leaders Convene to Improve Trade Relations; Explosions Shock Diplomats Across the Middle East; Positive Shift in Middle East Talks.

The objective is to capture participants' tendency to select negative headlines over positive headlines, across a range

[2] A "contingent feedback" version of BeanFest offers feedback on whether a bean is healthy or unhealthy only when participants select *approach* (equivalent to *win* in Hot Rod); if participants choose not to approach (equivalent to *lose* in Hot Rod) they are offered no feedback. Using the contingent feedback version of the game, Fazio et al. (2004) found that much of the negativity bias in learning can be attributed to an asymmetry in approach behavior whereby participants are increasingly wary of unhealthy beans. That said, a negative bias in generalization is evident regardless of feedback; and subsequent work focused on individual-level variation in the learning bias (e.g., Shook et al., 2007) relies on the full-feedback variant of the game. Our car race version does not lend itself well to the contingent feedback manipulation (where participants would get information only when they said *win*). For these reasons, we rely on a full-feedback variant only here, with one caveat: In the Qualtrics fielding of the game we included a *skip* button that allowed respondents to simply skip a guess and move on (without any points change). We fielded versions of the game in which that skip button resulted in feedback anyway, or no feedback; but use of the skip button was extraordinarily low, that is, less than 1% of the time. Our inclusion of the button was thus of no consequence, and we pool all respondents in analyses here.

[3] The sample matching procedure is roughly as follows: a target sample is drawn from the US population, defined by Census Bureau and other surveys; general population target samples are selected via stratification by age, race, gender, education, and voter registration, and by simple random sampling within strata; online panelists are then matched based on a range of demographics to this hypothetical target sample. For a discussion of the advantages of this approach, see Vavreck and Rivers (2008).

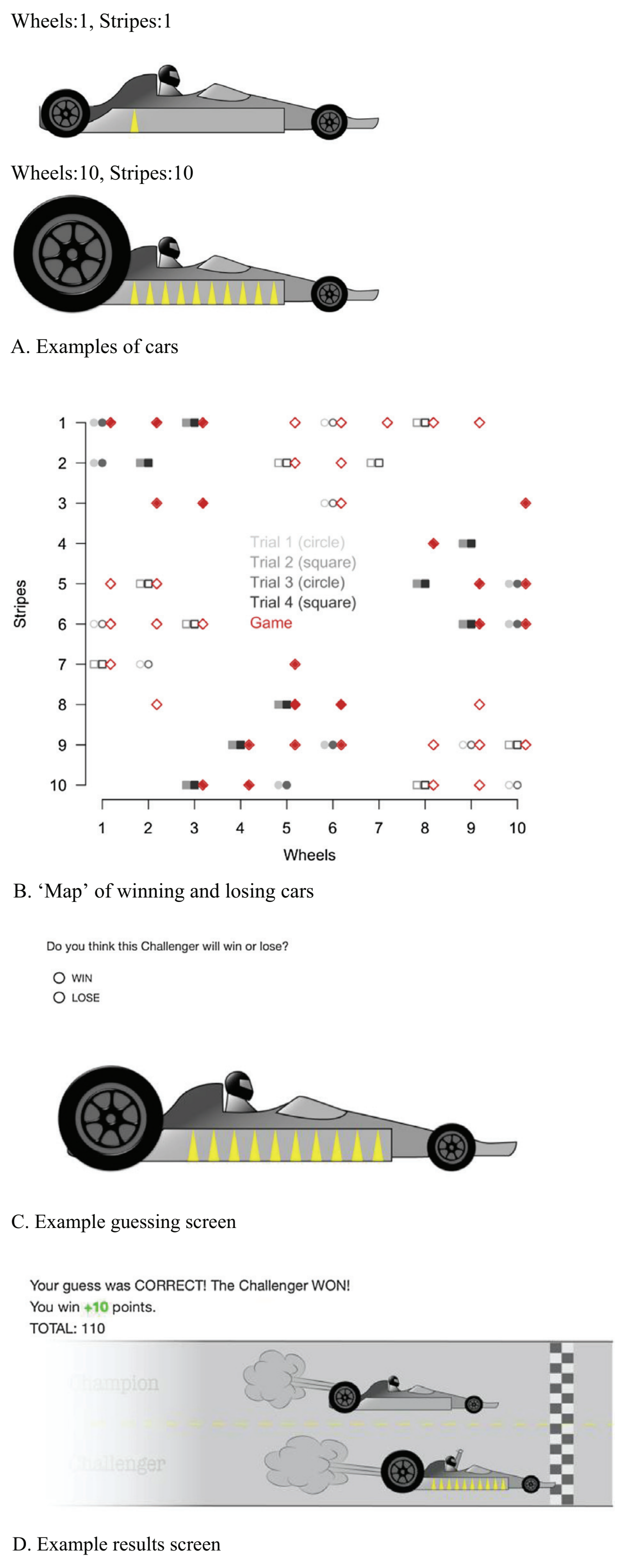

Figure 1. The Hot Rod game.

of subjects. Bachleda et al. (2020) discussed in some detail the reasoning behind using multiple different topics; they also confirmed that the measure is robust to changes in

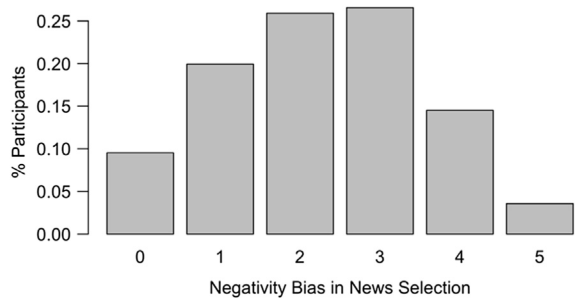

Figure 2. The distribution of news selection.

topics and headlines. As in that work, we summed the number of questions in which a respondent selected a negative headline. The resulting measure is shown in Figure 2, ranging from 0 (= *no negative headlines selected*) to 5 (= *all negative headlines selected*).

The survey captured a range of demographics, some of which we used as controls: gender (0 = male, 1 = female); age (included as an interval level variable with 6 categories: 0 = 18–24 years; 1 = 25–34 years; 2 = 35–44 years; 3 = 45–54 years; 4 = 55–64 years; 5 = 65 and over); education (0 = high school or less; 1 = more than high school diploma); employment (1 = full- or part-time employment; 0 = otherwise); and income (a 15-category variable capturing ranges of income). The survey also includes measures of risk and policy preferences, including the Domain-Specific Risk-Taking (DOSPERT) scales of financial and personal risk (Weber et al., 2002). These items have been found to be associated with behavior in BeanFest; they were included in this instance only as a conceptual replication of that prior work and a test of the concurrent validity of Hot Rod. As expected, behavior in Hot Rod is associated with measures of risk. We include these results in the Appendix.

Results

We begin with some basic diagnostics regarding Hot Rod gameplay. There was moderate evidence of learning over the course of the game. On average, participants guessed correctly 46% of the time in Round 1, and 53% of the time in the game round (whether or not novel cars were included). Low levels of both correct guesses and learning reflect just how difficult the game is; they also mask a lot of variation across individuals – roughly 25% of all participants were correct more than 60% of the time when assessing non-novel beans in the final round. We expected more variation in learning in a representative sample of Americans in contrast to university students, of course. We also anticipated some noise in an online sample in which we

Table 1. NBNS and the learning bias

	DV: NBNS			
	Model 1		Model 2	
Learning bias	−0.302** (0.143)	*−0.068*	−0.286** (0.141)	*−0.064*
Male			−0.009 (0.085)	*NA*
Age (categorical)			−0.127*** (0.029)	*−0.154*
University education			−0.048 (0.088)	*−0.019*
Employment			−0.064 (0.093)	*−0.024*
Income			−0.044*** (0.015)	*−0.105*
Constant	2.308*** (0.046)		3.019*** (0.132)	
Observations	953		953	
R^2	0.005		0.042	

Note. Cells contain OLS regression coefficients with standard errors in parentheses. Standardized coefficients are italicized. *$p < .10$; **$p < .05$; ***$p < .01$.

had limited control over attentiveness. Even so, there is evidence of learning in our data.[4]

There are valence-based asymmetries in learning as well. Figure 3 shows the distribution of our measure of the learning bias, which is *win % correct* minus *lose % correct*, where *win % correct* is the percent of winning (non-novel) cars guessed correctly in the game round, and *lose % correct* is the percent of losing (non-novel) cars correctly guessed in the game round. This measure, drawn from past work (e.g., Pietri et al., 2012), captures the degree to which respondents are correct (i.e., have learned more) about winning cars versus losing cars. To be clear: In the game round respondents are presented with a set of cars that they have already seen in prior practice rounds; and based on game-round responses we can calculate the degree to which each respondent has learned more about the wining or the losing cars. *This* is the learning bias.

Note that participants were inclined to guess *win* in the online Hot Rod game, and thus the distribution is centered right of zero, that is, on the betting to win side. There is nevertheless a roughly normal distribution around the mean. Some respondents learned more about winning cars than losing cars; others learned more about losing cars than winning ones.

To what extent does the variation in Figure 3 reflect valence-based biases in learning rather than random noise? More importantly, is there evidence that this learning bias is correlated with negativity biases in news selection? Table 1 shows the results, first using a bivariate OLS model in which news selection is regressed on the learning bias,

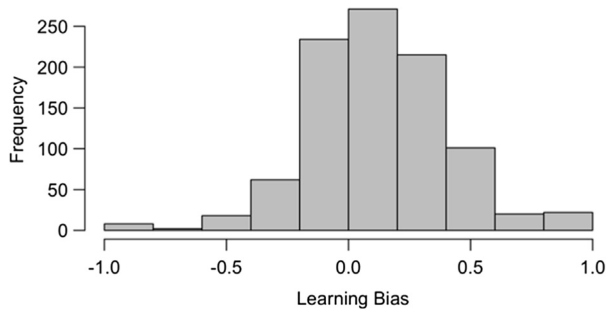

Figure 3. The distribution of the learning bias.

and then in a model that adds demographic controls. Raw estimates are shown alongside standardized estimates (in italics). Controls make little difference.[5] In each model there is a robust relationship between the estimated learning bias and negativity biases in news selection. The relationship is robust and negative, although relatively small in magnitude. This is as we expect. Where the direction of the coefficient is concerned, those who learn more about wins relative to losses also tend to select less negative news content. Where the magnitude of the effect is concerned, a one-standard-deviation shift in the learning bias is associated with a roughly −0.064-standard-deviation shift in headline selection. This is a relatively small shift, to be sure; although it is important to keep in mind that we relied on relatively noisy data from online game play as well as OLS models of a simple five-item headline selection task.[6]

[4] There is evidence of attitude generalization in our data as well, in line with results using BeanFest. As noted earlier, we include a brief exploration of attitude generalization in the Appendix.

[5] We do not interpret control variables in any detail here, although it is worth noting that the estimated null effects of most demographics, as well as the negative impact of age, are in line with prior work on negativity biases in news selection (Bachleda et al., 2020).

[6] We expect our results to be "noisy" in comparison with data based on laboratory experiments because we have no control over the environment in which respondents are playing the game. In a laboratory we can be relatively sure that respondents are focused; but in this case we expect respondents to be playing the (long) game on many different devices, and with many different distractions. We regard this as a reasonable price to pay for a more broadly representative sample, but it will of course make it more difficult to detect relationships, all else equal.

Given the range of the learning bias (−1 to +1; see Figure 3) and the range of the news selection variable (0 to 5; see Figure 2), the results in Table 1 suggest that moving across the range of the learning bias variable is associated with an average increase of roughly 0.6 positive rather than negative headlines. Put differently: A person with a strong negativity bias in learning will select one more negative headline out of 10 than will a person with a strong positivity bias in learning. The association is small, but robust to the inclusion of demographics and the inevitable noise in an online survey-based video game. We reject the null hypothesis for H1.

Discussion

The objective in this study has been to test the possibility that individual-level differences in positive/negative news selection are a function at least in part of valence-based differences in learning. Exploring this requires a measure of valence-based asymmetries in learning, which we have captured using Hot Rod, an online variant of a well-known game, BeanFest. Results suggest that the learning bias is correlated with news-headline selection behavior.

These findings add to the existing literature in several ways. Demonstrating a negativity bias in learning is not new, of course; it has been shown in past work using BeanFest. But our work offers an extension of that literature, with an adjusted game and a large, more broadly representative sample of Americans. That the valence-based biases in learning are evident in our work is thus a useful confirmation of findings in the extant literature.

The critical finding where media consumption is concerned is that valence-based differences in news selection behavior are linked to differences in learning more broadly. We see these results as an important backdrop to the literature that considers news consumption as, in some instances at least, "information-motivated" (Lee, 2013) or learning-oriented behavior. They are also a helpful reminder that news consumers are not just following flashy headlines. Our decisions to engage with or avoid news content are governed by a range of factors, including our own biases in learning. Ceteris paribus, those of us who learn more from negative information will tend to select more negative stories, and those of us who learn from more positive information will do otherwise.

Biases in news selection, driven by biases in learning or not, can have fundamental consequences for individuals' perceptions of the world around them. An inclination to focus mainly on negative rather than positive information about the economy can make for a rather different outlook than an inclination to focus more on the positive information, for instance. Economic, political, and social behavior may all reflect the valence-based asymmetries examined here. For this reason, we see this paper as an important step toward better understanding the sources and consequences of valence-based asymmetries in news selection.

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Appendix

Sample Descriptives

Sample descriptives are shown in Table A1.

The Weighting Bias

Table A2 illustrates the asymmetry in attitude generalization seen in past work focused on BeanFest. The table shows results of an OLS regression model in which the dependent variable is *net guesses* – the average guess for all novel cars in the game round, where *win* is scored as 1 and *lose* is scored as −1. This is regressed on two independent variables: *win % correct*, which is the percent of winning (non-novel) cars guessed correctly in the game round, and *lose % correct*, which is the percent of losing (non-novel) cars correctly guessed in the game round. The measure is drawn from past work (i.e., Pietri et al. 2012), and intended to capture the degree of which learned information, separated by valence, is evident in generalization.

As was found in laboratory-based versions of BeanFest, the coefficient for *lose % correct* is larger than the coefficient for *win % correct*, in this instance by roughly 40% (F-tests indicate that the difference between coefficients is statistically significant at $p < .001$). The implication of this finding is that, in line with previous work, negative information is weighted more heavily than positive information in attitude generalization. Guesses about novel cars are connected more to what participants have learned about losing cars than by what they have learned about winning cars. Put differently: on average, respondents are inclined to generalize more based on losing cars than on winning cars.

The Weighting Bias and Risk Preferences

As noted in the text, our survey includes DOSPERT measures of risk that allow for a replication of the findings by Pietri et al. (2012), suggesting the weighting bias in attitude generalization is correlated with risk preferences. The DOSPERT indices are based on the following questions:

Financial

For each of the following statements, please indicate the likelihood that you would engage in the described activity or behavior if you were to find yourself in that situation. Provide a rating from *Extremely Unlikely* to *Extremely Likely*, using the following scale: [*Extremely Unlikely* (1) *Moderately Unlikely* (2) *Somewhat Unlikely* (3) *Not Sure* (4) *Somewhat Likely* (5) *Moderately Likely* (6) *Extremely Likely* (7)]

Betting a day's income at the horse races.
Investing 10% of your annual income in a moderate growth diversified fund.
Betting a day's income at a high-stakes poker game.
Investing 5% of your annual income in a very speculative stock.
Betting a day's income on the outcome of a sporting event.
Investing 10% of your annual income in a new business venture.

Recreational

For each of the following statements, please indicate the likelihood that you would engage in the described activity or behavior if you were to find yourself in that situation. Provide a rating from *Extremely Unlikely* to *Extremely Likely*, using the following scale: [*Extremely Unlikely* (1) *Moderately Unlikely* (2) *Somewhat Unlikely* (3) *Not Sure* (4) *Somewhat Likely* (5) *Moderately Likely* (6) *Extremely Likely* (7)]

Going camping in the wilderness.
Going down a ski run that is beyond your ability.
Going whitewater rafting at high water in the spring.

Table A1. Sample

Total sample	953
Gender	
Male	431
Female	522
Age	
18–24	53
25–34	157
35–44	141
45–54	154
55–64	221
65+	227
Education	
Less than university	504
Some university+	449
Party ID	
Democrat	331
Republican	252
Independent	370

Table A2. The differential impact of negative and positive information on generalization

	DV: net guesses
Win % correct	.459*** (.042)
Lose % correct	−.632*** (.044)
Constant	.105*** (.037)
Observations	953
R^2	0.306

Note. *p < .10; **p < .05; ***p < .01.

Table A3. Risk preferences and the weighting bias

	DV:			
	DOSPERT financial		DOSPERT recreational	
Weighting bias	0.321** (0.160)	0.420*** (0.150)	0.147 (0.192)	0.286 (0.175)
Male		0.468*** (0.075)		0.633*** (0.087)
Age (categorical)		−0.204*** (0.025)		−0.319*** (0.029)
University education		−0.182** (0.077)		0.026 (0.089)
Employment		0.152* (0.081)		0.141 (0.095)
Income		0.034*** (0.013)		0.024 (0.015)
Constant	1.595*** (0.039)	1.811*** (0.115)	1.634*** (0.046)	2.099*** (0.134)
Observations	953	953	953	953
R^2	0.004	0.134	0.001	0.179

Note. *p < .10; **p < .05; ***p < .01.

Taking a skydiving class.
Bungee jumping off a tall bridge.
Piloting a small plane.

As reported by Pietri et al. (2012), we use a "residual approach" to estimating individuals' *weighting bias*. We began with the model in Table A2 and estimated predicted values for all respondents. We then used the difference between the predicted value and the actual value for *net guesses* (i.e., the residual) as a measure of the extent to which an individual's guesses are more negative or positive then we might expect, given what they learned about winning and losing cars, relative to other participants.

Table A3 shows results from OLS models regressing the two DOSPERT indices on this measure. In each case, we show the bivariate and then a multivariate specification, where the latter controls for basic demographic variables.[7] Controlling for demographics makes a difference to the estimation of the coefficient for the *weighting bias*, which makes sense given the strong connections between demographics and risk preferences. Even so, the weighting bias is significantly related to risk, above and beyond demographic predictors (see also Footnote 1). Results in Table A3 confirm that those who are more positive than average on the weighting bias are more risk acceptant, while those who are more negative than average on the weighting bias are more risk averse. These results are similar to those found using the BeanFest game (Pietri et al. 2012).

We take results in Table A3 as evidence that our race car-based game captures a quantity that is similar to one captured in the lab using BeanFest. This is not to say that the two are identical, of course – we really cannot tell without running them on the same respondents. Even so, at a minimum, Tables A2 and A3 offer evidence of the concurrent validity of Hot Rod as a means of capturing biases in learning associated with attitudes toward risk.

[7] Roughly 150 respondents refused to answer the income question; rather than drop the respondents we replaced those missing values here with the sample mean (6 on a 16-point scale). Note that dropping the respondents with missing data increased somewhat the estimated effect of the weighting bias.

