

*Journal of Social and Clinical Psychology, in press*

**Predicting Changes in Depressive Symptoms from Valence Weighting during Attitude  
Generalization**

Evava S. Pietri

Indiana University-Purdue University Indianapolis

Michael W. Vasey, Matthew Grover, and Russell H. Fazio

Ohio State University

Please address correspondence to:

Evava S. Pietri

Indiana University-Purdue University Indianapolis

Department of Psychology, LD 124

402 N. Blackford Street

Indianapolis, IN 46202

email:epietri@iupui.edu

phone:317-274-6753

**Abstract**

Negative cognitive biases both characterize and predict depressive symptoms. In the current study, we explored the role of individual differences in valence weighting, people's tendency to weight resemblance to a known positive versus a known negative more strongly when generalizing from their existing attitudes to novel objects. To assess participants' valence weighting proclivities, we had participants play a game in which they interacted with novel objects that had the ability to either decrease or increase participants' points. Following the game participants classified as good or bad (i.e., would increase or decrease points) the objects they saw during the game, as well as new objects that varied in resemblance to both positive and negative game objects. Participants had to generalize their positive and negative attitudes to these new objects and weight the negative and positive characteristics (i.e., their resemblance to good and bad objects encountered during the game). Thus, we could assess participants' valence weighting tendencies by indexing their classification of these new objects. This measure of participants' weighting bias predicted changes in depressive symptoms across the academic term, and did so above and beyond a traditional self-report measure of negative and positive affect. Specifically, participants who strongly weighted negative information when generalizing their attitudes towards novel objects reported relatively more depressive symptoms at the end of the term.

## Introduction

Negative biases are pervasive in depression. For example, in comparison to non-depressed people, depressed individuals attend more to negative stimuli (e.g., sad faces; Hankin, Gibb, Abela, & Flory, 2010), disambiguate information in a negative fashion (Mogg, Bradbury, & Bradley, 2006), and remember better negative self-descriptive words and sad faces (Mathews & Macleod, 2005; Matt, Vazquez, & Campbell, 1992). Cognitive theories also posit that negativity biases are prevalent in the thinking patterns of individuals who are vulnerable to developing depression (Beck, 1967; Abramson, Alloy & Metalsky, 1989). For example, Beck's (1967) theory of depression asserts that depressed people possess negative schemas, or cognitive structures, that shape how they process information, interpret experiences, and predict the future. Abramson et al.'s (1989) hopelessness theory of depression also emphasizes the negative thinking patterns associated with depressive symptoms. Specifically, this theory asserts that when people who are at risk for depression experience a negative event, they believe it is a result of global stable causes, assume it will lead to extreme negative consequences, and attribute it to their unworthiness. Empirically testing these theories, researchers have found that these negative cognitive styles prospectively predict the onset of depression (Alloy, Abramson, Hogan, Whitehouse, Rose, & Robinson, 2000; Alloy, Abramson, Whitehouse, Hogan, Panzarella, & Rose, 2006). Given these cognitive models of depression, it also logically follows that the tendency to overgeneralize negative experiences would be detrimental for psychological wellbeing. Indeed, individuals' propensity to overgeneralize from a single failure to their total sense of self-worth also predicts the onset of depressive symptoms (Carver, 1998).

Thus, we hypothesize that individuals' tendencies to generalize negative attitudes more strongly than positive attitudes will also predict changes in depressive symptoms. Our prediction

was based on the notion that when individuals encounter a new object or situation, they must weight any good or bad characteristics associated with the object or situation to come to an evaluation of it. In effect, they must weight the extent to which the novel object bears resemblance to objects toward which they already have developed a positive attitude against the degree to which it resembles objects toward which they have a negative attitude. In line with this reasoning, past research has found that individuals who tend to generalize their negative attitudes more strongly than their positive attitudes are likely to weight resemblance to a known negative more heavily when evaluating a new situation (Fazio, Pietri, Rocklage, & Shook, 2015; Pietri et al., 2013a; Rocklage & Fazio, 2014). Specifically, the tendency to strongly generalize negative attitudes correlates with increased negative expectations regarding new objects and a variety of novel situations. Thus, the propensity to overweight and generalize negatives when forming an attitude may ultimately have implications for one's psychological wellbeing.

### **Attitude Generalization**

To examine valence weighting in attitude generalization's relationship to depressive symptoms, the current research utilized a paradigm that measures attitude formation and generalization, BeanFest (Fazio, Eiser, & Shook, 2004). In BeanFest, participants play a computer game in which they are presented with novel objects, or beans, which vary in shape (circular to oblong) and speckles (1 to 10) on a 10 by 10 matrix, and that either increase or decrease participants' points when selected. In a typical game of BeanFest, participants see subsets of the beans from the matrix and decide whether or not to select each bean in order to gain and avoid losing points. Following the game, participants complete a test phase in which they classify all the game beans as good or bad, as well as novel beans from the matrix, i.e., ones that were not shown during the game.

Thus, during the test phase, we can assess how individuals weight positive and negative information when generalizing the attitudes they developed toward the game beans to the new beans. There are some notable trends that occur during this attitude generalization process. First, attitudes formed during the game do generalize to the novel beans. Novel beans bearing greater resemblance to positive (negative) game beans are more likely to be considered positive (negative) (Fazio, et al. 2004). Second, people typically show a negative generalization asymmetry (Fazio et al., 2004; Shook, Fazio, & Eiser, 2007). That is, on average, individuals' negative attitudes generalize more strongly than their positive attitudes. Despite these general proclivities, there is substantial variability around these trends, and it is that variability that provides an estimate of individuals' *weighting bias*.

Because past attitudes do generalize, to avoid confounding the weighting bias with individuals' memory for the valence of the game beans, the weighting bias is indexed as the average response to the novel beans (+1 for positive, -1 for negative), while controlling for participants' learning of positive and negative game beans (see Pietri et al., 2013a). In other words, the regression residual, i.e., the extent to which individuals' assessment of novel beans deviates from what is to be expected on the basis of their pattern of learning, serves as the estimate of their valence weighting tendencies. Some individuals classify more of the novel beans as positive (or negative) than is to be expected on the basis of their learning of the positive and negative game beans, and hence, show a stronger weighting of positive (or negative) information. Although the regression residual undoubtedly involves some random error, it also includes a systematic component that reflects individuals' valence weighting. The evidence attesting to this meaningful variability is summarized in the next section.

**Correlates of the weighting bias.** This valence weighting in attitude generalization predicts a variety of judgments. In comparison to individuals with a neutral or positive bias, individuals who weighted negatives stronger also reached more negative judgments about (a) hypothetical scenarios related to the possibility of interpersonal rejection (b) ambiguously threatening situations, (c) entering new situations, (d) approach/avoidance behavior, and (e) pursuing riskier options (Pietri et al., 2013a; Rocklage & Fazio, 2014). They also reported greater emotional reactivity in response to a novel stressor in the laboratory (Pietri et al., 2012). Relative to those with a positive or neutral weighting bias, participants with a negative weighting bias were in a worse mood after failing at what was, unbeknownst to them, an impossible anagram task. Interestingly, the weighting bias was specifically predictive of reactions to new situations that individuals were unlikely to have experienced in the past (Pietri et al., 2013a). It is when evaluating a new situation that individuals must weight the positives and negatives associated with it. Thus, judging a new bean in the context of BeanFest and a new object, event, or situation in the real world (e.g., one's courses when starting a new academic term) involve a similar attitude generalization process and, hence, reflect individuals' chronic valence weighting proclivities.

### **Current Research**

Individuals who have adverse reactions to stressors are at increased risk for depression (Parrish, Cohen, & Laurenceau, 2011) and adjusting to the demands of a new academic term in college can create new stressful situations. For example, students are taking new classes, which can pose a new challenge, and they must ultimately form attitudes and evaluations of these new courses. Individuals might remember similar classes that were difficult or led to a failure experience and ultimately generalize that negative occurrence to their new classes. Thus, certain

people may be particularly vulnerable to developing depressive symptoms in college over the course of an academic term (Voelker, 2004). In particular, individuals who overweight and overgeneralize negatives during a new academic term should be relatively more susceptible to developing such symptoms because they may be more inclined to generalize any negative experiences to the new classes and feel more stress as a result.

The current study explored whether a valence weighting bias in attitude generalization prospectively predicted depressive symptoms. We also examined if the weighting bias did so over and above the impact of a more traditional trait correlate of depressive symptoms. Specifically, researchers have found that trait negative and positive affectivity predicts increases in depressive symptoms even when controlling for baseline symptoms (Merz, & Roesch, 2011; Watson, Clark, & Tellegen, 1988). Our goal was to demonstrate that the performance-based measure of valence weighting tendencies is an important process-oriented variable that contributes uniquely to the prediction of depressive symptoms.

## **Method**

### **Participant**

One-hundred and forty-three Ohio State University students began this study for psychology course credit, and 123 (62% female) participants completed all the relevant measures, and were included in our analyses. In addition to receiving course credit, participants were also paid \$1 every time they reached 100 or points or won during the BeanFest game phase, and were penalized \$0.50 when they hit 0 or lost during the game (maximum won=\$6). These contingencies were intended to motivate participants during the game.<sup>1</sup>

### **Procedure**

Participants were taking part in a larger study on the risk factors associated with depression. Prior to coming to the laboratory, all participants completed a measure of trait NA and PA. High level of NA and low levels of PA are associated with elevated risk for depressive symptoms (Clark, Watson, & Mineka, 1994; Klein, Kotov, & Bufferd, 2011). Specifically, participants completed the trait version of the Positive and Negative Affect Schedule (T-PANAS; Watson, Clark, & Tellegen, 1988). On this scale participants rated how much they generally felt ten negative (e.g. Distressed, Upset) and positive (e.g. Interested, Excited) emotions on a 5-point scale from 1 (very slightly) to 5 (very much). We summed across participants' ratings for the positive and negative emotions to create trait NA ( $\alpha = .87$ ) and positive affect (PA;  $\alpha = .91$ ) scores.

Before coming to the lab, participants also completed a measure of effortful control (EC). EC is the dispositional ability to override reactivity tendencies in favor of more adaptive responses (Rothbart & Bates, 1998), and thus, low level of EC are associated with depressive symptoms (see Carver, Johnson, & Joormann, 2008). Specifically, participants completed the Persistence and Low Distraction subscale of the Effortful Control Scale (ECS-PLD; Lonigan, 1998). The ECS-PLD consists of 12 statements that are rated on a 5-point scale assessing how often each statement (e.g., "Even little things distract" [R] and "Once I'm involved in a task, nothing can distract me from it") describes the person from "not at all" to "very much" ( $\alpha = .85$ ).

Individuals who are high in NA, low in PA and low in EC are particularly at risk for increased depressive symptoms over time (see Vasey et al., 2014). Therefore, to increase the likelihood that the sample would include participants who were at elevated risk for depressive symptoms, potential participants were screened using the ECS-PLD and T-PANAS NA and PA scales and recruited based on their scores. Specifically, all individuals in the prescreening pool



who scored above the median or in the lower quartile on NA (were low or high on NA) and in the upper or lower quartiles on ECS-PLD (were low or high in EC) and PA (were low or high in PA) were invited to participate along with a random subset of ten percent of the remainder of the sample. In this manner we sought to recruit a sample that varied widely in risk for depressive symptoms. Although many of those invited based on this screening procedure did not choose to participate, examination of the final sample suggested it nevertheless contained more individuals at the extremes of NA, PA, and EC than is typical in a college sample.

For the larger study, participants came to the laboratory at three time points: near the beginning, middle, and end of the quarter. When the final time point was collected, final exams were imminent, which was a stressful time for our undergraduate participants. The variables of interest for the current study were collected during the first (Time 1 [T1]) and last session (Time 2 [T2]), and the average interval between these time points was approximately seven weeks ( $M=40.2$  days,  $SD=3.1$  days). At the beginning of their first session, participants completed the BeanFest paradigm. The procedure for BeanFest was the same as that in Experiment 4 of Fazio et al. (2004) and Shook et al. (2007). During a trial, participants saw a bean in the upper part of the monitor, and indicated whether or not they wished to select it. If participants selected the bean, their points changed according to the value of the bean (+10 or -10). If participants did not select the bean, their current point value did not change, but they learned the value of the bean, i.e., they were informed of the effect the bean would have had if it had been selected.

Participants interacted with a total of 36 beans during the game, which were selected from the 10 by 10 matrix varying from the circular to oblong and from one to ten speckles (see Figure 1). Specifically, these beans were taken from six regions in the matrix consisting of five to seven beans. Each of these regions had an associated -10 or 10 value (we counterbalanced

which regions we assigned a 10 or -10 value). These regions were carefully selected to ensure that there were no linear relationships between the shape of a bean or the number of speckles and the valence of the bean. Thus, participants could not learn a simple linear rule to recall the valence of the bean.

Participants' points could range from 0 to 100, and participants started the game with 50 points. If participants reached 0 points, they lost the game, and if they reached 100, they won the game. Any time participants won or lost, the game would restart with 50 points. All participants were shown three blocks of 36 beans no matter how many times they won or lost, after which, the game ended.

Following the game, participants completed the test phase. They were shown each of the 100 beans from the matrix in two blocks of 50 randomized trials, and indicated whether they believed a given bean to be good or bad, that is, would have increased or decreased their points. Thus, participants saw the 36 game beans and 64 novel beans varying in resemblance to the game beans.

After BeanFest, to establish participants' baseline depressive symptom scores, participants completed the Depression Anxiety Stress Scales (DASS; Lovibond & Lovibond, 1995). This scale consists of depression, anxiety and stress subscales. Because we were specifically interested in changes in depressive symptoms, we focused our analysis on the depression (DASS-D) subscale. However, we also collected the data from the two other subscales for exploratory purposes (see Footnote 2). For the DASS-D subscale, participants rated how much 14 statements (e.g., "I felt sad and depressed," and "I could see nothing in the future to be hopeful about") applied to them on a 0 ("Did not apply to me at all") to 3 ("Applied to me very much, or most of the time") scale. The DASS-D score reflects the sum of these 14 items

( $M=5.90$ ,  $SD=7.32$ ,  $\alpha=.94$ ). Finally, participants completed the trait version of PANAS, yielding PA ( $M=32.79$   $SD=7.06$ ) and NA ( $M=20.84$   $SD=6.40$ ) scores.

At T2, participants again completed the DASS. Thus, we could examine the DASS-D subscale ( $M=5.66$ ,  $SD=6.91$ ,  $\alpha=.90$ ) and prospectively predict participants' depressive symptoms at the end of the quarter.

## Results

We first examined participants' learning of the game beans by calculating the phi coefficient between the valence of the bean (10 or -10) and participants' classification of the bean during the test phase (1 for positive or -1 for negative). The average phi coefficient was significantly better than chance ( $M=.24$ ,  $SD=.25$ ;  $t(122)=10.68$ ,  $p<.001$ ), indicating that participants, on average learned, and were actively engaging in the BeanFest game.

We next indexed the weighting bias using the method put forth by Pietri et al., (2013a). We first calculated the average response to the 64 novel beans (1 for positive response and -1 for negative). As in past research, participants on average were more likely to classify novel beans as negative than as positive ( $M=-.07$ ,  $SD=.21$ ,  $t(122)=3.54$ ,  $p<.001$ ). Importantly, we were interested in how participants classified the novel beans over and above how well they learned positive and negative game beans. In this sample, we utilized a regression equation predicting average response to novel beans from proportion of positive and negative correct, and used the unstandardized residuals as an estimate of the weighting bias (see, e.g., Darlington, 1990; Kerlinger & Pedhazur, 1973; for discussion of the use of residuals as indices, as well as illustrative research examples). The residual indexes the extent to which participants weight positive and negative information when classifying a novel bean beyond what we would expect from their learning of positive and negative game beans (i.e., essentially controlling for the

proportion of positive and negative game beans classified correctly). As noted earlier, a considerable amount of past research has established the value of estimating valence weighting via this regression residual; the resulting index predicts a variety of evaluations that involve integrating positive and negative information (Fazio et al., 2015; Pietri, Fazio, & Shook, 2012; 2013a). Higher scores indicate a more positive weighting bias.

### **Weighting Bias Predicting Depressive Symptoms**

We next examined if participants' weighting bias scores predicted depressive symptoms later in the quarter. The DASS-D scores at T1 and T2 did not have a normal distribution. Both distributions were positively skewed and had skewness scores of 1.73 and 1.76 respectively. These distributions suggested that, as is typical, our college sample tended to have relatively low depression scores. So we added 1 to participants' DASS depression scores at T1 and T2 (to ensure no score was 0), and took the natural log of these scores. These transformations resulted in a skewness score of .05 for both DASS scores and T1 and T2.

We conducted a hierarchical regression analysis predicting participants' depressive symptoms at T2 from their depressive symptoms at T1 and their weighting bias. In the first step, initial DASS-D scores were a significant predictor of depressive symptoms at time 2 ( $R^2$ -Change=.50,  $F(1,121)=123.11$ ,  $p<.001$ ;  $\beta=.70$ ,  $t(120)=11.10$ ,  $p<.001$ ). In the next step we added the weighting bias and found that it too was a significant predictor of T2 depressive symptoms ( $R^2$ -Change=.03,  $F(1,120)=6.37$ ,  $p<.02$ ;  $\beta=-.16$ ,  $t(120)=-2.53$ ,  $p<.02$ ). Thus, participants who gave less weight to negative information when generalizing their attitudes had lower depression scores later in the quarter.<sup>3</sup>

**Trait Positive and Negative Affect.** We were next interested if the weighting bias would predict depressive symptoms above and beyond participants' general positive and negative

affectivity. We again ran a hierarchical regression equation, which had T1 DASS-D scores in the first step. In the second step we added Trait PA and NA ( $R^2$ -Change=.03,  $F(1,119)=3.18$ ,  $p<.05$ ). Trait NA significantly predicted depression at time 2 ( $\beta=.16$ ,  $t(119)=2.23$ ,  $p<.03$ ), but trait PA was not a significant predictor even though the effect was in the expected direction ( $\beta=-.11$ ,  $t(119)=-1.39$ ,  $p=.17$ ). Adding the weighting bias to the model significantly increased  $R^2$  ( $R^2$  change=.02,  $F(118)=5.05$ ,  $p<.03$ ); a more negative weighting bias significantly predicted increases in depression ( $\beta=-.14$ ,  $t(118)=-2.25$ ,  $p<.03$ ).

### Discussion

In the current study, participants who weight negative information relatively less when generalizing their attitudes had lower depressive symptoms later in the academic term, controlling for baseline symptoms. It is likely that these individuals were also less likely to generalize from past negative experiences (e.g., failure experiences in past classes) when evaluating new and potentially stressful situations such as new classes during the academic term. This valence weighting in attitude generalization was also predictive above and beyond a more traditional self-report of trait NA and trait PA. Trait NA also predicted an increase in T2 depressive symptoms, and trait PA related to a decrease in depressive symptoms, but that relationship was not significant. Thus, valence weighting in attitude generalization appears to be an important cognitive bias related to the development or reduction of depressive symptoms in a new situation or term.

Past research examining the weighting bias in attitude generalization found that valence weighting related to a variety of judgments and behaviors including sensitivity to the possibility of rejection, fear of new situations, approach/avoidance behavior regarding unknown stimuli, risky tendencies, and reactivity to a stressor in the laboratory (Fazio, et al., 2015; Pietri, Fazio, &

Shook, 2012, 2013a; Rocklage & Fazio, 2014). These past findings suggest that the weighting bias may be an important predictor of psychological wellbeing especially when individuals must generalize from past positive and negative experiences and evaluate new and potential stressful situations, such as new classes during a new academic term. However, there was no research testing this possibility or exploring the positive mental health implications of giving less weight to negative information. Thus, the current findings add to the existing research on valence weighting by demonstrating that the tendency to weight negative valence less is beneficial for wellbeing because it decreases the risk of developing depressive symptoms. This finding further suggests that the propensity to weight positive versus negative information is a fundamental individual difference that has important consequences outside of the laboratory.

All participants were potentially facing a stressful period of adjusting to new demands in which they are forming new attitudes with the beginning of the academic term. Our assumption was that participants with a relatively less negative weighting bias were reacting more adaptively by forming less negative attitudes towards new challenges, resulting in lower depressive symptoms. However, in the current study we did not assess participants' reactions to or number of stressors (i.e., challenging new classes). Thus, although it seems likely that participants who experience many new stressors and are more likely to weight and generalize similar past negative experiences should be most at risk for increased depressive symptoms, we could not examine this possibility in the current study. Future research should explore this empirical question.

Beyond adding to our knowledge regarding the importance of valence weighting tendencies, the current findings also contribute to the understanding of cognitive vulnerabilities to depression. Past research in the depression literature has identified a number of negative cognitive biases that relate to depressive symptoms. For example, biases in favor of negative

information with regard to attention (Hankin, Gibb, Abela, & Flory, 2010), interpretation (Mogg, Bradbury, & Bradley, 2006), and memory (Mathews & Macleod, 2005; Matt, Vazquez, & Campbell, 1992) all correlate with depressive symptoms. Furthermore, cognitive theories of depression assert that people's tendency to generalize from negative life experiences is an important predisposition to developing depression (Beck, 1987; Abramson, Alloy & Metalsky, 1989). For example, people who attribute a negative instance (e.g., doing poorly on a test) to something stable in their personality and generalize this one bad occurrence to their total sense of self-worth are especially vulnerable to depression (Alloy, Abramson, Hogan, Whitehouse, Rose, & Robinson, 2000; Alloy, Abramson, Whitehouse, Hogan, Panzarella, & Rose, 2006; Carver, 1998). The current research suggests that overgeneralizing negatives need not only relate to personally relevant life experiences. Rather, the overweighting of negative information when generalizing attitudes to new objects also predicts depressive symptoms.

A benefit of using performance-based measures and paradigms such as BeanFest, is that these paradigms can be adapted to modify cognitive biases (see Hertel & Mathews, 2011 for review). Recently, experiments have successfully manipulated the weighting bias by providing BeanFest participants with trial-by-trial feedback as to whether they were appropriately weighting the extent to which a novel bean resembled a positive game bean versus a negative game bean (Pietri, Fazio, & Shook, 2013b). Individuals who began with a negative bias were recalibrated to give more weight to positive information when generalizing their attitudes towards the beans. This recalibration resulted in more positive attitude generalization towards other novel objects, more positive interpretations of ambiguous information, and less risk aversion. Thus, future research might attempt to recalibrate individuals with negative weighting biases at the beginning of a new academic term. Furthermore, this intervention may be

particularly useful for reducing the vulnerability to depressive symptoms that characterizes individuals high in trait NA or other traits that predispose individuals to developing these symptoms. However, we do acknowledge that this study examined changes in depressive symptoms among college students and did not consider individuals who were diagnosed with depression. Nevertheless, the recalibration paradigm may function as an intervention to train vulnerable individuals to give more weight to positives and, hence, eventually reduce the likelihood of experiencing depressive symptoms. Furthermore, this training would help establish that a valence weighting bias exerts a causal influence on depression. Such possibilities should be explored in future research.

The findings of the current study represent a promising and important first step towards understanding the role of valence weighting in depression. This study indicates that individuals who weight negative information less during attitude generalization are more likely to subsequently experience less depressive symptoms after entering a new situation. Thus, this basic process of weighting positive versus negative valence has important downstream consequences for wellbeing. Having established that this process relates to depressive symptoms, future research can now productively examine if training people to give less weight to negative valence decreases their vulnerability to developing depressive symptoms later in time.



**Work Cited**

- Abramson, L.Y., Metalsky, G.I., & Alloy, L.B. (1989). Hopelessness depression: A theory-based subtype of depression. *Psychological Review*, *96*, 358-372.
- Alloy, L.B., Abramson, L.Y., Hogan, M.E., Whitehouse, W.G., Rose, D.T., Robinson, M.S., Kim, R.S., & Lapkin, J.B.(2000). The Temple-Wisconsin cognitive vulnerability to depression project: Lifetime history of Axis I psychopathology in individuals at high and low cognitive risk for depression. *Journal of Abnormal Psychology*, *109*, 403-418.
- Alloy, L.B, Abramson, L.Y., Whitehouse, W.G., Hogan, M.E., Panzarella, C, & Rose, D., T. (2006). Prospective incidence of first onsets and recurrences of depression in individuals at high and low cognitive risk for depression. *Journal of Abnormal Psychology*, *115*, 145-156.
- Beck, A.T. (1987). Cognitive models of depression. *Journal of Cognitive Psychotherapy*. *1*, 5-37.
- Beck, A. T. (1967). *Depression: Clinical, experimental, and theoretical aspects* (Vol. 32). University of Pennsylvania Press.
- Carver, C. S. (1998). Generalization, adverse events, and development of depressive symptoms. *Journal of Personality*, *66*, 607-619.
- Carver, C. S., Johnson, S. L., & Joorman, J. (2008). Serotonergic function, two-mode models of self-regulation, and vulnerability to depression: What depression has in common with impulsive aggression. *Psychological Bulletin*, *134*, 921–943.
- Clark, L. A., Watson, D., & Mineka, S. (1994). Temperament, personality, and the mood and anxiety disorders. *Journal of Abnormal Psychology*, *103*, 103–116.
- Darlington, R. B. (1990). *Regression and Linear Models*. New York: McGraw-Hill.

- Fazio, R. H., Eiser, J. R., & Shook, N. J. (2004). Attitude formation through exploration: Valence asymmetries. *Journal of Personality and Social Psychology*, *87*, 293.
- Fazio, R. H., Pietri, E. S., Rocklage, M.R. & Shook, N. J. (2015). Positive versus negative valence: Asymmetries in attitude formation and generalization as fundamental individual differences. In J. M. Olson & M. P. Zanna (Eds.), *Advances in Experimental Social Psychology* (Vol. 51, pp. 97-146). Burlington: Academic Press..
- Hankin, B. L., Gibb, B. E., Abela, J. R., & Flory, K. (2010). Selective attention to affective stimuli and clinical depression among youths: role of anxiety and specificity of emotion. *Journal of Abnormal Psychology*, *119*, 491.
- Hertel, P. T., & Mathews, A. (2011). Cognitive Bias Modification Past Perspectives, Current Findings, and Future Applications. *Perspectives on Psychological Science*, *6*, 521-536.
- Kerlinger, F.N. & Pedhazur, E.J. (1973). Multiple regression in behavioral research. New York: Holt, Rinehart, and Winston.
- Klein, D., Kotov, R., & Bufferd, S. (2011). Personality and depression: Explanatory models and review of the evidence. *Annual Review of Clinical Psychology*, *7*, 269–295.
- Lonigan, C. J. (1998). Development of a measure of effortful control in school-age children. Unpublished rawdata. Florida State University.
- Lovibond, S. H., & Lovibond, P. F. (1995). *Manual for the depression anxiety stress scales*. Sydney: Psychology Foundation.
- Mathews, A., & MacLeod, C. (2005). Cognitive vulnerability to emotional disorders. *Annual Review of Clinical Psychology*, *1*, 167-195.
- Matt, G. E., Vázquez, C., & Campbell, W. K. (1992). Mood-congruent recall of affectively toned stimuli: A meta-analytic review. *Clinical Psychology Review*, *12*, 227-255.

- Merz, E. L., & Roesch, S. C. (2011). Modeling trait and state variation using multilevel factor analysis with PANAS daily diary data. *Journal of Research in Personality, 45*, 2-9.
- Mogg, K., Bradbury, K. E., & Bradley, B. P. (2006). Interpretation of ambiguous information in clinical depression. *Behaviour Research and Therapy, 44*, 1411-1419.
- Pietri, E. S., Fazio, R. H., & Shook, N. J. (2012). Valence weighting as a predictor of emotional reactivity to a stressful situation. *Journal of Social and Clinical Psychology, 31*, 746-777.
- Pietri, E. S., Fazio, R. H., & Shook, N. J. (2013a). Weighting positive versus negative: The fundamental nature of valence asymmetry. *Journal of Personality, 81*, 196-208.
- Pietri, E. S., Fazio, R. H., & Shook, N. J. (2013b). Recalibrating positive and negative weighting tendencies in attitude generalization. *Journal of Experimental Social Psychology, 49*, 1100-1113.
- O'Neill, S. C., Cohen, L. H., Tolpin, L. H., & Gunthert, K. C. (2004). Affective reactivity to daily interpersonal stressors as a prospective predictor of depressive symptoms. *Journal of Social and Clinical Psychology, 23*, 172-194.
- Rothbart, M. K., & Bates, J. E. (1998). Temperament. In W. Damon, & N. Eisenberg (Eds.), *Handbook of child psychology: Vol. 3. Social, emotional, and personality development* (pp. 105–176, 5th ed.). New York: Wiley.
- Shook, N. J., Fazio, R. H., & Richard Eiser, J. (2007). Attitude generalization: Similarity, valence, and extremity. *Journal of Experimental Social Psychology, 43*, 641-647.
- Vasey, M. W., Harbaugh, C. N., Fisher, L. J., Heath, J. H., Hayes, A. F., & Bijttebier, P. (2014). Temperament synergies in risk for depressive symptoms: A prospective replication of a three-way interaction. *Journal of Research in Personality, 53*, 134-147.

Voelker, R. (2004). Stress, sleep loss, and substance abuse create potent recipe for college depression. *JAMA: The Journal of the American Medical Association*, *291*, 2177-2179.

Watson, D., Clark, L. A., & Tellegen, A. (1988). Development and validation of brief measures of positive and negative affect: the PANAS scales. *Journal of Personality and Social Psychology*, *54*, 1063-1070.

Table 1

*Regression results predicting T2 DASS depression scores*

	R <sup>2</sup> -Change	F	$\beta$	t
<u>Step 1</u>	.50	123.11 <sup>***</sup>		
T1 DASS depression			.71	11.10 <sup>***</sup>
<u>Step 2</u>	.03	3.18 <sup>*</sup>		
NA			.16	2.23 <sup>*</sup>
PA			-.11	-1.39
<u>Step 3</u>	.02	5.05 <sup>*</sup>		
Weighting bias			-.14	-2.25 <sup>*</sup>

*Note.* \*\*\* $p < .001$ , \*\* $p < .01$ , \* $p < .05$

	Y1	Y2	Y3	Y4	Y5	Y6	Y7	Y8	Y9	Y10
X1	10	10	10			-10	-10	-10		
X2	10	10			-10	-10	-10			
X3						-10				
X4									10	
X5		-10						10	10	10
X6	-10	-10	-10						10	10
X7	-10	-10								
X8					10					
X9				10	10	10			-10	-10
X10			10	10	10			-10	-10	-10

*Figure 1.* The Bean Matrix with X= shape from oval (1) to oblong (10). Y= number of speckles from 1 to 10. The cells with a point value present the beans presented during the game.

### Footnotes

<sup>1</sup>We ran a MCAR test to examine if our missing data from Time 2 was missing completely at random on our variables of interest (i.e., Gender, Effort Control Scale, Negative Affect, Positive Affect, DASS-D T1 and the valence weighting bias index), and found that it was (Chi-square = 12.88,  $df = 15$ ,  $p = .611$ ). We also ran t-tests comparing subjects with and without T2 data and found that the two groups did not differ significantly on any of the variables used in the study (all  $ps > .187$ ). Furthermore, we ran the main analysis (the weighting bias predicting depressive symptoms, control for initial depressive symptoms) using multiple imputation (20 data sets) and found that the weighting significantly predicted T2 depressive symptoms in all 20 cases, and the pooled  $p$ -value for that test was  $p = .013$ .

<sup>2</sup>Because participants also had completed the stress and anxiety subscales of the DASS at time 1 and time 2, we did similar analyses with these two components. As with the depression scores, we natural log transformed the stress and anxiety scores to create a normal distribution. We found that DASS stress scores at time 1 ( $R^2$ -change=.62;  $\beta$ =.77,  $t(120)=13.70$ ,  $p < .001$ ) significantly predicted, and the weighting bias ( $R^2$ -change=.01;  $\beta$ =-.10,  $t(120)=-1.80$ ,  $p < .08$ ) marginally predicted, DASS stress scores at time 2. The DASS anxiety scores at time 1 ( $R^2$ -change=.64;  $\beta$ =.77,  $t(120)=13.70$ ,  $p < .001$ ) significantly predicted, and the weighting bias ( $R^2$ -change=.01;  $\beta$ =-.11,  $t(120)=-1.50$ ,  $p = .14$ ) showed a weak directional relation with, DASS anxiety scores at time 2. This analysis provides some suggestive evidence that having a negative weighting bias may lead to higher stress and anxiety scores during a new academic term. However, the clearest relationship emerged between the weighting bias and depression scores.

<sup>3</sup>We ran subsequent regression equations to ensure that other potentially important variables were not influencing our results. Specifically, we examined the effect of gender, the academic

term in which they completed the study (Autumn vs. Winter), number of years in college, and age on T2 depressive symptoms controlling for T1 depressive symptoms. We found no effect of gender (1 being female, 0 being male) ( $\beta=.07$ ,  $t(118)=1.09$ ,  $p=.28$ ), the weighting bias was still a significant predictor ( $\beta=-.14$ ,  $t(118)=-2.36$ ,  $p<.03$ ) while controlling for gender, and the interaction between the weighting bias and gender was not significant ( $\beta=-.14$ ,  $t(119)=-.03$ ,  $p=.98$ ). We next examined the term in which participants provided data for the study (0 for Autumn and 1 for Winter Quarter), and found no effect of quarter ( $\beta=-.10$ ,  $t(118)=-.82$ ,  $p=.41$ ), the weighting bias was still significant while controlling for quarter ( $\beta=-.16$ ,  $t(118)=-2.45$ ,  $p<.02$ ), and the interaction between the weighting bias and quarter was not significant ( $\beta=.06$ ,  $t(118)=.46$ ,  $p=.45$ ). We also examined the influence of a participant's year in college and found no effect for year ( $\beta=.08$ ,  $t(118)=1.29$ ,  $p=.20$ ), the weighting bias was still significant while controlling for year ( $\beta=-.17$ ,  $t(118)=-2.63$ ,  $p=.01$ ), and the interaction between the weighting bias and year was not significant ( $\beta=.01$ ,  $t(118)=.11$ ,  $p=.92$ ). Finally, age did not significantly predict T2 depressive symptoms ( $\beta=.05$ ,  $t(118)=.75$ ,  $p=.41$ ), the valence weighting bias remained significant while controlling for age ( $\beta=-.15$ ,  $t(118)=-2.44$ ,  $p<.02$ ), and the interaction between the weighting bias and age was not significant ( $\beta=-.07$ ,  $t(118)=-.81$ ,  $p=.42$ ). Thus, we did not include gender, academic term, or age in the model.