

Depression Induced Quantity Estimation Bias Manifests Only Under Time Constraints

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Journal of Numerical Cognition, 2022, Vol. 8(1), 183–201, <https://doi.org/10.5964/jnc.6515>

Received: 2021-04-08 • Accepted: 2021-12-11 • Published (VoR): 2022-03-31

Handling Editor: Geetha Ramani, University of Maryland, College Park, MD, USA

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Abstract

Here, we assess whether quantity representations are influenced by the perceptual biases hypothesized to manifest in depressive individuals. In contrast to this clinical model, several prominent models of numerical cognition assume that quantity representations are abstract, and therefore are independent of the items that are being quantified. If this is the case, then the depression induced perceptual biases should not manifest with respect to the perception of quantity. We tested these predictions in two experiments in which we presented participants with a number-line with a tick mark that indicated the time until a positive, neutral, or negative event. The participant's task was to estimate the quantity of time indicated by the tick mark. In both experiments, we assessed participants' BDI-II score. To assess the role of controlled, strategic processing on the manifestation of these biases, we manipulated the amount of time that participants were able to study the number-line prior to responding. In Experiment 1, we attempted to motivate participants to respond quickly voluntarily. The results revealed no influence of time pressure on participants' RTs, nor any relation between quantity bias and depression. In Experiment 2, we restricted the amount of time participants could spend viewing the number-line. The results revealed estimation biases consistent with the perceptual biases predicted by Beck's cognitive theory of depression for the short presentation times. These findings (1) confirm that level of depression is linked to the predicted perceptual biases of quantity and (2) implicate controlled processing in the masking of perceptual bias.

Keywords

perceptual bias, depression, controlled processing, unbounded number line

Although five apples, five clouds, and the Arabic digit “5” written on a mathematics exam exist in the physical world, the concept of “fiveness” has no concrete existence. The psychological understanding of this concept is termed a *quantity representation*. There is a debate concerning whether there exists a single quantity representation that is independent of the symbols or items that link to it (e.g., apples, clouds, digits, etc.), or whether there exist multiple quantity representations, each potentially influenced by those symbols or items. This debate has wide ranging implications. For example, if a single, independent quantity representation exists, then one's psychological understanding of quantity should be immune to some of the perceptual biases hypothesized to be associated with mental illness. In two experiments, we test this prediction by assessing whether and how one's psychological understanding of quantity is influenced by level of depression and affective valence of the quantity being measured.

If only a single quantity representation exists that is independent of the symbol or items that it represents, this quantity representation is said to be *abstract*. If quantity is represented by a single, abstract representation, then one's notion of a given quantity (e.g., five) will not be influenced by the items the quantity is modifying (e.g., clouds vs



apples vs guns, etc.), the format of the numerical symbol (e.g., the English written word “five,” the Arabic digit “5,” the spoken word “fiv,” the Spanish written word “cinco,” etc.), or any other feature. An abstract representation that changes as a function of any feature of that which it is modifying, would be theoretically indistinguishable from multiple non-abstract representations. As such, this independence is a defining feature of an abstract representation. Examples of models of numerical cognition that assume an abstract quantity representation include McCloskey’s single representation model (McCloskey, Caramazza, & Basili, 1985; McCloskey & Macaruso, 1995; McCloskey, Sokol, & Goodman, 1986) and Dehaene’s Triple Code model (Dehaene, 1992). Support for abstract quantity representation theories has been demonstrated for parity judgments (Dehaene, Bossini, & Giraux, 1993), number reading, writing, and arithmetic in brain-damaged patients (McCloskey et al., 1986; McCloskey et al., 1985), and for numerical processing in neurologically healthy adults (Dehaene, 1992).

Models of numerical cognition that do not assume a single, abstract quantity representation are termed non-abstract quantity representation models (Campbell, 1994; Cohen, 2009; Cohen, Ferrell, & Johnson, 2002; Cohen Kadosh & Walsh, 2009; González & Kolers, 1982). Non-abstract quantity representations are not independent of the symbol or items that they represent. One such model is the Multiple Quantity Representation Model (e.g., Warren & Cohen, 2013; Cohen et al., 2002; Cohen, 2009; Cohen, Warren, & Blanc-Goldhammer, 2013). The Multiple Quantity Representation Model posits quantity representations vary, for example, as a function of number format. Support for non-abstract quantity representation theories has been demonstrated for a variety of number formats, such as roman numerals, Arabic digits, written/spoken number words, relative frequencies/decimals, and odds (e.g., Cohen et al., 2002; Cohen, 2009; Cohen et al., 2013; González & Kolers, 1982; Warren & Cohen, 2013).

Whether quantity is represented abstractly or not has implications beyond the field of numerical cognition. For example, some theories of mental illness propose that an individual’s state of mind will influence how they perceive the environment (e.g., Williams, Mathews, & MacLeod, 1996). These perceptual biases are hypothesized to both influence behavior and (perhaps) contribute to the maintenance of mental illness. Critically, if quantity representations are abstract, then perceptions of quantity should be immune to some of these perceptual biases. If, however, quantity representations are non-abstract, then perceptions of quantity should exhibit the same biases as other perceptions.

Hamamouche, Niemi, and Cordes (2017) demonstrate evidence of emotional stimuli influencing numerosity estimation. The authors asked participants to judge the quantity of items in displays containing icons of threatening stimuli (e.g., spiders) and non-threatening stimuli (e.g., flowers). The data revealed a decrease in accuracy when estimating the threatening stimuli. However, participants were more accurate at discriminating quantities when a threatening stimulus (e.g., a spider) was presented first, followed by a discrimination task using a neutral quantity stimulus (i.e., dots). Other researchers found similar results (Baker, Rodzon, & Jordan, 2013; Infante & Trick, 2020; Young & Cordes, 2013).

Although researchers provide evidence of the influence of emotional stimuli on quantity estimation, the observed biases may not necessarily implicate the quantity representation as the source of these biases. Because participants were asked to estimate the quantity of non-symbolic stimuli, that estimation is dependent on the accurate encoding of multiple stimuli dispersed across the display. Importantly, encoding such stimuli requires attentional resources and strategies. As such, the emotional/threat manipulations may have influenced these attentional or other encoding strategies, rather than the quantity representations per se (e.g., Carretié, Hinojosa, Martín-Loeches, Mercado, & Tapia, 2004). One can, however, minimize the influence of attentional processes on numerical processing by using symbolic (e.g., “5”), rather than non-symbolic (e.g., five dots), to indicate quantity.

Rather than focus on the emotional content of the stimuli, per se, here we examine the interaction between the perceiver’s state of mind and the content of the stimuli. Beck’s (1970) cognitive theory of depression asserts that depressed individuals exhibit systematic biases that are supported by negative schematic content (Beck, 1970). Consistent with Beck’s theory, researchers have found that depressed individuals differ from non-depressives in the ways that they think about and anticipate future events (Dunning & Story, 1991; MacLeod & Byrne, 1996; MacLeod & Croypley, 1995; Moore, 2007; Pyszczynski, Holt, & Greenberg, 1987). For example, Pyszczynski and colleagues (1987) presented depressed and non-depressed participants with 20 hypothetical positive and negative event statements. Each participant made judgments regarding the likelihood that each event would happen to themselves or others (Pyszczynski et al., 1987). Depressed individuals consistently rated negative events as more likely to happen to themselves, whereas non-depressed individuals rated positive future events as more likely to happen to themselves. Dunning and Story (1991) expanded

on these findings by surveying students at both the beginning and end of a semester. The initial survey revealed that depressed students reported significantly higher confidence levels, predicted higher likelihood of the occurrence of unlikely events, and were significantly more pessimistic than non-depressed students. Results from the second survey indicated that depressed students reported experiencing fewer positive events and more negative events than they originally anticipated. Together these findings support Beck's predictions.

Recently, Cohen, Barker, and White (2019) assessed whether the perceptual biases associated with depression influenced the perception of quantity. Here, Beck's cognitive theory of depression predicts that depressed individuals will perceive the same quantity (e.g., 5) differently if it is paired with a positive future event (e.g., winning the lottery) than if it is paired with a negative future event (e.g., losing a friendship). Importantly, if quantity representation is abstract then these biases should not manifest.

Cohen and colleagues (2019) tested whether quantity representations are susceptible to the perceptual biases associated with depression using a symbolic number bisection task. In a symbolic number bisection task, participants are traditionally presented two quantities (as numerals) and are instructed to estimate the midpoint of the interval without performing calculations. The direction and degree of estimation error provides some evidence for the form of the participants' quantity representations (e.g., Loftus, Nicholls, Mattingley, Chapman, & Bradshaw, 2009; Longo & Lourenco, 2007). That is, quantity representations are often thought to exist along what is sometimes referred to as a mental number line, a continuum where numbers are spatially located according to magnitude, with smaller numbers located on the left and larger numbers located on the right. If quantity representations are linear, then midpoint errors should be random around 0. However, number bisection judgments of neurologically healthy individuals consistently reveal a leftward bias, where individuals overestimate the left side of the presented interval (Göbel, Calabria, Farnè, & Rossetti, 2006; Longo & Lourenco, 2007). The leftward perceptual biases indicate that smaller numbers take up more room on an internalized mental number line, whereas larger numbers are perceived to take up less room on the number line. This is consistent with other data concerning the form of quantity representations (Cohen & Blanc-Goldhammer, 2011; Loftus et al., 2009; Longo & Lourenco, 2007) and existing findings from non-symbolic bisection tasks (e.g., de Hevia & Spelke, 2009).

On each trial of Cohen and colleagues' (2019) number bisection task, participants were first presented two event statements, each associated with a quantity: one positive (i.e., you will accomplish a life goal in 115 months) and one negative (you will lose a friendship in 180 months). Participants were also presented a third number and asked to indicate which number within either of the two event statements was closest to this third number. Consistent with traditional number bisection tasks, time pressure was used to ensure that participants did not perform calculations when making their midpoint judgments. To assess levels of depression, all participants completed the BDI-II. As predicted, low BDI scorers perceived quantities associated with positive events as smaller than quantities associated with negative events, whereas high BDI scorers perceived quantities associated with negative events as smaller than quantities associated with positive events. These findings indicate that the representation for the same quantity (e.g., 5) within the same individual differed as a function of the affective event.

Cohen and colleagues' (2019) results contradict the predictions of an abstract quantity representation. The results, however, raise several questions. First, the number bisection task in Cohen and colleagues' (2019) study implemented a reaction time threshold. The time threshold was intended to inhibit strategic controlled processing that could mask perceptual biases. In the case of the number bisection task, controlled processing could take the form of simple mathematical calculations. If the participant carried out such calculations, they would arrive at the correct answer without activating their quantity representation (Göbel et al., 2006; Zorzi, Priftis, & Umiltà, 2002). This raises the question: "can controlled processing strategies that are not as straightforward as mathematical calculation inhibit quantity related perceptual biases?"

Second, although Cohen and colleagues' (2019) data is consistent with Beck's cognitive theory of depression, alternative theories provide a different account of the results. Specifically, depressed individuals may have negative perceptual biases (Beck, 1970; Dunning & Story, 1991) or non-depressed individuals may have positive biases (Alloy & Abramson, 1979, 1982). The latter alternative is predicted by the theory of *depressive realism*. In short, this theory suggests that depressed individuals routinely demonstrate accurate, unbiased cognitions and perceptions about themselves, the future, and the world. In contrast, non-depressed individuals systematically demonstrate unrealistic cognitions that

are influenced by optimistic biases (Dykman, Abramson, Alloy, & Hartlage, 1989). For example, Alloy and Abramson (1979) explored whether depressed or non-depressed individuals are influenced by perceptual distortions that affect their performance when asked to make contingency judgments. The results showed that when responses were unrelated to task outcomes, non-depressed participants reliably overestimated the degree of control that they exerted whereas depressed participants were able to consistently detect the uncontrollability of outcomes. These results were replicated in experiments designed to mimic “real-world” situations (see also Alloy & Abramson, 1982).

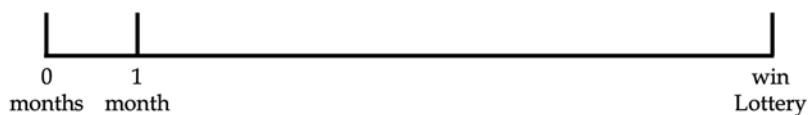
Here, we assess whether depressive and non-depressive individuals’ quantity representations are influenced by context using the unbounded number-line task (Cohen & Blanc-Goldhammer, 2011). The unbounded number-line task is frequently used to assess quantity representations and recent review has shown that it does so relatively accurately (Reinert & Moeller, 2021). Therefore, the unbounded number-line task has the potential to provide converging evidence for the results of Cohen and colleagues (2019). Furthermore, because the strategic processes associated with the unbounded number-line task are well understood (Cohen, Blanc-Goldhammer, & Quinlan, 2018), it can also provide insight into whether and when these strategies inhibit the influence of depression and context on quantity representations. Such insight may provide a deeper understanding of the relation between quantity representations and the symbols and items to which they link. Equally important, by pairing affective events with the unbounded number-line task, we will be able to pit the predictions of Beck’s theory of depression against those of depressive realism. Pitting these two competing theories against one another provides a more stringent test of each theory alone.

Experiment 1

To explore effects of depression and event valence on quantity perception, in Experiment 1 we used a modified number-line estimation task that linked various life event statements to number-line targets. On each trial, participants were presented a life event and asked to identify the event as either positive or negative. This ensured the participant attended to the life event, rather than just attending to the number. Following this, participants were presented an unbounded number-line with the first single unit labeled “1 month” and the previously shown life event statement positioned at the opposite end of the number-line (see Figure 1). The participant’s task was to estimate the time until the life event occurred, given the length of the single unit. Half of the participants were assigned to a reaction time-pressure condition, whereby they were encouraged to respond quickly. The other half were under no time pressure.

Figure 1

The Unbounded, Affective Number-Line



Beck’s cognitive theory of depression predicts that depressive participants should display pessimistic biases by perceiving future negative events as nearer and future positive events as more distal respective to their actual positions along a number-line (underestimating quantities linked to negative events and overestimating quantities linked to positive events). In contrast, the theory of depressive realism predicts that non-depressive participants should display optimistic biases by perceiving future positive events as nearer and future negative events as more distal respective to their actual positions along a number-line (underestimating quantities linked to positive events and overestimating quantities linked to negative events).

Recall that Cohen and colleagues (2019) implemented a reaction time threshold in the number bisection task. It may be that perceptual biases are more salient when controlled processing is inhibited. If this is the case, then time limitations are necessary to assess perceptual biases. We implemented the reaction time pressure condition to test

this hypothesis. If controlled processing masks perceptual biases, then there will be no effect of depression level in the no-reaction time pressure condition. Alternatively, if the reaction time pressure effectively interferes with the participant's ability to rely on strategy during the estimation task (i.e., interferes with controlled processing), then effects of depression and event valence will be observed only in the reaction time pressure condition.

Method

Participants

One hundred and forty-one subjects volunteered to participate in Experiment 1 using UNCW's Sona-System subject pool. Subjects who volunteered to participate were nineteen years old on average ($M = 19.14$, $SD = 1.87$). For information regarding participant demographics, see Table 1.

Table 1

Experiments 1 and 2 Participant Demographic Characteristics Before and After Filtering

| Characteristic | Experiment 1 | | Experiment 2 | |
|----------------------------------|--------------|-----------------|--------------|-----------------|
| | Full Dataset | After Filtering | Full Dataset | After Filtering |
| Gender | | | | |
| Male | 26 | 21 | 36 | 29 |
| Female | 113 | 96 | 169 | 147 |
| Unknown | 2 | 0 | 2 | 0 |
| Hispanic/Latino | | | | |
| Yes | 15 | 11 | 9 | 7 |
| No | 123 | 104 | 195 | 168 |
| Unknown | 3 | 2 | 3 | 1 |
| Ethnicity | | | | |
| American Indian/Alaska Native | 1 | 1 | 0 | 0 |
| Asian | 3 | 3 | 4 | 3 |
| Black/African American | 7 | 4 | 7 | 6 |
| Native Hawaiian/Pacific Islander | 0 | 0 | 0 | 0 |
| White | 115 | 98 | 180 | 154 |
| Unknown | 3 | 2 | 3 | 2 |
| Multiple | 10 | 9 | 11 | 11 |

Note. Filtering refers to the removal of participants for any reason, including missing BDI scores and missing or outlier b values.

Apparatus and Materials

All stimuli were presented on a 24-inch LED color monitor controlled by a Mac mini. The monitors used have a resolution of 1920×1200 pixels and a 72-Hz refresh rate.

Life Events — The life events used in the current study were standardized and validated in a previous study (Cohen, Barker, & White, 2018). In this earlier study, Cohen, Barker, and White (2018) developed a life event list comprised of 171 hypothetical event statements. Life event statements included in this list were organized according to event valence, creating three distinct event valence categories corresponding with positive, negative, and neutral events. Importantly, events chosen for the final list were shown to consistently invoke the intended valence (ambiguous events were excluded from the final life event list). Events within each category were also organized according to valence intensity, which provided valuable information about the strength of the valence, or emotion, that each event elicited.

In their original form, life event statements are short, simple phrases that often begin with a verb. Examples of positive event statements used in the current study include “win a million dollars,” “accomplish a life goal,” and “spend valuable time with close friends.” Examples of negative event statements include “have a loved one die,” “be convicted

of a felony,” and “lose your job.” Examples of neutral event statements include “sit at a different desk,” “use a calculator,” and “make a grocery list.” Findings from a follow-up experiment indicated a strong correlation between event valence and event triviality, where positive and negative event items were rated as significant and neutral event ratings were rated as insignificant (Cohen, Barker, & White, 2018). These ratings of significance reflect the strong affect elicited by the positive and negative event items as well as the indifference or feelings of neutrality elicited by the neutral event items.

The current study altered the format of these event statements by presenting statements in the second-person, future tense (i.e., “you will win a million dollars”) and pairing life events with quantities presented in month increments. However, due to the nature of the number-line estimation task used, a month increment was not specified in the event statements that were initially presented prior to each number-line. Instead, presented event statements followed the format “you will in months” (i.e., “you will win a million dollars in months”). Importantly, it is this quantity that the participant must estimate during the estimation task. Specific details regarding the estimation task are outlined below.

Number Line Estimation Task — The unbounded number-line estimation task used closely resembles Cohen and Blanc-Goldhammer’s (2011) original number-line estimation task, where participants are first presented the left bound of a number line, followed by the remainder of the number-line. The left bound of the number line, presented for 500 milliseconds, serves as a fixation point. After 500 milliseconds have elapsed, the remainder of the number-line becomes visible. At this point, the subject views the entire number line, which includes the left bound (representing the placement of 0 on the number line), a vertical line that indicates one unit on the number line, and a right bound, which serves as the target position that is to be estimated. Target positions are points along the number-line that represent the positions of integers ranging from 2-21. Participants complete the task by estimating the number that best describes the position of the right bound of the number line. To do this, participants are instructed to use the one-unit segment of the presented number-line as a reference.

In the current study, each presented number-line may be thought of as a timeline. As such, the left vertical bound of each number-line was labeled “0 months,” representing the current point in time. The vertical bound positioned to the right of the “0 months” bound was labeled “1 month,” representing one month in the future. Thus, the small horizontal line connecting these two bounds represent the distance of a single unit, or 1 month. A far right bound extended past the “1 month” bound and served as the target position that was to be estimated. Details regarding both the features of a single trial and the response method used during the estimation task are illustrated in Figure 2 and outlined below.

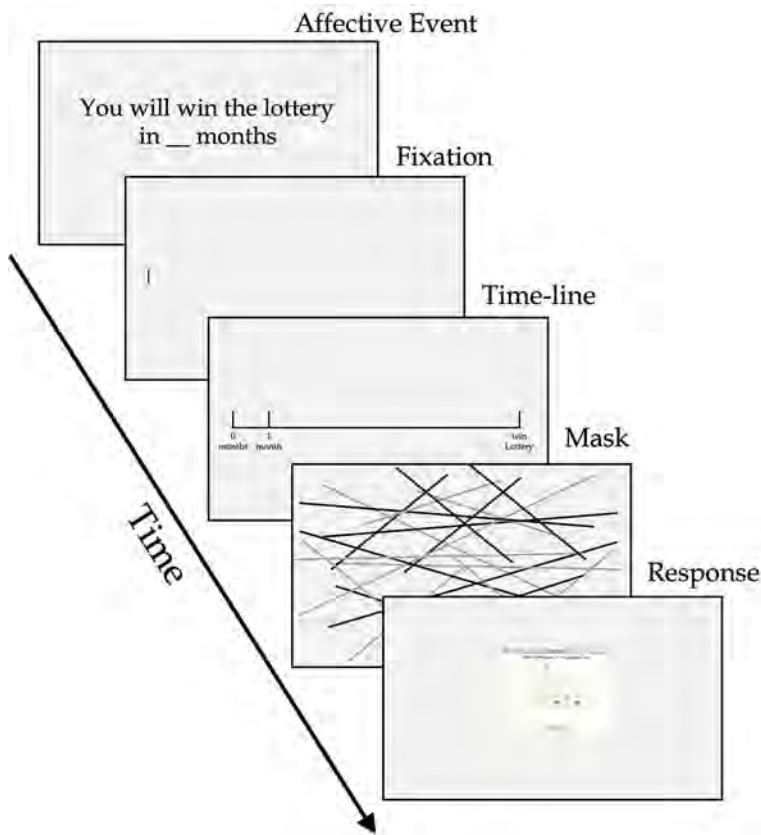
The number line used for the estimation task consisted of red 3-pixel-thick horizontal and vertical lines. The portion of the horizontal line that represented a single one-month unit was made to vary anywhere from 10 to 30 pixels in length and appeared in the center of the screen’s y-axis. The vertical lines of the number line, which served as end bounds, remained at a constant height of 20 pixels. To ensure that participants did not rely on spatial cues or external reference points to strategize when making their estimates, the position of the number line was randomly placed anywhere between 100-200 pixels from the left side of the screen. For this same reason, landmarks on the monitor were covered using black tape.

Each trial of the number-line estimation task included the presentation of an event statement randomly chosen from the 171 events compiled by Cohen, Barker, and White (2018). For event valence to impact judgments during the number-line task, participants must attend to the events associated with presented targets. To confirm that participants read presented event descriptions and to ensure that participants attended to event valence, participants indicated whether each presented event was positive or negative prior to making their number-line estimations (refer to the Procedure section for details regarding event rating judgments).

Once the participant made an event judgment, the event statement disappeared and was replaced by the left bound of the number-line, which served as a fixation point. After 500 ms, the entire number-line became visible. During the number-line task, shortened versions of life event descriptions were placed directly below the number-line’s right end-bound.

Figure 2

A Graphic Representation of the Course of a Single Trial in the Unbounded Affective Number-Line Task



When participants were finished studying a number-line and ready to record their estimate, they pressed the space key on the keyboard. Immediately following this key press, a mask composed of randomly placed red and gray lines was displayed for 1000 ms. Once this mask disappeared, a response dialogue box appeared which the participant used to enter in the estimated position of the presented number-line's right bound (see Figure 2). Centered at the top of the response dialogue box was the question “What is the target of this number line?” Below this question were three single-digit windows, appearing as 00.0, that the participant filled in to form their estimate. The participant entered their estimate into these windows using a digital 0-9 number pad that was included in the response dialogue box.

Participant estimates were allowed to vary from 00.1 to 99.9. To use the number pad, participants clicked numbers on the pad using their mouse. Left and right arrow buttons were also included on the digital number pad so that participants could easily move the cursor across each of the single-digit windows by clicking either arrow button with their mouse. Once a participant was satisfied with their estimate, they submitted their response by clicking an “OK” button at the bottom of the dialogue box. For participants assigned to the RT pressure condition, a “beep” sound was played after a participant submitted their estimate using the provided response box if too much time was spent viewing a presented number-line. This process continued until all 171 trials were completed.

Reaction Time Pressure — In an effort to prevent strategy use during the number-line estimation task, half of the participants were assigned to a reaction time pressure condition (RT pressure). The remaining participants were assigned to a no reaction time pressure condition (NO pressure). Reaction time (RT) was measured from presentation of the extended number-line to the pressing of the spacebar. For those participants in the RT pressure condition, an RT deadline was calculated for every trial. If the RT for a trial exceeded its deadline, an auditory signal (transmitted

via headphones) was presented after the participant submitted their response. This auditory signal indicated to the participant that too much time was spent studying the number-line and that they should spend less time examining number-lines in the future.

At the beginning of the experiment, the RT deadline was set at 10 seconds. Following this initial deadline, the RT deadline changed as a function of the participant's previous ten trials. Specifically, the RT deadline was set at the 80th percentile RT of the last ten trials (the second slowest RT) if it was faster than the current RT deadline. Otherwise, there was no change in the RT deadline. This algorithm had the advantage of slowly decreasing the RT deadline as the participant's performance gradually improved.

BDI-II – To assess participants' depression levels, all participants were required to complete the BDI-II at the end of the experiment. The BDI-II is a popular inventory that is often used to assess levels of depression (Beck, 1970). Scores may range from 0-63, with higher scores indicating more severe levels of depression. Scores on the BDI-II are traditionally organized into the following categories of depression severity: non-depressed (BDI score 0-13), mildly depressed (BDI score 14-19), moderately depressed (BDI score 20-28), and severely depressed (BDI score 29-63) (Beck, 1970). The version of the BDI-II used in the current study omitted one question regarding suicide in order to comply with university and IRB ethical procedures.

Procedure

Upon their arrival at the lab where the study was to take place, all participants read and signed an informed consent form. Next, each participant was directed to an individual testing room, where they were asked to read the instructions for the number-line task (presented on a computer screen). Once participants finished reading the instructions, they completed a series of four practice trials. Prior to, during, and following the practice trials, participants were provided opportunities to ask the supervising researcher any questions that they had concerning the task. Once the participant confirmed that they understood the task, they were permitted to begin the experiment.

The current study used an event rating task and the modified version of the unbounded number-line estimation task developed by Cohen and Blanc-Goldhammer (2011) earlier described. The formal experiment contained 171 experimental trials, one trial for each of the 171 life event statements. Each trial during the number-line estimation task included the presentation of an event statement, followed by a number-line trial that included a shortened version of the same event statement. To confirm that participants read presented event descriptions and to ensure that participants attended to event valence, participants were asked to indicate whether each presented event was positive or negative using a left or right mouse click prior to making their number-line estimations. We did not provide a "neutral" response option because (a) the requirement to respond to the affective content of the event was central to promoting reading of the event, whereas the participant's actual response choice to the event was less relevant, and (b) the mouse only had two buttons, so a two-choice response option was practical. Participants' left/right mouse click responses for the event rating task (indicating positive or negative event judgment ratings) were randomized between subjects.

Prior to their arrival, participants were randomly assigned to either (1) the reaction time pressure condition or the control (no reaction time pressure) condition. For both conditions, the 171 experimental trials were divided into two sections by one self-timed break, which was signaled by the appearance of a dialogue box halfway through the experiment that invited participants to take a break. To begin the second half of the experiment, participants clicked the "OK" button for this dialogue box. For each participant, the 171 experimental trials were randomized so that each event statement was randomly selected and paired with a random target quantity.

After completing all 171 experimental trials, participants were instructed to notify the supervising researcher. Immediately following the completion of the number-line estimation task, the researcher then issued the BDI-II to each participant to assess levels of depression. The BDI-II was always administered after the number-line task was complete so that the naiveté of subjects was preserved, thus eliminating any potential expectancy effects or biases that might otherwise confound results. Participants completed the BDI-II in their individual testing rooms and were told not to write any identification information on the form to ensure total anonymity.

Data Analysis

Estimating Numerical Bias — Cohen and Blanc-Goldhammer (2011) have shown that participants complete the unbounded number-line task using a dead-reckoning strategy that is best described by variations of a Scalped Power Model. Perceptual biases are an inherent feature of the Scalped Power Model, regardless of variation, and are described by an exponent, termed b . Thus, participants' strategic variations are simply a single strategy that implement different sized estimation windows (see Cohen, Blanc-Goldhammer, & Quinlan, 2018). Because the estimation errors that manifest in the estimation task are inverse of those that manifest from the more popular production task, one estimates the bias by taking the inverse of the b parameter in the fit equations (see Cohen, Blanc-Goldhammer, & Quinlan, 2018). Thus, a β of 1 indicates unbiased, or accurate, responding. A β of less than 1 indicates bias that is described by a negatively accelerating (or logarithmic) function in the production task (and the inverse in the estimation task), whereby the difference between successive small numbers is perceived as greater than the difference between successive large numbers. Finally, a β of greater than 1 indicates bias that is described by a positively accelerating (or exponential) function in the production task (and the inverse in the estimation task), whereby the difference between successive small numbers is perceived as smaller than the difference between successive large numbers.

To estimate numerical bias, we fit each participants' data to the Scalped Power Model (SPM) (Cohen & Blanc-Goldhammer, 2011) using a generalized nonlinear least squares (gnls) method. To get a robust fit for each participant, the gnls was bootstrapped on the data. For each participant by condition, a random sample of data (n = the number of trials completed by the participant), with replacement, was selected. The mean estimates were calculated for each target number used in the task (target numbers ranged from 2-21). The SPM was fit to these values. This bootstrapping procedure was repeated one hundred times per participant, per condition. Any variation of the SPM model that had more than 5% poor fits returned NA for β values and fit statistics for that participant, indicating a failure for the model to consistently predict the participant's estimations. Following this, averaged BIC goodness-of-fit statistics were used to determine which of the SPM models (single scallop, dual scallop, or multi scallop) best fit the estimation patterns observed for each subject.

Testing Model Prediction — To assess whether Beck's cognitive theory of depression or the theory of depressive realism best accounted for the participants' perceptual biases (β), we first calculated β difference scores as follows:

$$\beta_{\text{diff}} = \beta_{\text{affective}} - \beta_{\text{neutral}} \quad (1)$$

where $\beta_{\text{affective}}$ is the estimated β from the negative event trials or the positive event trials. To code the affective statement associated with β_{diff} , we coded the following variable:

$$S_{\text{type}} = \begin{cases} 1 & \text{if event is positive} \\ -1 & \text{if event is negative} \end{cases} \quad (2)$$

Beck's theory predicts that depressed individuals will underestimate quantities associated with negative events (i.e., perceive that negative events will happen sooner compared to neutral events) and overestimate quantities associated with positive events (i.e., perceive that positive events will happen later compared to neutral events). Alternatively, non-depressed individuals should respond with typical bias during the estimation task, regardless of the event valence associated with presented targets.

To assess whether the data are predicted by Beck's cognitive theory of depression, participants' numerical bias was fit to the following linear model:

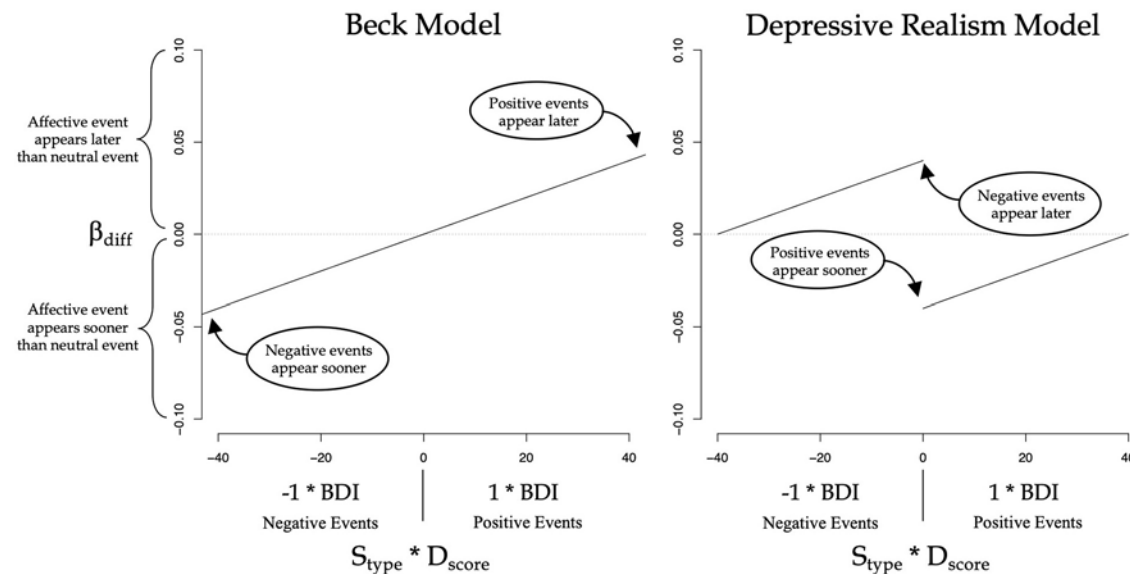
$$\beta_{\text{diff}} = S_{\text{type}} * D_{\text{score}} \quad (3)$$

where D_{score} is the participant's BDI score. To ensure that each D_{score} was given equal weight in the regression, β_{diff} was averaged across D_{score} . In this model, the positive and negative affect functions meet at BDI = 0 and diverge at equal rates as BDI scores increase. Because BDI score is multiplied by -1 when participants are shown negative events (the

negative affect function) and +1 when participants are shown positive events (the positive affect function), this model is a simple linear regression with no intercept parameter. Beck's model predicts a significant positive slope (see Figure 3).

Figure 3

The Predictions of the Beck and the Depressive Realism Models



Note. The y-axis represents the participants' quantity estimation of time until the affective event relative to their quantity estimation of time until the neutral event. Positive numbers indicate the participants estimated the time until the affective event as being in the more distant future than the same quantity associated with a neutral event. The reverse is true for a negative number. The x-axis represents depression level. When b_{diff} is associated with a negative event, we multiplied BDI by -1. When b_{diff} is associated with a positive event, we multiplied BDI by +1.

The theory of depressive realism, in contrast, predicts that depressed individuals should respond with typical bias during the estimation task, regardless of the event valence associated with presented targets. Non-depressed individuals, however, are expected to underestimate number-line targets associated with positive events (i.e., perceive that positive events will happen sooner compared to neutral events) and overestimate number-line targets associated with negative events (i.e., perceive that negative events will happen later compared to neutral events). To assess whether the data are predicted by the theory of depressive realism, participants' numerical bias was fit to the following linear model:

$$\beta_{diff} = -1 * S_{type} + S_{type} * D_{score} \quad (4)$$

Equation 4 is identical to Equation 3, with the exception of the *affect intercept term* ($-1 * S_{type}$). The affect intercept term adds separate, opposite intercepts for the positive and negative affect functions. In this model, the positive and negative affect functions converge at high BDI scores and diverge at equal rates as BDI scores approach 0. This model produces two parallel linear functions, whereby the Depressive Realism model predicts a significant positive intercept and a significant positive slope (see Figure 3).

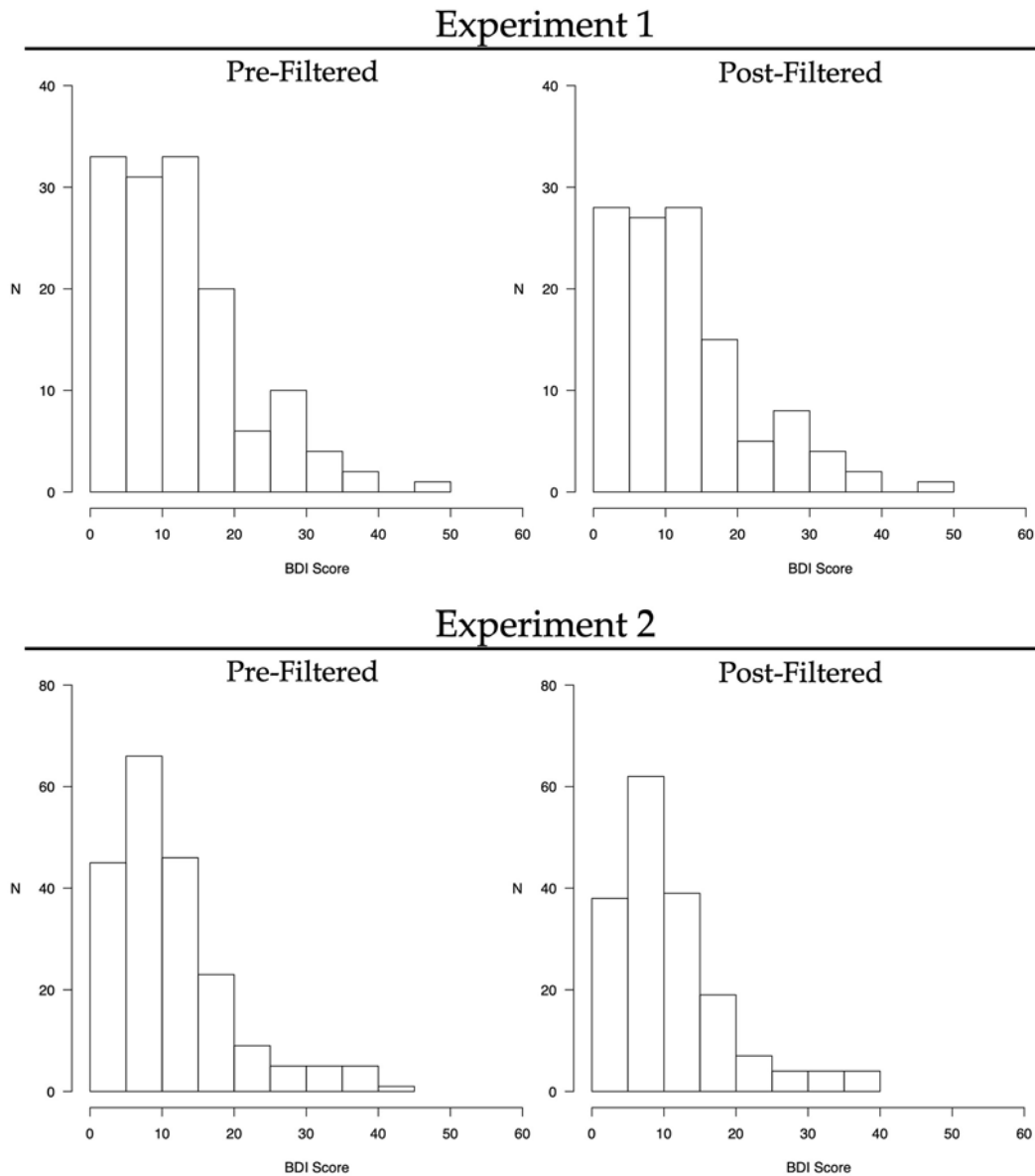
Results

Each participant's depression level was estimated by their scores on the BDI-II, where the higher the score, the higher the level of depression. One participant was removed from data analysis due to a missing BDI-II score. Figure 4 presents a histogram of the BDI-II scores obtained on the remaining 140 participants. Individual trials with participant responses faster than 400 ms (too fast to perceive and complete the task) and slower than 45 seconds (the most extreme outliers)

were excluded from data analysis (see Cohen, Blanc-Goldhammer, & Quinlan, 2018; Cohen & Blanc-Goldhammer, 2011). This removed approximately 1% of the data. Practice trials were also excluded from data analysis.

Figure 4

Histogram of the BDI-II Scores for Experiments 1 and Pre- and Post-Filtering



Note. Filtering refers to the removal of participants for any reason, including missing BDI scores, and missing or outlier b values.

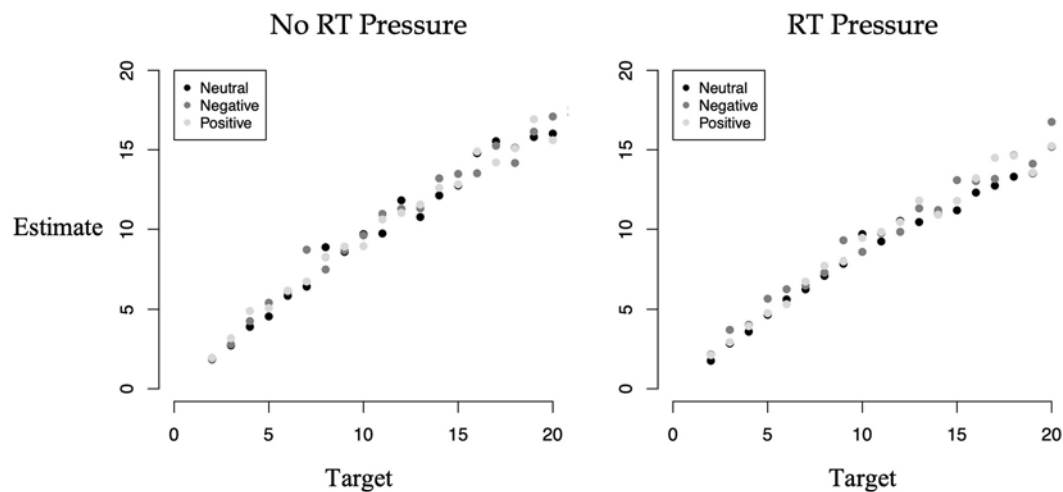
We first ran a mixed ANOVA on the Percent Absolute Error (PAE) by RT pressure condition (between SS) and event valence (within SS). This analysis provides a global assessment of error as a function of the two variables. Figure 5 presents the mean estimates by target for each RT pressure condition by event valence. PAE is calculated using the following formula:

$$PAE = \frac{|response - target|}{target} \quad (5)$$

There was no significant effect of RT pressure on PAE, $F(1,111) = 0.76$, $p = .39$, $\eta^2 = 0.0$, nor was there a significant interaction between RT pressure and event valence on PAE, $F(2,230) = 0.68$, $p = .51$, $\eta^2 = 0.0$. There was, however, a significant main effect of event valence, $F(2,230) = 5.36$, $p = .005$, $\eta^2 = 0.04$. Tukey post hoc analysis ($p < .05$) shows that the PAE for the negative valence events ($M = 0.35$, $SD = 0.8$) was significantly greater than that for the neutral valence events ($M = 0.31$, $SD = 0.43$), but not different from the positive valence events ($M = 0.34$, $SD = 0.7$). The PAE for the positive valence events was not significantly different from that for the neutral valence events.

Figure 5

Mean Estimate by Target for Each Event Valence in the No RT Pressure and RT Pressure Conditions



Note. Because the number-line task was an estimation (rather than production) task, the data decelerate with target. This deceleration translates to an acceleration in the production task.

Next, we explored the influence of RT pressure on numerical bias. The procedure to estimate numerical bias described in the Data Analysis section generated three β values, or degree of bias estimates, for each subject, corresponding with estimates for (1) positive events, (2) negative events, and (3) neutral events. These β values were extracted in order to explore whether (1) degree of bias varies as a function of event valence, and whether (2) bias also relates to level of depression. If this procedure failed to generate a β value for a participant for at least one event valence, that participant was removed. This criterion removed nineteen participants from the data analysis (approximately 15% of the participants)¹. Visual inspection of each participant's data revealed relatively random response patterns that indicated either a lack of understanding in the task or response method, or a lack of motivation that affected participants' performance during the task. To eliminate the influence of outliers in the remaining participants, all β values with more than 5 SDs away from the mean were removed. This removed less than 1% of the data. For information regarding how the spread of BDI-II scores changed following participant removal, see Figure 4.

To assess the overall influence of RT pressure on the time taken to complete the task (RT) and observed perceptual biases (b), we calculated two t -tests that compared the RT pressure group with the no RT pressure group. There was a trend toward an effect of RT pressure on RT, $t(115) = 1.78$, $p = .08$, Cohen's $d = .33$. Thus, RT pressure had minimal influence on the amount of time that participants viewed number-lines before responding. There was, however, a significant effect of RT pressure on estimated perceptual bias, $t(109) = 2.41$, $p = .02$, Cohen's $d = 0.43$. This indicates that

¹ The 15% removal appears high in this instance. However, the analysis required that every participant have a valid b estimate for every event valence. Therefore, the inability to fit the SPM to a single event valence required us to remove the participant from the analysis. It was this strict inclusion criteria that forced the high removal rate. Importantly, Figure 4 reveals that removal of these participants did not change the distribution of BDI scores. Thus, the influence of BDI on numerical bias should not be influenced by the removal of these participants.

participants' perceptual bias in the RT pressure condition was greater than the perceptual bias displayed by those in the no RT pressure condition (see Table 2).

Table 2

Experiment 1 RT Means and Standard Deviations for Positive, Negative, and Neutral Events

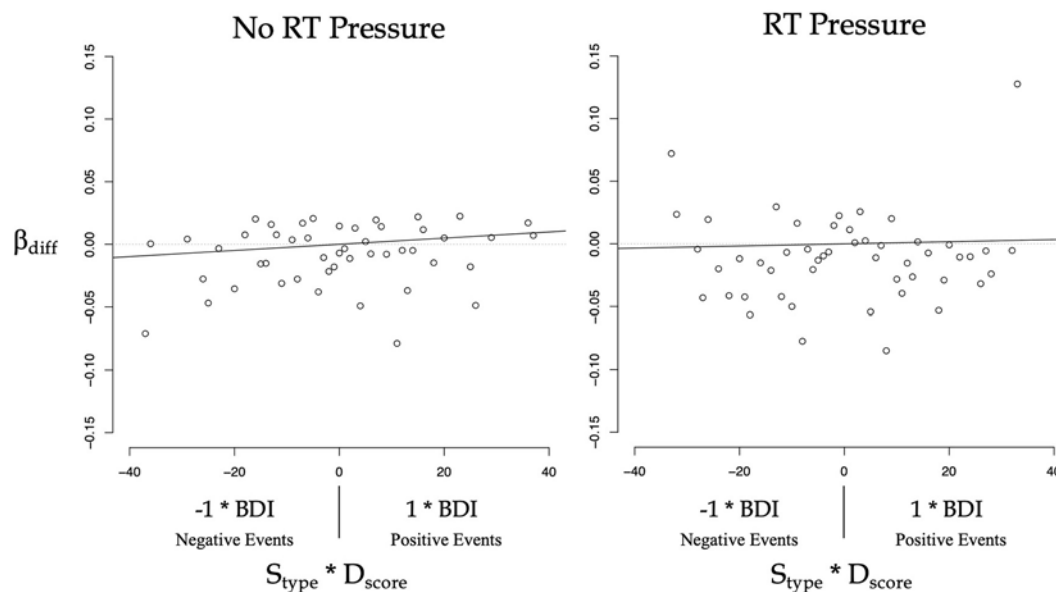
| Experiment | RT | b |
|---------------------|-------------|-------------|
| Experiment 1 | | |
| RT Pressure | 3194 (2266) | 1.15 (0.16) |
| Control | 3932 (2460) | 1.09 (0.11) |
| Experiment 2 | | |
| 500 ms | NA | 1.15 (0.16) |
| 1000 ms | NA | 1.13 (0.13) |
| Control | 3486 (2270) | 1.10 (0.12) |

Finally, we assessed whether Beck's cognitive theory of depression or the theory of depressive realism best accounted for the participants' perceptual biases (β) using the procedure to assess model predictions described in the Data Analysis section above. Because strategy use may mask effects of depression and event valence during the number-line estimation task, we tested each model separately for each experimental condition (RT pressure vs. control). To eliminate the influence of outliers, all β_{diff} values more than 5 SDs from the mean were removed. This removed four participants' data.

Results for Beck's model were not significant for participants assigned to the RT pressure condition (see Figure 6), $F(1, 49) = 0.09$, $p = .77$, $r^2 = 0.002$, or the no RT pressure condition, $F(1, 49) = 1.95$, $p = .17$, $r^2 = 0.04$. Findings related to the depressive realism model were also not significant for the RT pressure condition, $F(2, 48) = 0.06$, $p = 0.94$, $r^2 = 0.002$, or the no RT pressure condition, $F(2, 48) = 1.25$, $p = .30$, $r^2 = 0.05$.

Figure 6

*Scatterplots Displaying the Function $b_{diff} = S_{type} * D_{score}$ for the RT Pressure Conditions of Experiment 1*



Note. There were no significant effects.

Discussion

In Experiment 1, participants completed a modified number-line estimation task either in isolation or under reaction time pressure. For both conditions (RT pressure versus no pressure), findings revealed no differential influence of depression on perceptual bias. These null results suggest either that depression does not induce quantity estimation bias as measured by the number-line task, or that controlled processing strategies masked the perceptual biases associated with depression *and* the reaction time pressure condition failed to limit the use of a controlled processing strategy. Indeed, the RT pressure manipulation did not significantly influence participants' viewing time of presented number-lines. To more stringently limit the use of strategy during the number-line task, in Experiment 2 we implemented more strict time thresholds that directly reduce the amount of time that number-lines are presented during the number-line estimation task.

Experiment 2

Experiment 2 restricts the amount of time that number-lines are visible. We expect this time restriction to interfere with the participants' ability to rely on controlled processing strategies that might mask perceptual biases during the estimation task. As such, we predict that when presentation times are short (e.g., 500 ms), perceptual biases associated with depression will be observed. This effect, however, will be masked when longer presentation times are permitted (e.g., no time restriction). It is unclear whether perceptual biases will be observed in conjunction with moderate time restriction (e.g., 1000 ms).

Method

Participants

Two hundred and seven subjects volunteered to participate in the experiment using UNCW's Sona-System subject pool. Subjects who volunteered to participate were nineteen years old on average ($M = 19.11$, $SD = 3.34$). For information regarding participant demographics, see [Table 1](#).

Materials

The materials and number-line estimation task used in Experiment 2 were identical to the number-line task used in Experiment 1, with a few important exceptions. These exceptions are described in detail below.

Control and Limited Presentation Time Conditions — Participants were randomly assigned to one of three groups: a control group, a 500 ms group, or a 1000 ms group. Participants assigned to the control group completed the estimation task in exactly the same manner as the control group in Experiment 1. Participants assigned to the limited presentation conditions were identical to the control condition with one exception. Whereas participants in the control condition were instructed to press the spacebar once they were finished studying the presented number-line, participants assigned to the 500 ms and 1000 ms conditions did not need to do this. Instead, the presented number-line automatically disappeared once the appropriate amount of time (either 500 or 1000 ms) elapsed. Following the disappearance of the number-line, participants were then presented the mask followed by the response box as in the other experimental conditions.

To ensure that participants were given ample opportunity to learn how to complete the task, practice trials included 1000 ms time constraints for both the 500 ms and 1000 ms conditions.

BDI-II — As in Experiment 1, all participants completed Beck's Depression Inventory-II to assess participants' depression levels (BDI-II; [Beck, Steer, & Brown, 1996](#)). Consistent with Experiment 1, the version of the BDI-II used in Experiment 2 omitted one question regarding suicide in order to comply with university and IRB ethical procedures.

Procedure

The procedure applied in Experiment 2 was identical to the procedure used in Experiment 1. Experimental conditions were balanced so that a third of the participants were assigned to each of the three conditions.

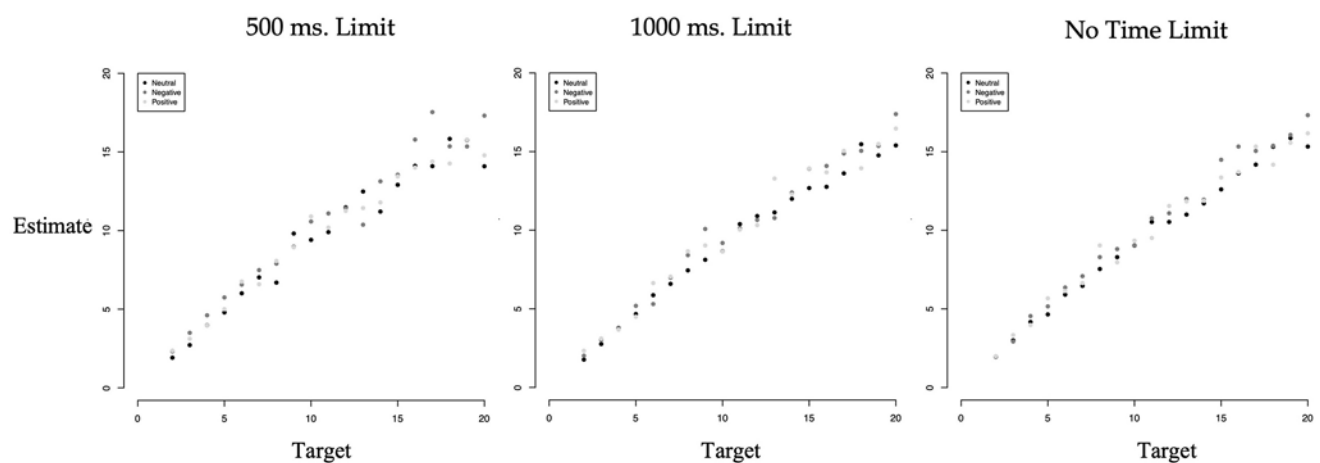
Results

Two participants were removed because they did not complete the BDI-II. Consistent with the analysis conducted in Experiment 1, individual trials with participant responses faster than 400 ms and slower than 45 seconds were excluded from data analysis. This removed approximately 1% of the data. Practice trials were also excluded from data analysis.

Following this, identical analyses were conducted for Experiment 2 as for Experiment 1. We first ran a mixed ANOVA on the PAE by presentation time (between SS) and event valence (within SS). Figure 7 presents the mean estimates by target for each time condition by event valence.

Figure 7

Mean Estimate by Target for Each Event Valence in the Presentation Time Conditions



Note. Because the number-line task was an estimation (rather than production) task, the data decelerate with target. This deceleration translates to an acceleration in the production task.

There was no significant effect of presentation time on PAE, $F(2, 171) = 2.72, p = .07, \eta^2 = 0.03$, nor was there a significant interaction between RT pressure and event valence on PAE, $F(4, 346) = 0.64, p = .64, \eta^2 = 0.0$. There was, however, a significant main effect of event valence, $F(2, 346) = 11.32, p < .001, \eta^2 = 0.06$. Tukey post hoc analysis ($p < .05$) shows that the PAE for the negative valence events ($M = 0.40, SD = 0.91$) was significantly greater than that for the neutral valence events ($M = 0.35, SD = 0.56$), but not different from the positive valence events ($M = 0.39, SD = 0.83$). The PAE for the positive valence events was significantly different from that for the neutral valence events.

Next, we explored the influence of presentation time on numerical bias. Again, we fit each participants' data to the Scalloped Power Model (SPM), generating three β values for each subject that corresponded with each event valence. Consistent with the analyses carried out in Experiment 1, any participants that did not fit the SPM model were removed. This process removed 28 participants from the data analysis (approximately 14% of the participants). Consistent with the visual inspection conducted in Experiment 1, patterns of responding observed for these participants indicated issues involving motivation or task comprehension that severely affected participants' task performance. To eliminate the influence of outliers, all β values with a SD of greater than 5 were also removed. No outliers were removed according to this criterion. Figure 4 presents a histogram of BDI-II scores obtained from the remaining participants.

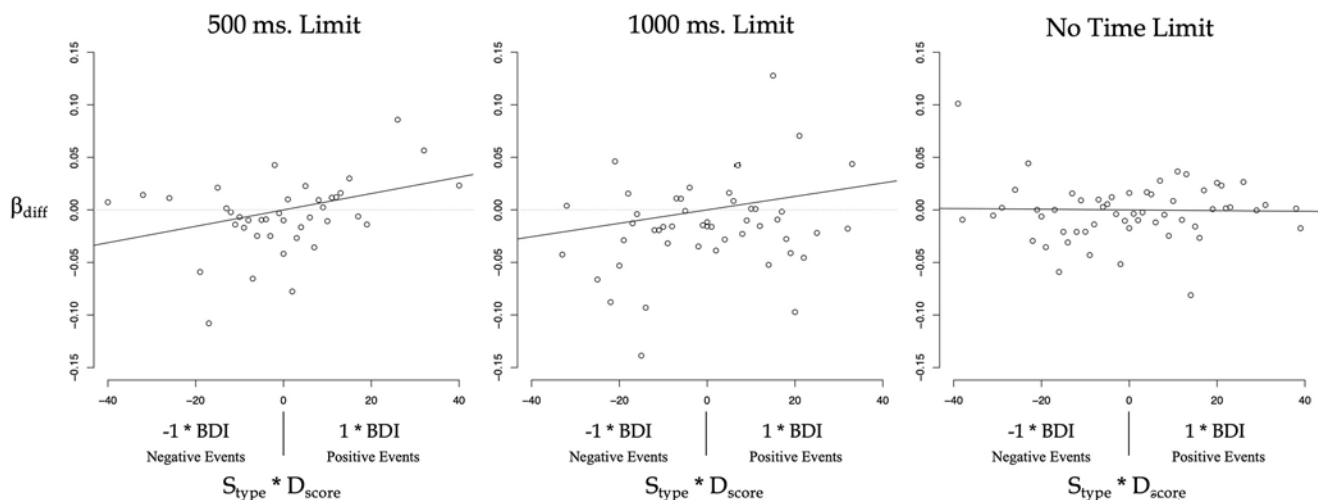
To test whether the limited presentation time conditions significantly reduced participant RTs compared to the control condition, a one-sample t-test was conducted that compared reaction times for the control condition to a mean reaction time of 1000 ms (representing the less restrictive 1000 ms condition). The participants in the control

condition viewed the number-line significantly longer than 1000 ms, $t(191) = 15.14$, $p < .001$, Cohen's $d = 1.1$, with significantly more time spent studying presented number-lines in the control condition ($M = 3486$, $SD = 2270$) versus the 1000 ms comparison mean. To assess whether the time limitations influenced overall perceptual biases, regardless of depression levels, we ran an ANOVA on b by time conditions. There was no significant influence of the time limitation manipulation on b , $F(2, 174) = 1.25$, $p = .29$, $\eta^2 = 0.01$, (see Table 2).

Finally, we assessed whether Beck's cognitive theory of depression or the theory of depressive realism best accounted for the participants' perceptual biases (β) using the same analyses performed in Experiment 1. As in Experiment 1, all β_{diff} values more than 5 SDs away from the mean were removed. One participant was removed according to this criterion. We tested both the Beck and Depressive Realism models for each experimental condition (control, 500 ms, and 1000 ms). Beck's model did not significantly predict estimation bias (β) for the control condition, $F(1, 55) = 0.03$, $p = .87$, $r^2 < 0.01$, or the 1000 ms condition, $F(1, 47) = 2.61$, $p = .11$, $r^2 = 0.05$. Beck's model did, however, significantly predict estimation bias (β) in the 500 ms condition, $F(1, 39) = 5.673$, $p = .02$, $r^2 = 0.13$, slope = 0.008. Figure 8 presents these data.

Figure 8

Scatterplots Displaying the Function $b_{diff} = S_{type} * D_{score}$ for the Time Pressure Conditions of Experiment 2



Note. There was no significant effect in the No Time Limit condition or the 1000 ms. condition, and a significant effect in the 500 ms condition.

The theory of depressive realism did not significantly predict estimation bias (β) for the control condition, $F(2, 54) = 2.148$, $p = .13$, $r^2 = 0.05$, the 500 ms condition, $F(2, 38) = 2.76$, $p = .08$, $r^2 = 0.13$, or the 1000 ms condition, $F(2, 46) = 1.28$, $p = .29$, $r^2 = 0.05$. Importantly, the trend toward significance in the 500 ms condition resulted from the influence of the slope parameter that it shares with the Beck model. The *affect intercept term* that distinguished the Depressive Realism model from the Beck model did not trend toward significance, $t = 0.01$, $p = .99$.

These findings support predictions made by Beck's cognitive theory of depression over the theory of depressive realism.

Discussion

The data revealed that Beck's model successfully predicted perceptual biases in the 500 ms condition, but not the 1000 ms condition or the control condition. These findings suggest that perceptual biases are most salient when participants are unable to initiate controlled strategic processing that might mask perceptual biases. We discuss these findings below in the General Discussion.

General Discussion

Here, we replicate and extend the results obtained by [Cohen and colleagues \(2019\)](#) using the unbounded number-line task. This was accomplished by pairing number-line targets with affective future event statements to determine whether estimation biases varied according to event valence. Across two experiments, our data indicate that when participants' viewing time is effectively limited, their perceptual biases are consistent with the predictions of Beck's cognitive theory of depression over those of depressive realism. However, when viewing times are unrestricted, controlled processing can mask the influence of perceptual biases. Although the pattern of results in the 1000 ms condition was not significant, the pattern was in the same direction as the 500 ms condition. This may indicate that the influence of time restriction is continuous, rather than acting as a threshold.

Unlike [Cohen and colleagues \(2019\)](#), the current paradigm allowed us to directly pit the predictions of Beck's cognitive theory of depression against those of depressive realism. The results support Beck's (1970) assertion that depression is related to pessimistic biases; as people score higher on the BDI-II, the strength of their perceptual biases increases. This result is important because it suggests that these biases may contribute to the severity and persistence of depressive symptoms. As such, correcting these biases may be one avenue for effective treatment. If, however, the predictions of depressive realism were supported, then such a treatment goal would not be effective.

Our research reveals that the relation between BDI-II scores and negative perceptual biases is only observed when controlled processing is inhibited. This finding suggests that perceptual biases may be most salient when depressed individuals are not able to engage in controlled processes, such as when they are under stress, time constraints, high cognitive load, etc. Alternatively, when depressed individuals have excess cognitive resources at their disposal, they may be more capable of recognizing and overcoming their perceptual biases.

The finding that controlled processing can reduce the impact of pessimistic bias in depressive individuals implies that the use of strategy in broader decision-making contexts may help to improve both judgment and performance in depressed groups. This finding reinforces the value of cognitive-based approaches in the treatment of depression within clinical contexts. By helping affected individuals to (1) recognize how pessimistic biases currently impact their perceptions and (2) apply strategy-based approaches designed to challenge these perceptual biases, depressed individuals may be afforded an opportunity to learn new skills that may reduce functional impairment and the impact of depressive thoughts over time. To explore whether the current findings extend to a clinically depressed sample, future research should examine the impact of time pressure during the modified version of the unbounded number-line task used in the current study when participants meet formal diagnostic criteria for depression.

The current findings also reveal that quantity representations are influenced by the stimuli and items that they modify. The influence of the stimuli and the items that they modify are most apparent when controlled processing is inhibited and participants are in a state of mind that is susceptible to perceptual biases. This suggests that researchers should inhibit controlled processing when conducting studies whose purpose is to assess the abstract nature of quantity representations. When such processes are inhibited, our data provide evidence in favor of non-abstract quantity representations. These findings support the conclusions of [Cohen and colleagues \(2019\)](#). The current findings also provide some support for the conclusion that estimation biases of non-symbolic threat/emotion stimuli implicate the quantity representation (e.g., [Hamamouche et al., 2017](#)). Research should, however, be conducted to directly rule out attentional processes on the encoding of non-symbolic stimuli.

Taken collectively, the findings from the current study reveal that the perceptual biases hypothesized by Beck's cognitive theory of depression ([Beck, 1970](#)) are present in quantity estimation. Importantly, however, these biases can be masked when participants are able to implement controlled, strategic processing.

Funding: The authors have no funding to report.

Acknowledgments: The authors have no additional (i.e., non-financial) support to report.

Competing Interests: The authors have declared that no competing interests exist.

Data Availability: The data and R code for the analysis of Experiments 1 and 2 can be downloaded at:

https://github.com/ccpluncw/ccpl_data_DepressionNL2021.git

Please cite this article if data is used in any way to produce a publication. These data cannot be used without the first author's consent for any for profit endeavor.

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Journal of Numerical Cognition (JNC) is an official journal of the Mathematical Cognition and Learning Society (MCLS).



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