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On the Form and Function of Forgiving: Modeling the Time-Forgiveness Relationship and Testing the Valuable Relationships Hypothesis

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In two studies, the authors sought to identify the mathematical function underlying the temporal course of forgiveness. A logarithmic model outperformed linear, exponential, power, hyperbolic, and exponential-power models. The logarithmic function implies a psychological process yielding diminishing returns, corresponds to the Weber-Fechner law, and is functionally similar to the power law underlying the psychophysical function (Stevens, 1971) and the forgetting function (Wixted & Ebbesen, 1997). By 3 months after their transgressions, the typical participant's forgiveness had increased by two log-odds units. Individual differences in rates of change were correlated with robust predictors of forgiveness. Consistent with evolutionary theorizing (McCullough, 2008), Study 2 revealed that forgiveness was uniquely associated with participants' perceptions that their relationships with their offenders retained value.

Keywords: forgiveness, evolution, change, multilevel modeling, nonlinear models

Scientific progress rests not only on testing hypotheses derived from theory, but also on describing empirical regularities that can become the grist for later theory-building projects. In fact, the "theories-to-laws ratios" of the various sciences—the number of theories relative to the number of laws mentioned in introductory textbooks—is virtually synonymous with the maturity, status, and immediacy of those sciences and their knowledge bases (Simonton, 2004). Within psychology, entire subfields of research on sensation, perception, and memory have arisen out of efforts to describe and formalize mathematical descriptions of seemingly simple bivariate relations, for example, the relationship between physical stimuli and their perceived sensory properties (Stevens, 1971), and the relationship between memory retention and the passage of time since learning occurred (Rubin & Wenzel, 1996; Wixted, 2004a, 2004b; Wixted & Ebbesen, 1997). Basic efforts such as these to identify simple empirical regularities often lead to enormous waves of theoretical progress (Wixted, 2004b).

In the present paper, we sought to describe a basic empirical regularity that should be of interest to emotion researchers: the relationship between forgiveness and time. Notwithstanding truisms such as "time heals all wounds," and the laws of "habituation" and "comparative feeling" that Frijda (1988) formulated, surprisingly few scientists have explicitly examined affective change over time. There are a few exceptions, of course. For example, Hemenover (2003) and more recently, Verduyn, Delvaux, Van Coillie, Tuerlinckx, and Van Mechelen (2008) tried to describe individual differences in rates of affective change over shorter (i.e., 20-min) and longer (i.e., 2-week) time intervals. Also, Carnelly, Wortman, Bolger, and Burke (2006) attempted to identify the best functions for describing the temporal trajectory of grief reactions. But aside from recent contributions such as these, research tells us little about the form of temporal changes in affect and motivation.

Forgiveness as a Model for Affective and Motivational Change

The concept of forgiveness provides an interesting model for considering affective and motivational change. Researchers have defined forgiveness in different ways, but all of these definitions rest on the idea that forgiveness involves temporal change. Enright, Gassin, and Wu (1992), for instance, defined forgiveness

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as "the overcoming of negative affect and judgment toward the offender, not by denying ourselves the right to such affect and judgment, but by endeavoring to view the offender with compassion, benevolence, and love . . ." (p. 101). Exline and Baumeister (2000) defined forgiveness as the "cancellation of a debt" by "the person who has been hurt or wronged" (p. 133). Finally, McCullough, Worthington, and Rachal (1997) defined forgiveness as "the set of motivational changes whereby one becomes (a) decreasingly motivated to retaliate against an offending relationship partner; (b) decreasingly motivated to maintain estrangement from the offender; and (c) increasingly motivated by conciliation and goodwill for the offender, despite the offender's hurtful actions" (pp. 321–322). Thus, most theorists concur that when people forgive, their psychological representations of a transgressor (e.g., thoughts, feelings, motivations, or behavioral inclinations) toward a transgressor become more positive and/or less negative—that is, they are restored to their pretransgression state (Karremans & Van Lange, 2004). This point of consensus led McCullough, Pargament, and Thoresen (2000) to propose that *intraindividual prosocial change in one's motivations or emotions toward a transgressor* is a foundational and uncontroversial feature of forgiveness (McCullough & Root, 2005).

Researchers have considered the forgiveness–time relation in three different ways. First, some researchers have statistically controlled the amount of time since a transgression elapsed before examining other potential correlates of forgiveness (Exline, Baumeister, Bushman, Campbell, & Finkel, 2004; Finkel, Rusbult, Kumashiro, & Hannon, 2002; Orcutt, 2006) to exert greater statistical control over diverse experiences (for a fuller treatment of these methodological issues see McCullough & Worthington, 1999; Tsang, McCullough, & Hoyt, 2005).

Second, Wohl and McGrath (2007) examined how the perceived passage of time between a transgression and the present influences forgiveness. They discovered that experimentally increasing the perceived amount of subjective time that had passed since a transgression occurred (by manipulating the left and right anchors on a time line that moved from a point either in the recent or distant past to the present, and then asking participants to place the transgression somewhere between those two anchors), made people more forgiving (via self-report). This finding suggests that the perceived passage of time is sufficient to cause forgiveness, though the mechanisms yielding this effect are not well understood.

A third way to consider the forgiveness-time relationship is to incorporate time explicitly in how forgiveness is modeled. McCullough and colleagues (McCullough, Fincham, & Tsang, 2003; McCullough & Root, 2005) explored the idea that forgiveness can be studied using mixed-effects (or multilevel) growth curve models in which change is modeled as a simple linear or curvilinear function of time. In two longitudinal studies, McCullough et al. (2003) found that people generally experience declines in their negative interpersonal motivations (e.g., revenge and avoidance motivation) following a transgression, but do not experience increases in their positive motivations (although there were individual differences in rates of linear change in all of these constructs). They also found that simple two-parameter linear models fit their data better than did three-parameter models that permitted curvature in people's trajectories via a quadratic effect for time.

However, several limitations of McCullough et al.'s (2003) work made it inadequate for completely describing the forgiveness-time function. First, their data sets had relatively few participants ($N = 73$ and 89, respectively) and relatively few (i.e., five or fewer) repeated observations per participant. Such limitations reduce one's ability to predict individual differences in growth parameters and reduce flexibility to evaluate a wide variety of growth models (Singer & Willett, 2003). Second, we suspect that they did not measure people frequently enough within the measured intervals to capture complex growth processes. Third, the scales they used to measure forgiveness were based on sums of raw score Likert-type scales. Raw score sums are ordinal-level data, which are constrained at the upper and lower extremes of the scale, and are likely to misrepresent the true scores of persons at extreme ends of the scale continuum (Embretson & Reise, 2000). Such floor and ceiling effects in previous research might have limited the ability to depict change faithfully. More advanced psychometric scaling procedures, such as Rasch scaling (Bond & Fox, 2001), can be used to convert ordinal raw scores to interval-level measures that are theoretically unbounded at the extremes, thereby removing such floor and ceiling effects. In Rasch scaling, person latent trait measures and item parameters are estimated on a common logit (log-odds) scale. The logit scale is a linear, interval-level metric in the sense that differences in logit measures maintain the same probabilistic interpretation throughout the scale continuum. More details of Rasch measurement procedures are provided in the methods section below.

Modeling Forgiveness Non-Linearly: A Precedent in Research on Forgetting

But perhaps most importantly, McCullough et al. (2003) did not model forgiveness using nonlinear models such as the logarithmic, exponential, and power functions that have been so fruitful for research on forgetting (e.g., Rubin & Wenzel, 1996; Wixted & Ebbesen, 1997). Exploring nonlinear models such as these seems particularly apt because despite the conceptual differences between forgiveness and forgetting (Enright et al., 1992), in both processes a mental representation (in the case of forgiveness, a suite of negative emotions and motivations tied to a specific person, and in the case of forgetting, a memory trace) is thought to subside or decay over time.

Moreover, a linear model of forgiveness (which only permits straight-line change) or even a quadratic model of forgiveness (which permits curvature) simply cannot be literally true in the long run. A linear model of forgiveness implies that someone who has forgiven an offender will proceed at a constant speed toward infinitely low levels of ill will toward the offender—an implication that is psychologically and conceptually problematic. Likewise, a quadratic model implies that people become more and more forgiving over time until they reach a trough. On the right side of that trough, they then proceed to become less and less forgiving over time until they become infinitely unforgiving. This too, seems psychologically unrealistic and conceptually suspect. In light of these limitations, it seems wise to consider two-parameter models that permit people to become monotonically more forgiving over time, but also with control parameters that enable smooth rates of deceleration toward an asymptote as time approaches infinity. Truly nonlinear models (i.e., models in which estimated values for the response variable cannot be estimated through a sum of individual growth parameters; Singer & Willett, 2003) such as the logarithmic model, the exponential decay model, and the power model allow for precisely these curve shapes and have proven to describe the decay of memories much better than linear models do (Rubin & Wenzel, 1996; Wixted & Ebbesen, 1997).

Exploring the Form of Forgiving

In the present article, we describe two longitudinal studies in which we attempted to surmount these problems by using (a) large data sets with large numbers of observations per individual that were spread out over several months following participants' transgressions; (b) a measure of forgiveness that yielded interval-level measurement and minimal restriction of range due to ceiling and floor effects; and (c) statistical techniques that enabled us to evaluate both linear and nonlinear models of change. Having evaluated this wider range of possible models for depicting the time-forgiveness relation, we then attempted to account for individual differences in our participants' rates of forgiveness with other "robust predictors" of forgiveness (e.g., offense severity, apology/making amends, relationship closeness/commitment, and the Big Five personality factors; see Exline et al., 2004) both to evaluate the construct validity of the resulting person-specific estimates of forgiveness and to learn more about the factors that predict individual differences in forgiveness.

Exploring the Function of Forgiving: Testing the Valuable Relationships Hypothesis

In Study 2 in particular, we also tested the "valuable relationships" hypothesis. The valuable relationships hypothesis specifies that two agents who encounter conflict with each other will be motivated to return to preconflict levels of positive interaction to the extent that their relationship is perceived to possess long-term value (McCullough, 2008). This hypothesis originates in the assumption that social animals' capacities to forgive and reconcile arose out of pressures for kin altruism (Hamilton, 1964), reciprocal altruism (Trivers, 1971) or other evolved strategies for the exchange of benefits between individuals (Krebs, 2008).

The role of relationship value in determining social animals' propensity to forgive and reconcile after conflict has been demonstrated in many simulations of the evolution of cooperation among interacting agents and within friendship groups (e.g., Axelrod, 1984; Hruschka & Henrich, 2006; Nowak, 2006). Hruschka and Henrich (2006), for instance, discovered that natural selection favors the evolution of very high levels of forgiveness in interactions within "cliques" of closely allied exchange partners. In addition, studies of nonhuman primates' conciliatory behaviors following conflict are consistent with the idea that computations of relationship value are based on partners' potential contributions to each others' fitness (Koski, Koops, & Sterck, 2007; Watts, 2006), and that it is in relationships with high fitness value to the interactants that forgiveness and/or reconciliation will be most likely.

Several studies now show that relationship commitment is a key predictor of forgiveness (Finkel et al., 2002; McCullough et al., 1998), and it is commonly assumed that people stay committed to relationships, in spite of the damage that a conflict might have caused these relationships, because of the relationship's value to the interactants. However, it has not yet been shown that computations of relationship value per se are associated with individual differences in forgiveness. We evaluated this important evolutionary hypothesis in Study 2.

Study 1

Method

Participants. Participants were $N = 372$ undergraduate students (74% female, 26% male) from Southern Methodist University and the University of Miami. By the time we obtained the first of the many repeated measures of forgiveness for our participants, an average of 5.95 days ($SD = 3.13$ days; range = 0–20 days) had passed since their transgressions occurred. More than three-quarters of participants' transgressions had occurred seven or fewer days before the first measurement point. To assemble the data set we used in Study 1, we combined data from three previous longitudinal studies. Presently, we describe those three data sets in detail.

Data set 1. Participants were 89 students in undergraduate psychology courses (69 women, 20 men; M age = 20.44 years, $SD = 3.09$ years) at Southern Methodist University. All participants, who had incurred transgressions in the past 7 days ($M = 4.66$ days, $SD = 1.86$ days), received extra course credit for participating. Students who completed all five repeated measures received $10. We recruited participants by visiting their undergraduate psychology courses to indicate our interest in surveying people who had recently incurred serious interpersonal offenses. We regularly visited these classes throughout the semester, and as interested participants incurred offenses that might make them eligible for the study, they enrolled and received introductory materials, including the first measures of forgiveness and the other measures that are relevant to the present study. We attempted to recontact participants on four other occasions throughout the semester (approximately every two weeks) by revisiting their classrooms to provide them with follow-up questionnaires. Thus, we tried to measure participants' forgiveness for their transgressors approximately 1, 3, 5, 7, and 9 weeks after their transgressions had occurred. McCullough et al. (2003, Study 2) report additional methodological details.

Most transgressions were committed by girlfriends/boyfriends (42%), friends of the same gender (23%), and friends of the other gender (15%). Smaller numbers detailed transgressions by relatives (10%), husbands/wives (3%), and "others" (8%). Participants described several types of transgressions, including betrayals of a confidence or insults by a friend (36%); neglect by a romantic partner, spouse, or ex-romantic partner (25%); infidelity by a romantic partner or spouse (13%); rejection, neglect or insult by a family member (10%); termination of a romantic relationship (7%); insults by people other than family or friends (3%); and rejection or abandonment by friend or prospective relationship partner (3%). Two participants declined to describe their transgressions.

Data set 2. Participants were 115 students in undergraduate psychology courses (91 women, 24 men; M age = 19.76, $SD = 2.61$) at Southern Methodist University. Participants had encountered interpersonal transgressions within the 7 days before recruitment ($M = 4.04$ days, $SD = 1.82$ days). As in Study 1, participants were recruited through presentations in their psychology courses in which we announced our interest in surveying people who had recently incurred an interpersonal transgression that they considered to be painful and morally wrong. Interested participants completed introductory materials and, if later deemed eligible, were scheduled for five visits (approximately 2 weeks apart) in the first author's laboratory. During the first laboratory visit, participants provided the first of the five measures of forgiveness and the other measures relevant to the present study. On the four subsequent visits, they completed the measures of forgiveness and other measures that are not relevant to the present study. Participants received up to $20 for participating. Other procedural details are reported elsewhere (McCullough, Bono, & Root, 2007; Study 2; McCullough, Orsulak, Brandon, & Akers, 2007).

Most participants described their transgressors as girlfriends or boyfriends (59%), friends of the same gender (19%), or friends of the other gender (11%). A few participants reported transgressions by relatives (10%), husbands/wives (3%) and "others" (9%). One person did not report the type of relationship involved. Participants experienced insults by a friend or betrayals of a confidence (28%); neglect by a romantic partner, spouse, or ex-romantic partner (22%); infidelity by a romantic partner or spouse (19%); rejection, neglect or insult by a family member (10%); termination of romantic relationship (11%); insults by people other than family or friends (3%); and rejection or abandonment by a friend or prospective relationship partner (2%). Five participants did not describe the transgression.

Data set 3. Participants were 163 students in undergraduate psychology courses (112 women, 51 men; *M* age = 19.61 years, *SD* = 3.82 years) at the University of Miami. Participants had incurred interpersonal transgressions just prior to enrollment (*M* = 4.37 days, *SD* = 1.85 days). They received extra course credit for participating and, if they completed the tasks described here and a separate laboratory session, $20. We recruited participants through regular visits to their undergraduate psychology courses, where we announced our interest in studying participants who had recently incurred interpersonal transgressions. Interested participants were given a set of introductory materials, including a booklet containing 21 daily questionnaires. Participants were advised to complete one of these daily questionnaires each day for the next 21 days, and were encouraged not to make false entries as this would not affect their compensation in any way, even though it would hurt the study. The introductory packet also contained the other measures that are relevant to the present study. After completing the packets, participants returned them so that they could complete other tasks not relevant to the present study. Other procedural details are reported elsewhere (McCullough, Bono, et al., 2007, Study 3).

Most reported transgressors were girlfriends/boyfriends (50%), friends of the same gender (19%), or relatives (13%). A smaller number of participants reported transgressions by friends of the other gender (9%), husbands/wives (1%) and "others" (8%). Participants described several types of transgressions, including infidelity by a romantic partner or spouse (29%); insults by a friend or betrayals of a confidence (20%); rejection, neglect or insult by a family member (13%); termination of a romantic relationship (13%); neglect by a romantic partner, spouse, or ex-romantic partner (10%); rejection or abandonment by a friend or prospective relationship partner (10%); and insults by people other than family or friends (5%).

Measures

Forgiveness. We conceptualize forgiveness as a process of reducing one's negative (viz., avoidance and revenge) motivations toward a transgressor and restoring one's positive, benevolent motivations regarding the transgressor (McCullough et al., 1997). To measure these motivational changes, we used the 18-item form of the Transgression-Related Interpersonal Motivations (TRIM) Inventory (McCullough, Root, & Cohen, 2006). The 7-item Avoidance subscale measures motivation to avoid a transgressor (e.g., "I live as if he or she doesn't exist, isn't around"). The 5-item Revenge subscale measures motivation to seek revenge (e.g., "I'll make him/her pay"). Both have high internal consistency (*alpha* $\geq$ .85), moderate test-retest stability (e.g., 8-week test-retest *r*s $\approx$ .50) and evidence of construct validity (McCullough et al., 1998, 2001). Items are rated on a five-point Likert-type scale (1 = *strongly disagree* and 5 = *strongly agree*). We recently added a six-item subscale for measuring benevolence motivation (e.g., "Even though his or her actions hurt me, I have goodwill for him/her") that also has good reliability (McCullough et al., 2003; McCullough & Hoyt, 2002). These six items are rated on the same five-point Likert-type scale as are the 12 avoidance and revenge items.

McCullough, Root, and Cohen (2006) found that two oblique principal components could be extracted from the TRIM-18 items (one of which represents avoidance vs. benevolence, and the other which represents revenge motivation), but here we explored the possibility that this apparent multidimensionality belies a unidimensional structure that might emerge under the Rasch (1960) model, which is a probabilistic conjoint measurement model (Fox & Jones, 1998). We used the Rating Scale version of the Rasch model (Andrich, 1978).

As Fox and Jones (1998) described, the simplest Rasch model expresses the probability of an individual's score on a single dichotomous (e.g., true/false) test item with two parameters: a parameter δ that represents the endorsability (or difficulty) of the item and a parameter β that represents the individual's level (or ability) on the psychological construct being measured. Differences in item endorsability (or difficulty) reflect differences in the likelihood that an item will be affirmed (e.g., answered "true") across all test-takers. For example, regardless of a person's level of forgiveness, it is probably more difficult to endorse the true/false statement "I have made a plan to physically attack the person who hurt me" than it is to endorse the statement "I wish something bad would happen to the person who hurt me." Individual ability levels on the measured construct reflect individual differences in test-takers' propensities to endorse items. For example, a person who is measured as high on forgiveness (i.e., who has a high forgiveness ability level in a certain instance) should find both of the statements above more difficult to endorse than someone who has not forgiven his or her offender (i.e., who has a low forgiveness ability level in a certain instance). By estimating item difficulties via summing the scores for each item across all persons, and by estimating individual differences in ability level via summing each individual's scores across all items, it becomes possible to model the probability p of endorsing an item x (where 0 = item not endorsed and 1 = item endorsed) as a function of a person's ability level β and item x's endorsability δ according to the following equation:

$$p(x = 1/\beta,\ \delta) = e^{(\beta-\delta)}/(1 + e^{(\beta-\delta)}), \tag{1}$$

(Fox & Jones, 1998, p. 31). Rasch models express the resultant item endorsability and person ability estimates on a common interval-level metric, called the log-odds, or logit. If items fit the Rasch model, then constant differences in person ability levels imply constant differences in log-odds for endorsing items, regardless of item difficulty level (Embretson & Reise, 2000), thereby meeting the criterion of interval-level measurement (Stevens, 1947). Because these logits can be added and subtracted as in Equation (1) above, it becomes possible to predict that a given participant will endorse a given item if his or her ability level exceeds the item's difficulty level (Fox & Jones, 1998). The rating scale extension of the Rasch model (Andrich, 1978) permits the modeling of polytomous (e.g., Likert-type) items. In the context of the rating scale method, odds can be thought of as the likelihood, for instance, of scoring a "3" instead of a "2," or, alternatively, a "4" instead of a "3," on a polytomous item of a given difficulty level by an individual with a given ability level.

Prior to our Rasch analyses, we reverse-scored the six benevolence items from the TRIM so that high scores indicated less forgiveness (as was the case with the avoidance and revenge items). We used an expectation-maximization routine to estimate missing values on the TRIM items for cases missing one or two items (approximately 9% of the cases) before we conducted the Rasch analysis. For results described here, we conducted our analyses on data from 362 participants who were observed on a total of 3812 person-occasions.

Item responses for all participants on all occasions were fit to the Rasch model in a single analysis, with data from each person-occasion contributing 18 items. This approach placed all of the person estimates over time on a common scale, thereby permitting us to study longitudinal change in persons over time (Wright, 1996). Pooling the data in this fashion maximized the precision of item calibrations (Linacre, 2003a), which would have been much lower if we simply took one measurement point from each of our 372 participants and calibrated item difficulties on that smaller sample and then applied those calibration values to the rest of the person-responses. Concerns about ignoring the possible dependencies that were created by the fact that the 3812 person-occasions worth of data did not come from 3812 separate individuals are not warranted in this instance because the effects of such dependencies are limited to their effects on standard errors (Linacre, 2003b). In this study, we were interested in the point estimates of item difficulties and person abilities rather than their standard errors (because we were not conducting any significance tests about the point estimates). Therefore, ignoring any potential dependency for the sake of more precise item calibrations was a reasonable tradeoff. (Note that we do account for the nested nature of the data below by using multilevel longitudinal models.)

The TRIM items fit the Rasch model successfully: Person and item separation reliabilities were 0.92 and 1.00, respectively. Person separation reliability is a measure of the spread of individual differences along the trait dimension. It is analogous to Cronbach's alpha coefficient (corrected for measurement error), and .92 therefore represents excellent reliability. Item separation reliability reflects the amount of spread in item difficulty estimates, and values greater than .80 are considered acceptable (Pesudovs, Burr, Harley, & Elliott, 2007). The fit of individual items to the Rasch model was assessed using unweighted mean-square fit statistics. These fit statistics have an expected value of 1. Fit statistics less than 1.5 contribute effectively to a measurement system, whereas fit values greater than 2 degrade measurement (Linacre, 2003a). In the present sample, item fit values ranged from 0.73 to 1.55. A single unidimensional measure accounted for 83% of the item variance. Based on simulation data, Linacre (2003b) suggests that values greater than 60% indicate good model fit to the data. After accounting for variation attributable to the unidimensional measure, a principal components analysis of residuals indicated that some structure remained in the residuals. Specifically, the largest residual factor appeared to contrast the revenge items from the avoidance and benevolence items. However, modeling this structure would have led to only a small increment in variance explained (only an additional 4% after accounting for the unidimensional measure). In other words, the measure accounted for 20.9 times as much variance as did the residual component. Therefore, we concluded that the TRIM-18 measures a unidimensional construct.

The item difficulties give some clue to the nature of this construct. The five revenge items were the most difficult, with the item reading "I wish something bad would happen to him/her" scoring the highest item difficulty (i.e., the lowest endorsability). The avoidance and (reverse-scored) benevolence items were less difficult. The least difficult items were the reverse-scored benevolence item that read, "I forgive him/her for what he or she did to me" and the avoidance item that read "I don't trust him/her." In other words, one does not have to be very unforgiving to indicate that he or she does not forgive, or trust, someone who has harmed him or her, but one must be considerably less forgiving to wish something bad upon one's offender.

Chang and Chan (1995) recommended evaluating the consistency of item estimates gathered from the same individuals across repeated measurement occasions to determine whether it is reasonable to pool items in a within-persons analysis. To do so, we examined uniform differential item functioning (DIF) across the 21 measurement occasions (Bond & Fox, 2001). DIF involves a comparison of item endorsability ("difficulty") estimates obtained from calibrations from two or more groups. Lack of DIF implies that item locations should be invariant across all calibration samples. To conduct the DIF analysis, we first calibrated item responses from participants across all 21 occasions, which provided anchor values for subject measures and the rating scale structure. Next, scaling was conducted on the data for each of the 21 measurement occasions separately, using anchor values from the combined analysis to equate the measures to a common scale (Bond & Fox, 2001). We evaluated DIF by subtracting difficulty estimates of each item at each occasion from the average estimate across all other time periods. Differences of less than half a logit are considered evidence of stability (Wright & Douglas, 1975). Of 378 contrasts (18 items $\times$ 21 time periods), only one contrast had a logit difference marginally greater than half a logit (.55). These results suggest that the individual items of the TRIM are stable in measurement structure across time.

On the basis of these results, we calculated Rasch-derived measures of forgiveness for each individual on each measurement occasion. We omitted two participants at this stage, one of whom apparently falsified some of his or her data, and another for whom the measurement model provided a poor fit (apparently because of misunderstanding the meaning of one of the items). We transformed the scale so that zero was the lowest estimated person measure and 10 units equaled one logit of difficulty. Because Rasch-derived measures are based on probabilities of item endorsement rather than the raw scale scores themselves, they enable interval-level interpretations. For every one-logit increase in one's standing on the measure, one's log-odds of endorsing an item at any given level of difficulty increases by a value of one. Exponentiating a logit yields an odds; therefore, a one-logit increase in ability implies an $\exp(1) = 2.718$ increase in one's odds of endorsing an item with a given score (e.g., a score of "5" instead of a score of "4").Similarly, a decrease of 1.10 ability logits would indicate a reduction by one third [$\exp(-1.10) = .33$] of the odds of endorsing a given score (Embretson & Reise, 2000).

Relationship-specific variables. Shortly after enrolling in the three protocols whose data were assembled for Study 1, participants rated their perceptions of closeness and commitment to the offender prior to the transgression using seven-point Likert-type scales (lower numbers implied less closeness and commitment, respectively). Participants also completed Aron, Aron, and Smollan's (1992) Inclusion of Other in the Self (IOS) Scale. This single-item, visual analogue measure consists of seven pictures, each of which comprises two circles marked "self" and "other" that use progressively increasing degrees of overlap between the two circles to symbolize increasing degrees of closeness that someone might experience toward another person. We created a linear composite of these three measures (*alpha* = .92), which has been correlated with forgiveness in previous work (McCullough et al., 1998).

Offense-specific variables. Participants rated the perceived painfulness of the transgression, the extent to which they attributed responsibility to the transgressor, and the extent to which they viewed the transgression as an intentional violation, on seven-point Likert-type scales (see also McCullough et al., 2003). Participants also used two seven-point Likert-type scales to indicate the extent to which their offender apologized and made amends for the transgression. We combined these latter two items to create a scale (*alpha* = .82).

Personality variables. Participants also rated their own personalities (in response to the stem, "I see myself as someone who . . .") using the Big Five Inventory (BFI; John, Donahue, & Kentle, 1991). The BFI comprises 44 brief descriptive phrases that are prototypical markers for five broad personality dimensions: Agreeableness (e.g., "is generally trusting"), Conscientiousness (e.g., "does a thorough job"), Extraversion (e.g., "is outgoing, sociable"), Neuroticism (e.g., "can be moody"), and Openness ("likes to reflect, play with ideas"), which participants rate on an 5-point scale (1 = *disagree strongly*; 5 = *agree strongly*). Alpha reliabilities and test—retest reliabilities for the five subscales range from .80 to .90 (John & Srivastava, 1999). Forgiving people tend to score low on Neuroticism and high on Agreeableness (McCullough, 2001).

Analyses

Major analyses proceeded in two steps. First, we evaluated the fit of the linear and nonlinear growth models that have been commonly used to model forgetting as a function of time since learning (Wixted & Ebbesen, 1997). These models appear in Table 1.

Because our data set involved a set of repeated measures nested within individuals, they conformed to a multilevel structure. Therefore, we ran linear and nonlinear mixed-effect models using the nlme library in the R statistical package (Pinheiro & Bates, 2000). Within a multilevel framework for longitudinal data, variation in a set of repeated measures is partitioned into between-persons effects and within-persons effects. For example, one might model the variation in a set of repeated measures y for person j on occasions 1 to i as a function of an initial status and a rate of linear change (as in McCullough et al., 2003) using the equation:

$$y_{ij} = \beta_{0j} + \beta_{1j}(\text{Time}_{ij}) + r_{ij} \tag{2}$$

where β_{0j} = person j's initial status, or expected value on y when Time is 0, β_{1j} = the expected rate at which person j's scores on y change as a linear function of time, and r_{ij} = a residual representing the difference between y_{ij} and the value that would be predicted on the basis of the β_{0j} and β_{1j}estimates. These residuals r_{ij} include measurement error and substantive variation in y_{ij} that might be explained with other variables that differ within person j as a function of time (McCullough & Root, 2005; Singer & Willett, 2003).

Between-persons variation in the β_{0j} and β_{1j} estimates is modeled as

$$\beta_{0j} = \gamma_{00} + u_{0j} \quad \text{and}$$
$$\beta_{1j} = \gamma_{10} + u_{1j}, \tag{3, 4}$$

where γ_{00} and γ_{10} estimate the expected initial status and rate of linear change for the entire population of individuals, respectively, and u_{0j} and u_{1j} represent person j's deviation from those population values. Between-persons variation in u_{0j} and u_{1j}, therefore, represents variation in the extent to which people manifested a negative reaction to their transgressions immediately after the transgressions occurred and in the rates in which those motivations became less negative over time (i.e., the rate at which they forgave), respectively. This between-persons variation can be predicted on the basis of variables that differ across participants (e.g., characteristics of their relationships with the transgressors, the transgressors' post-transgression behaviors, or personality variables).

In addition to the linear within-persons model of Equation (2), we also evaluated a quadratic model by introducing a term for the squared

Table 1
Candidate Equations for the Forgiveness Function, Plus the Bayesian Information Criterion (BIC) Values That Resulted for Each Model (Study 1)

Function	Equation	BIC
Intercept only	$y_{ij} = \beta_{0j} + r_{ij}$	27164.00
Linear (initial status + slope)	$y_{ij} = \beta_{0j} + \beta_{1j}(Time_{ij}) + r_{ij}$	25424.57
Quadratic	$y_{ij} = \beta_{0j} + \beta_{1j}\,(Time_{ij}) + \beta_{2j}(Time_{ij})^2 + r_{ij}$	25318.35
Exponential	$y_{ij} = \beta_{0j} * \exp(-\beta_{1j} * Time_{ij})$	25659.12
Logarithmic	$y_{ij} = \beta_{0j} + \beta_{1j} * \ln(\text{Time}_{ij}) + r_{ij}$	25399.98
Power	$y_{ij} = \beta_{0j} * \text{Time}^{-\beta 1j} + r_{ij}$	25822.16
Hyperbolic	$y_{ij} = 1/(\beta_{0j} + \beta_{1j} * \text{Time}_{ij}) + r_{ij}$	26953.45
Exponential-power	$y_{ij} = \beta_{0j} * \exp(-2 * \beta_{1j} * \text{sqrt}(\text{Time}_{ij})) + r_{ij}$	25668.12

effect of time to identify whether it was appropriate to evaluate more sophisticated nonlinear models. Growth models that permit curvilinearity to enter the model through a linear transformation of time (e.g., the quadratic model, which allows for a bend in people's trajectories by adding time-squared as a predictor) are useful for detecting curvilinearity, but they do not model nonlinearity realistically because they imply infinite increases (or infinite decreases) in the dependent variable as one moves in either direction away from the point where slope = 0. For realistic models of change, one must turn to truly nonlinear models in which the parameters have the potential to carry substantive psychological meaning (Singer & Willett, 2003). Thus, after evaluating the quadratic model in detail, we proceeded to evaluate the exponential, logarithmic, power, hyperbolic, and exponential-power functions, which have been commonly used to approximate forgetting (Wixted & Ebbesen, 1997). For all of these models, change estimates were scaled in such a way that as scores became smaller and smaller, more and more forgiveness was occurring. In other words, the more that an individual's scores appeared to decay or decline over time, the more forgiveness that participant experienced over time.

We evaluated relative model fit with the Bayesian Information Criterion (BIC; Pinheiro & Bates, 2000). Raftery (1995) proposed that a BIC difference ≥10 between two models should be taken as "very strong" evidence in favor of the model with the smaller BIC because it implies a posterior probability >99% in favor of the model with the smaller BIC. Likewise, a model whose BIC is 6–10 units smaller than a competing model has "strong" evidence in its favor, as this implies a posterior probability of 95–99% in favor of the model with the smaller BIC.

After assessing the strengths and weakness of various mathematical models of the forgiveness function, we extracted person-specific estimates of initial status and forgiveness and attempted to predict the individual differences in forgiveness rates based on initial status and the relationship-specific, offense-specific, and personality variables described above.

Results

Table 2 shows means and standard deviations for major study variables, and Table 3 shows their correlations. Figure 1, which depicts the data from 15 randomly selected participants, shows that most participants' scores declined over time or stayed flat (that is, most participants appeared to experience some forgiveness, or very little forgiveness, but relatively few appeared to become more unforgiving over time). Such trajectories can be easily modeled with two-parameter models that permit varying initial status estimates and varying rates of change.

The Multilevel Models for Depicting Change

Table 1 provides the BIC values for each of the multilevel models we tested. As Table 1 shows, a linear model that describes people's trajectories in terms of an initial status plus a constant rate of change as time since the transgression increases (BIC = 25424.57) provided a better fit than did the "intercept-only" model (BIC = 27164.00). Thus, true change occurred for some participants. A third model in which we added the squared effect for time to permit curvature in people's trajectories provided an even better fit (BIC = 25318.35), suggesting that the shape of change was not strictly linear. In the quadratic model, the term for linear change was negative (suggesting that people tended to experience forgiveness over time), but the term for quadratic change was positive (suggesting that the rate of forgiveness itself became smaller with the passage of time).

As noted above, quadratic models are unrealistic in the long run for describing a psychological process like forgiveness because they imply growth without limit on either side of the point where slope = 0; that is, they imply that people become more and more forgiving over time until they reach a trough, and then they become *less and less* forgiving as time approaches infinity.[1] Therefore, we suspected that the upward curvature in our data that the quadratic model identified was caused by a methodological artifact known as *reactivity* (Haynes, 1978), by which values of a construct change as a result of the measurement process itself: By overmeasuring participants in the first few days following their transgressions, their TRIM scores might have dropped more quickly (or more slowly) than if we had measured them less frequently.

We reasoned that we might be able to identify the operation of such a measurement artifact by simultaneously regressing partic-

Table 2
Means and Standard Deviations for Major Study Variables (Study 1)

Variable	*M*	*SD*
Rasch Derived TRIM Scores[a]	51.09	15.00
Openness[b]	3.73	0.62
Conscientiousness[b]	3.67	0.68
Extraversion[b]	3.70	0.74
Agreeableness[b]	3.87	0.65
Neuroticism[b]	3.01	0.84
Closeness/commitment[c]	3.02	1.94
Transgression painfulness[c]	4.02	1.28
Responsibility attribution[c]	4.93	1.37
Intentionality attribution[c]	3.23	1.93
Apology/making amends[c]	2.25	1.82

[a] N = 3812 (because multiple observations were nested within individuals). [b] N = 361. [c] N = 368.

[1] There is also an important practical reason to avoid depictions of longitudinal change that use power polynomials (e.g., quadratic effects for time) to depict curvature: the basis coefficients used to represent linear change and higher-order forms of change will be extremely highly correlated. Consider the correlation of the vector [0 1 2 3 4 5], which might be used as basis coefficients to represent linear change across six equally spaced time points, and the vector [0 1 4 9 16 25] which might be used as basis coefficients to represent quadratic change across the same time interval. Their correlation is r = .96. Because of this high degree of collinearity, the random effects (i.e., individual differences in estimates of linear and quadratic change) will also be very highly correlated—especially when the data sets are unbalanced due to missing data or person-specific measurement regimes (Hedeker, 2004). In Studies 1 and 2, the random effects for linear change and quadratic change were correlated at r = −.96 and −.98, respectively. In other words, neither the linear component nor the quadratic component carries unique information about individual differences in change, and this is a serious dilemma because they must be partialed from each other to faithfully represent linear and quadratic effects, respectively (Cohen, 1978). There are no good ways to resolve these shortcomings of using power polynomials in longitudinal research if one wishes to preserve the psychological meaning of the initial status value, as we do here (Hedeker, 2004).

Table 3
Correlations of Major Study Variables (Study 1)

	Initial status	# of TRIMs	Length of follow-up	Openness	Conscien.	Extravers	Agreeab.	Neurot.	Sex	Closeness/ commit.	Transgr. painful.	Respons. attribut.	Intent. attribut.
# of TRIMs	.34***												
Length of follow-up	−.23***	−.53***											
Openness	.02	.03	−.10										
Conscien.	.01	.03	.09	.10									
Extravers.	.06	−.02	−.01	.23***	.10								
Agreeabl.	−.07	.03	.01	.06	.34***	.10							
Neurotic.	.01	−.04	.02	.06	−.23***	−.25***	−.24***						
Sex	.00	.08	−.16**	.03	−.15**	−.08	−.14*	−.23***					
Closeness/commit.	−.37***	−.26***	.10	.00	.02	−.02	−.06	.05	−.05				
Transgr. painfulness	.20***	.15**	−.01	.08	.10	−.12*	.01	.17**	−.16**	.07			
Respons. attribution	.20***	.03	.06	.02	.05	−.01	.02	.01	−.02	−.12*	.14**		
Intention. attribution	.13*	.02	−.03	.11*	−.01	−.01	.00	.01	.01	−.19***	.02	.18**	
Apology/amends	−.09	−.09	−.01	−.13*	−.03	−.02	−.03	−.04	.04	.42***	.07	−.06	−.32***

* $p < .05$. ** $p < .01$. *** $p < .001$.

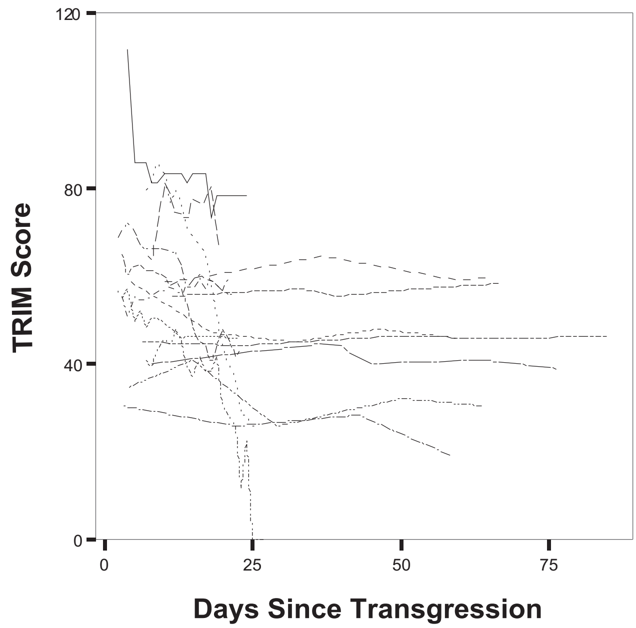

Figure 1. Trajectory plots for 15 randomly selected cases (Study 1).

ipants' person-specific estimates of quadratic change onto (a) their estimates of initial status (to control for any dependencies between people's initial status estimates and their rates of change), (b) the number of TRIMs participants completed ($M = 10.53$, $SD = 7.73$, range = 1–21); and (c) the amount of time between the occurrence of the transgression and the last measurement taken, which we called "length of follow-up" ($M = 41.57$ days, $SD = 23.23$ days, range = 1–100 days). This third variable is important because if the amount of time between the transgression and the final measurement is relatively long, that final observation becomes particularly influential on the overall shape of the fitted function, and should reduce the appearance of any curvature imposed on the curves by too-frequent measurement during the first few weeks post-transgression (Singer & Willett, 2003). In other words, a measurement that is a very long way away from the offense should help to smooth out artificially fast rates of forgiveness caused by too-frequent measurement early on in the measurement process.

In this regression model, length of follow-up was negatively associated with the degree of upward curvature in participants' data (*beta* = −.21, $t = -3.57$, $p < .001$), suggesting that we may indeed have introduced artificial curvature into participants' data by measuring their TRIM scores too frequently in the initial weeks following their transgressions. Initial status also had a significant unique association with quadratic change (*beta* = .29, $t = 5.64$, $p < .001$), but the number of TRIMs completed did not (*beta* = −.00, $t = -0.07$, $p = .95$). With all three predictor variables controlled, the intercept for the regression did not differ significantly from zero (B = −.003, $SE = .002$, $t = -1.37$, $p = .17$), suggesting that when we control for individual differences in the features of participants' measurement regimes, quadratic change disappears.

On this basis, we decided to explore a series of two-parameter models to determine which of them provided the best fit to the data (in between-persons analyses to be summarized below, we controlled for number of TRIMs completed and length of follow-up to control for measurement artifact). Of the nonlinear models, the logarithmic model provided the best fit to the data (BIC = 25399.98), and by Raftery's (1995) rules of thumb, the evidence in favor of the logarithmic model relative to the other two-parameter models was "very strong:" the next-best-fitting two-parameter model (the linear model) had a BIC that was 24 units higher than the BIC for the logarithmic model, and the other nonlinear models had BICs that were hundreds of units higher than the BIC for the logarithmic model. Thus, we concluded that the best two-parameter model depicted forgiveness as linear in the natural log of time. Figure 2 demonstrates the typical trajectories implied by the fixed effects results from the eight growth models in Table 1.

Of the 326 participants for whom we could run within-subjects ordinary least squares growth models, only 19 (5.8%) of them had rates of logarithmic change that were significantly larger than zero. In other words, the idea that forgiveness is produced by a decay mechanism that varies in strength across persons provided a good description for 94% of participants. In Figure 3, we have depicted the estimated logarithmic functions (based on estimated initial statuses and rates of logarithmic change) for three participants: (a) a participant whose estimated initial status was approximately one standard deviation below the mean; (b) a participant whose estimated initial status was at the mean, and a participant whose estimated initial status was approximately one standard deviation above the mean. These functions illustrate the diversity of forms that the logarithmic model can accommodate effectively.

According to the population-level parameters (or "fixed effects") of the logarithmic model, the typical person in the sample had an initial status of 60.93 and a change (or forgiveness) rate of 4.49 units (with 10 units equal to one logit of difficulty) per log-day. In other words, after three months (i.e., 91 days) had passed following the transgression, the typical person would have been expected to experience a reduction of $4.49*\ln(91) = 20.25$ units, or 2.03 logits. Exponentiating 2.03 reveals that the typical person therefore would have experienced a 7.61-fold reduction in their odds of endorsing any particular item with a certain response (e.g., "strongly agree") versus the less intense response (e.g., "agree").

The initial status and logarithmic change (i.e., forgiveness) rates varied significantly across persons ($SD = 21.03$ and 7.68, respectively, $ps < .05$), and were significantly and negatively correlated ($r = -0.79$). Thus, people who were relatively unforgiving immediately after they were harmed (i.e., those people who had high initial status estimates) also had relatively high rates of forgiveness (i.e., more negative rates of logarithmic change) during the follow-up period (see also McCullough et al., 2003, who reported a negative correlation between initial status and rate of change).

Predicting Individual Differences in Forgiveness (Measured as Rates of Logarithmic Change)

Table 4 summarizes the results of an ordinary least squares regression in which we regressed the person-specific estimates of forgiveness (expressed as rates of change with respect to the natural log of time) onto people's initial status estimates and the personality variables, relationship-specific predictors, and offense-specific predictors (as well as the number of TRIMs they completed and the length of observation period, which as noted above, help to correct for the likely effects of measurement reactivity).

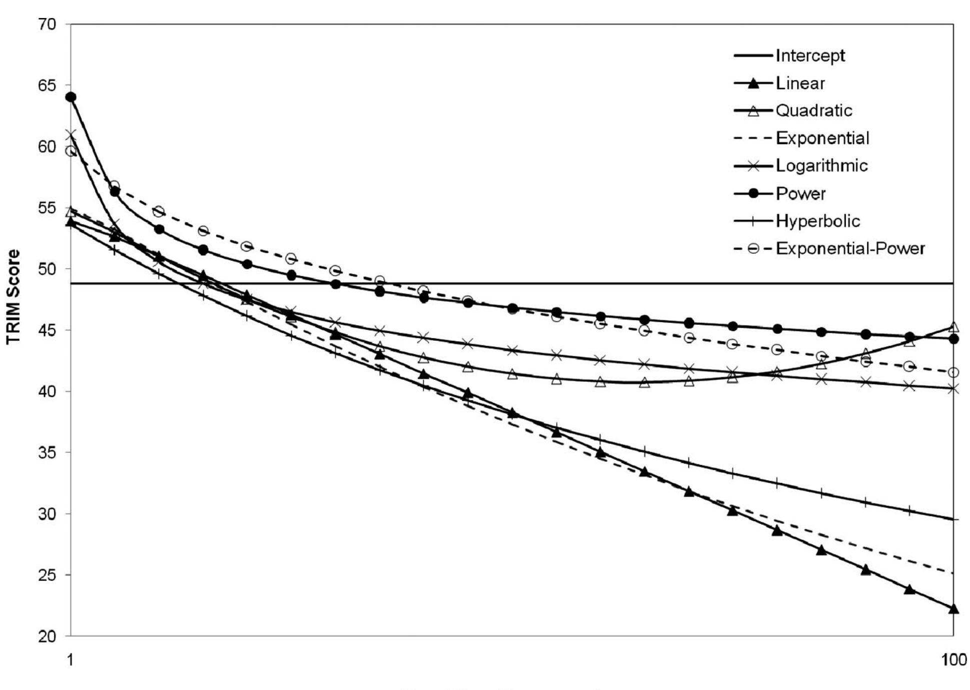

Figure 2. Expected forgiveness trajectories under eight different models of the forgiveness change process (Study 1).

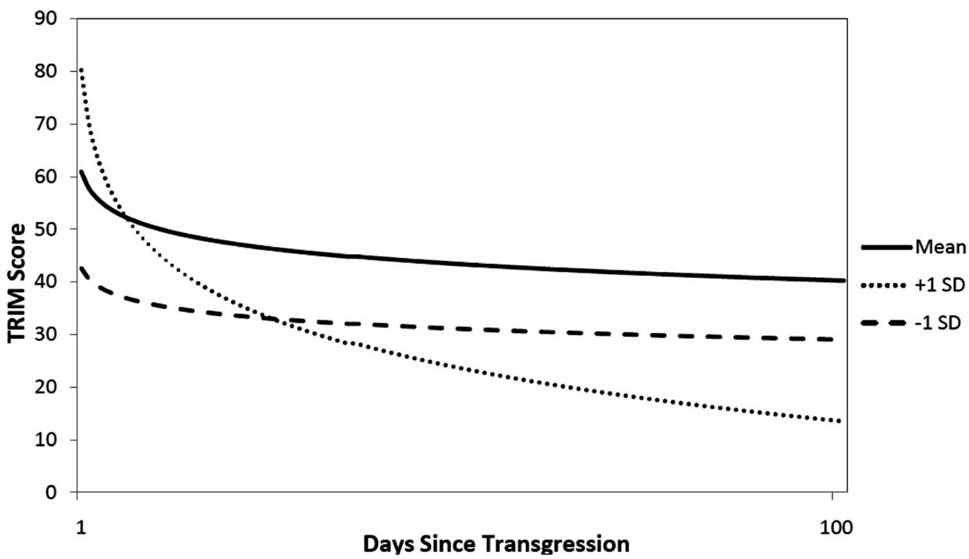

Figure 3. Actual estimated logarithmic functions for participants whose initial status estimates were approximately one standard deviation above the mean, approximately at the mean, and approximately one standard deviation below the mean (Study 1).

Overall, this equation predicted 68.0% of the variance in forgiveness. The personality, relationship-specific, and offense-specific variables accounted uniquely for 10.4% of the variance in forgiveness even after controlling for initial status estimates, number of TRIMs completed, and length of follow-up.

In particular, people who were high on Agreeableness had significantly higher rates of logarithmic decay, as did people who had higher levels of closeness/commitment to their transgressors prior to the transgression and whose transgressors made a lot of effort to apologize and make amends. People who evaluated the transgressions as intentionally committed, and who viewed their transgressors as highly responsible for the transgression, had lower decay rates. These findings provide evidence for the construct validity for interpreting logarithmic decay as "forgiveness:" Agreeableness, transgression painfulness, closeness/commitment, and so forth are well-known cross-sectional correlates of forgiveness (McCullough, 2001; but cf. McCullough et al., 2003, who found that high attributions of responsibility were correlated with faster rates of forgiveness).

Study 1 Discussion

In Study 1, we found evidence that forgiveness can be conceptualized as a logarithmic function of time, with the apparent superiority of a quadratic model evidently due to measurement artifact. The logarithmic model provided a better fit to these data

Table 4
Regression of Between-Persons Differences in Forgiveness (Rate of Logarithmic Decay) on Personality, Relationship-Specific, and Offense-Specific Variables (Study 1)

Predictor	Coefficient	Standard Error	Standardized β	Semi-partial *r*
Initial status	.33	.01	.92***	.77
No. of TRIMs	−.05	.04	−.06	−.05
Length of follow-up	−.02	.01	−.05	−.04
Openness	.06	.36	.01	.01
Conscientiousness	.64	.35	.06	.06
Extraversion	.25	.31	.03	.02
Neuroticism	−.01	.29	−.03	−.00
Agreeableness	.86	.36	.08*	.07
Participant gender	.60	.53	.04	.03
Closeness/commitment	.78	.13	.22***	.18
Transgression painfulness	−.33	.19	−.06	−.05
Responsibility attribution	−.55	.16	−.11**	−.10
Intentionality attribution	−.24	.12	−.07*	−.06
Apology/making amends	.43	.14	.11**	.10

Note. $N = 355$; Model R-squared = .68.
* $p < .05$. ** $p < .01$. *** $p < .001$.

than did any of the other two-parameter models that are regularly used to model forgetting (Wixted & Ebbesen, 1997). Furthermore, we found that individual differences in participants' rates of logarithmic decay were associated with several of the offense-specific, relationship-specific, and personality characteristics (e.g., relationship closeness/commitment, perceived intentionality of the transgression, apology/making amends, and Agreeableness) that have commonly been associated with forgiveness in previous research. These latter associations lend confidence that the rates of logarithmic decay that we estimated for each person were indeed measuring the construct that we presumed they were measuring.

We wished to characterize further the process that promotes forgiveness—that is, decay in people's transgression-related interpersonal motivations, and at the same time, test a key evolutionary hypothesis regarding forgiveness. Based on an understanding of the selection pressures that gave rise to humans' propensity to forgive (Hamilton, 1964; Trivers, 1971) as well as more recent work from theoretical biology (Axelrod & Hamilton, 1981; Hruschka & Henrich, 2006; Nowak, 2006) and primatology (Watts, 2006), McCullough (2008) proposed that psychological representations of relationship value are fundamental to the computations that activate humans' propensities to forgive. When people who are harmed by another person perceive that the individual who harmed them, and their relationship with that person, have long-term value, then they will tend to forgive the individual who harmed them. The effects of relationship value are indirectly shown in many studies (Finkel et al., 2002; Karremans, Van Lange, Ouwerkerk, & Kluwer, 2003; McCullough et al., 1998), including the present Study 1, which demonstrated that measures of relationship commitment/closeness are positively associated with forgiveness. Therefore, we explicitly evaluated the role of perceived relationship value as a predictor of forgiveness in Study 2.

We also wished to address some of Study 1's limitations. The cobbled-together nature of the data set in Study 1 meant that some participants provided intensive data (i.e., up to 21 measurements) for 4–5 weeks following the transgressions they had incurred, whereas other participants provided relatively few measurements (e.g., no more than 5) for up to several months following their transgressions. It therefore seemed important to confirm the relatively good fit of the logarithmic model using a data set in which the same participants provided intensive data for several weeks following their transgressions as well as long-term follow-up data. In addition, the unexpectedly good fit of the quadratic model, and our speculations that it was due to measurement reactivity, merited further exploration. To address these issues, we conducted Study 2.

Study 2

Method

Participants. Participants were $N = 125$ undergraduate students (92 women, 33 men; M age = 19.24 years; SD = 2.04 years) from the University of Miami. On a measure of racial identity, 65.6% of participants identified themselves as "White," 12% identified themselves as "Black or African American," 6.4% identified themselves as "Asian," 1.6% identified themselves as "Native Hawaiian or Other Pacific Islander," and 14.4% declined to provide a response. On a separate item regarding Hispanic/Latino ethnicity, 75.2% identified themselves as "not Hispanic/Latino," 21.6% identified themselves as "Hispanic/Latino," and 3.2% declined to provide a response.

All participants reported that they had recently incurred an interpersonal transgression. By the time we obtained participants' first self-report measures of forgiveness, an average of 10.68 days had passed since their transgressions occurred. Participants received credit in their introductory psychology courses for their participation, and up to $100 for participating in the tasks described herein and other tasks not relevant to this study. Of the 125 participants, 62 participants also completed a follow-up measure of the TRIM approximately three months after completing an initial group of up to 21 daily measures.

Measures

Participants completed repeated measures of the TRIM Inventory, as did participants in Study 1. Shortly after enrolling in the study, participants also completed self-report measures of closeness/commitment, perceived transgression painfulness, perceived responsibility/blameworthiness of the transgressor, perceived intentionality of the transgressor's actions, and perceived apology/making amends as in Study 1.

Perceived relationship value. Shortly after enrolling in the study, participants also completed 10 self-report items, using a five-point Likert-type scale (1 = *strongly disagree* to 5 = *strongly agree*) that measured their thoughts about the offender's continued value to them as a relationship partner, which we call the Perceived Relationship Value Scale (see Appendix A). The internal consistency of the unweighted linear composite of these 10 items was *alpha* = .92.

Procedure

We contacted potential participants through short presentations in their psychology courses, and through a web site that introductory psychology students used to select and register for studies to complete in fulfillment of a research participation requirement. All interested potential participants then received an initial screening packet that included an informed consent form and several short screening questions. Participants whom we deemed eligible for participation on the basis of this information were then enrolled in the study. At this time, participants came to the first author's laboratory to pick up an initial packet containing the relationship-specific and offense-specific measures described above. In addition, we e-mailed to participants a set of 21 unique URL links to a secure Internet server, asking them to activate one of those links each day so that they could complete a brief daily questionnaire (including the TRIM-18 inventory for measuring forgiveness). After finishing each daily survey, participants' responses were automatically time-stamped and saved on an SSL-encrypted server.

Approximately one month after enrollment, participants subsequently completed a variety of other tasks in the laboratory that are not relevant to the present project. Then, approximately three months after their last laboratory visit, we e-mailed participants a final URL that enabled them to complete a final TRIM measurement. Thus, we attempted to acquire intensive (i.e., daily) TRIM measurements from each participant for up to 21 occasions after enrollment, and then a follow-up measurement some three months after their transgressions occurred.

Analyses

Analyses were essentially identical to those used in Study 1. First, we applied the rating scale version of the Rasch model (Andrich, 1978) to the TRIM data as in Study 1. To ensure comparability of our measurement structure across studies, we used the item structure obtained in Study 1 to anchor the items in Study 2. In other words, item locations in Study 2 were fixed at the values obtained from Study 1. To check the feasibility of this procedure, we examined the displacement of item locations from the anchor values. Displacement refers to the difference between the anchored (fixed) item locations and the locations that are freely estimated from the current data. Displacements $< |.5|$ logits have little impact on measurement structure (Linacre, 2003b; Wright & Douglas, 1975), and our item displacements ranged from $-.37$ to .24 logits.

Next, we evaluated the linear and nonlinear multilevel models as in Study 1 to determine which model of change provided the best fit to the TRIM data. Third, we regressed the individual differences in forgiveness onto the offense-specific and relationship-specific variables mentioned above, including the Perceived Relationship Value Scale.

Results

Table 5 shows means and standard deviations for major study variables, and Table 6 shows their correlations. Figure 4 represents the data points from 15 randomly selected participants. As in Study 1, these curves suggest that most participants experienced either declines in their scores over time, or else fairly flat trajectories.

The Multilevel Models for Depicting Change

Table 7 provides the BIC values for each of the linear and nonlinear models we used to describe the relations between the TRIM scores and time since the transgression, and Figure 5 demonstrates the expected longitudinal trajectories for each of these models. As can be seen, a linear model that describes people's trajectories in terms of an initial status plus a constant rate of change (BIC = 11644.38) provided a better fit than did an "intercept-only" model (BIC = 12095.34). This suggests that true change occurred for some participants. A third model, in which we added the squared effect for time to permit curvature in people's trajectories, provided an even better fit (BIC = 11237.45), suggesting that the shape of change was not strictly linear. In this quadratic model, the term for linear change was negative (suggesting that people tended to experience forgiveness over time), but the term for quadratic change was positive (suggesting that the rate of forgiveness became smaller as time passed, and after a trough, proceeded upward toward infinity as time approached infinity), closely mirroring the results of Study 1.

As in Study 1, we suspected that the appearance of upward curvature in our data might have been caused by overmeasuring participants in the first few weeks following their transgressions. We evaluated this possibility by simultaneously regressing participants' person-specific estimates of quadratic change on their (a) estimates of initial status; (b) the number of TRIMs participants completed ($M = 15.54$, $SD = 6.03$, range = 1–22); and (c) the amount of time between the occurrence of the transgression and the last measurement taken—that is, length of follow-up ($M = 81.69$ days, $SD = 54.90$ days, range = 5.68–174.50 days). In this regression model, length of follow-up was, with marginal statistical significance, negatively associated with the degree of upward curvature in participants' estimated trajectories (*beta* $= -.17$, $t = -1.71$, $p = .09$). As in Study 1, this result implies that simply measuring participants' TRIM scores after a large amount of time has passed leads to reduced estimates of curvature, probably due to the fact that measurements that are far from the zero value for time are highly influential in estimating growth forms (Singer & Willett, 2003). Neither initial status (*beta* $= .11$, $t = 1.14$, $p = .26$), nor the number of TRIMs completed (*beta* $= .09$, $t = 0.96$, $p = .34$) had significant unique associations with quadratic change. As in Study 1, with all three predictor variables controlled, the intercept for the regression did not differ significantly from zero (B = .000, $SE = .002$, $t = 0.13$, $p = .90$). From this set of results, we inferred that the relatively good fit of the quadratic model here, as in Study 1, was due to overmeasurement in the earliest weeks post-transgression, which led people's rates of forgiveness to be initially steeper than they would have been had we not measured participants so frequently. In other words, we concluded that the relatively good fit of the quadratic models was an artifact of measurement reactivity (Haynes, 1978).

On this basis, we turned to testing the fit of the two-parameter nonlinear models that we explored in Study 1. Of these nonlinear models, the logarithmic model provided the best fit (BIC = 11401.28)—as was the case in Study 1. The hyperbolic model did not converge in Study 2. The fact that the next-best-fitting nonlinear model had a BIC value that was 97 units higher than the value for the logarithmic model is "very strong" evidence that the logarithmic model is superior to the other two-parameter models we estimated (Raftery, 1995). Thus, we concluded that the best two-parameter model depicts forgiveness as linear in the natural log of time.

Of the 110 participants for whom we could run within-subjects ordinary least squares growth models, only 5 (4.5%) had logarithmic rates of change that were significantly larger than zero. These five participants appeared to become more *unforgiving with time*.

Table 5
Means and Standard Deviations for Major Study Variables (Study 2)

Variable	M	SD
Rasch derived TRIM scores[a]	46.69	13.78
Closeness/commitment[b]	4.74	1.45
Transgression painfulness[b]	4.95	0.85
Responsibility attribution[b]	5.15	1.07
Intentionality attribution[b]	3.25	2.01
Apology/making amends[b]	2.17	1.83
Perceived relationship value[b]	2.53	1.13

[a] $N = 1819$ (because multiple observations were nested within individuals). [b] $N = 115$.

Table 6
Correlations of Major Study Variables (Study 2)

Variable	Initial status	Sex	Closeness/ commitment	Transgress. painfulness	Respons. attribution	Intentionality attribution	Apology/ amends
Sex	.02						
Closeness/commitment	−.06	−.09					
Transgress. painfulness	.05	−.14	.31**				
Respons. attribution	.25**	−.01	−.21*	.09			
Intentionality attribution	.02	.06	−.28**	−.17	.11		
Apology/amends	−.16	−.01	.34***	.21*	−.02	−.27**	
Perceived relationship value	−.29**	.10	.44***	−.01	−.25**	−.33***	.17

* $p < .05$. ** $p < .01$. *** $p < .001$.

In other words, the idea that forgiveness is produced by a decay mechanism that varies in strength across persons described 95% of the participants in our sample (vs. 94% in Study 1). In Figure 6, we have depicted the estimated logarithmic functions (based on estimated initial statuses and rates of logarithmic change) for three participants: (a) a participant whose estimated initial status was approximately one standard deviation below the mean; (b) a participant whose estimated initial status was at the mean, and a participant whose estimated initial status was approximately one standard deviation above the mean. These functions illustrate the diversity of forms that the logarithmic model can accommodate effectively.

According to the population-level parameters (or "fixed effects") of the logarithmic model, the typical person in the sample had an initial status of 59.05 (vs. 60.93 in Study 1) and their scores declined at a rate of 4.26 units (vs. 4.49 units in Study 1) per log-day, with 10 units equal to one logit of difficulty. In other words, after 3 months (i.e., 91 days) had passed following the transgression, the typical person would have experienced a reduction of $4.26 * \ln(91) = 19.22$ units, or roughly 1.92 logits (which was extremely close to the estimate of 2.03 logits from Study 1). Exponentiating 1.92 shows that the typical person would have experienced a 6.82-fold reduction (vs. 7.61 in 2 Study 1) in their odds of endorsing any TRIM item (all of which are scored so that higher scores equal less forgiveness) at a given level of difficulty.

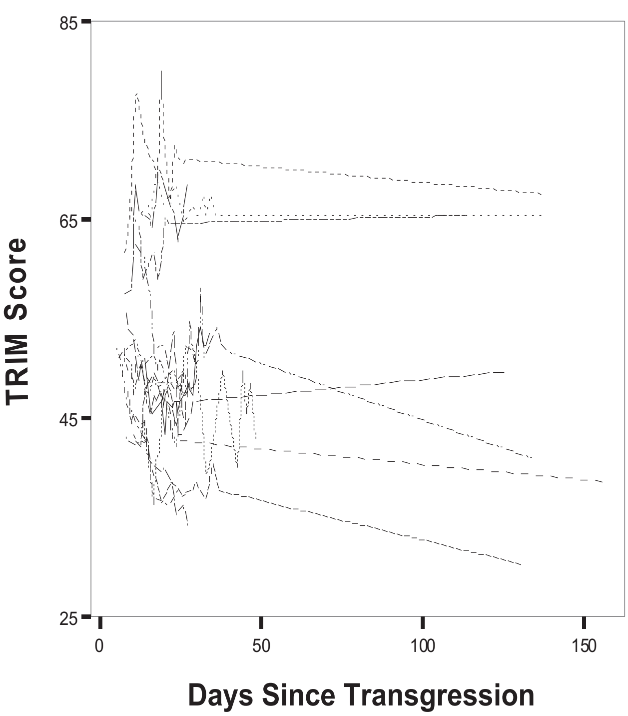

Figure 4. Trajectory plots for 15 randomly selected cases (Study 2).

The initial status and logarithmic change (i.e., forgiveness) rates varied significantly between persons ($SD = 18.44$ and 6.09, respectively, $ps < .05$), and they were significantly and negatively correlated ($r = -0.76$, vs. -0.79 in Study 1). Overall, the data from Study 2 replicated with a high degree of fidelity the basic conclusions from Study 2 regarding forgiveness as a process of logarithmic decay.

Predicting Individual Differences in Rates of Forgiveness

Table 8 summarizes an ordinary least squares regression in which we regressed the person-specific estimates of forgiveness (expressed as rates of change with respect to the log of time) onto initial status, the relationship-specific and offense-specific predictors, and the number of TRIMs participants completed and the length of follow-up, which as noted above, help to correct for the likely effects of measurement reactivity. As in Study 1, the perceived intentionality of the transgression was uniquely and negatively related to forgiveness, as was the extent to which the transgressor was viewed as responsible/blameworthy for the transgression.

Table 7
Candidate Equations for the Forgiveness Function, Plus the Bayesian Information Criterion (BIC) Values That Resulted for Each Model (Study 2)

Model	BIC
Intercept only	12095.34
Linear	11644.38
Quadratic	11237.45
Exponential	11556.09
Logarithmic	11401.28
Power	11506.43
Exponential power	11498.56

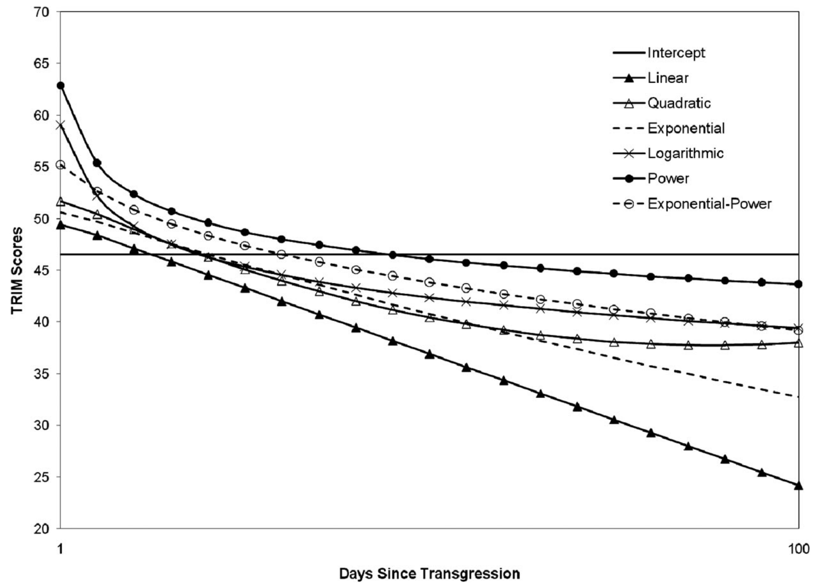

Figure 5. Expected forgiveness trajectories under seven different models of the forgiveness change process (Study 2).

Perceived transgression painfulness was also negatively associated with forgiveness.

Perceived relationship value was also positively associated with forgiveness ($p = .01$) even with all of the other predictor variables in Table 8 simultaneously controlled. In a separate model (omitted here out of regard for manuscript length), perceived relationship value uniquely predicted 2% of the variance in forgiveness after the other predictors in Table 8 were controlled. This result is particularly noteworthy because perceived relationship value was positively correlated with closeness/commitment, r ($N = 125$) = .44, and negatively correlated both with perceived responsibility, r ($N = 124$) = −.25, and perceived intentionality of the transgression, r ($N = 133$) = −.33, all ps < .001. Thus, people who think about the positive and valuable qualities of their transgressors and their relationships with those transgressors end up forgiving to a greater extent, and this is true even after controlling for several other predictors with which perceived relationship value is associated.

Study 2 Discussion

Using a data set in which we measured people's TRIM scores intensively for up to 21 days, and then again approximately 3 months later, Study 2 replicated the results of Study 1 with remarkable precision. As in Study 1, Study 2 revealed that the logarithmic model of change provided the most realistic fit to the

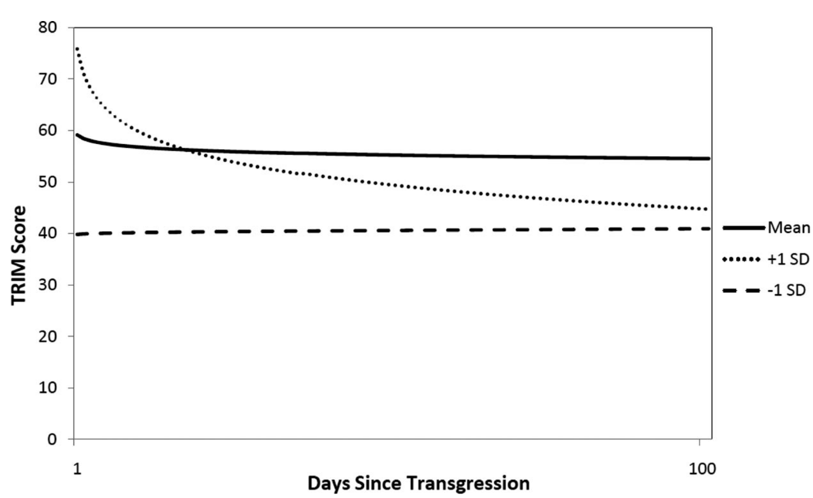

Figure 6. Actual estimated logarithmic functions for participants whose initial status estimates were approximately one standard deviation above the mean, approximately at the mean, and approximately one standard deviation below the mean (Study 2).

Table 8
Regression of Between-Persons Differences in Forgiveness (Rate of Logarithmic Decay) on Personality, Relationship-Specific, and Offense-Specific Variables (Study 2)

Predictor	Coefficient	Standard error	Standardized β	Semi-partial *r*
Initial status	0.29	0.02	0.85^{***}	.77
No. of TRIMs	.00	.06	.00	.00
Length of follow-up	−.01	.01	$-.13^{*}$	−.12
Participant sex	.30	.72	.02	.02
Closeness/commitment	.08	.28	.02	.02
Transgression painfulness	−.82	.30	$-.17^{**}$	−.15
Responsibility attribution	−.90	.31	$-.17^{**}$	−.16
Intentionality attribution	−.37	.18	$-.13^{*}$	−.11
Apology/making amends	.28	.19	.09	.08
Perceived relationship value	.93	.36	$.19^{*}$	.14

Note. $N = 115$; Model R-squared = .65.
$^{*}p < .05$. $^{**}p < .01$. $^{***}p < .001$.

data, and yielded plausible descriptions of the longitudinal trajectories for 95% of the people in the sample. Study 2 also replicated the finding from Study 1 that the amount of forgiving that takes place in the first 3 months following a transgression for the typical person is quite substantial—around 2 logits—which implies approximately a sevenfold reduction in odds of endorsing any single negatively worded item (or a sevenfold increase in odds of endorsing any single positively worded item) at any scale score point (e.g., a "4" on a 1–5 scale) versus the adjacent scale score point. (e.g., a "5"). Also, Study 2 replicated the findings of Study 1 regarding the correlates of forgiveness (in particular, attributions of responsibility and intentionality). Finally, Study 2 revealed that participants' perceptions that their relationships with their offenders retained value (despite the offense) predicted forgiveness, consistent with recent evolutionary theorizing about the environmental inputs that motivate forgiveness (McCullough, 2008).

General Discussion

Scientific progress rests upon the identification of empirical regularities, and the best-established sciences have high numbers of established facts relative to the number of theories devoted to explaining them (Simonton, 2004). In the present paper, we tried to contribute to scientific progress on forgiveness in two ways that should be of value to emotion researchers: (a) identifying an empirical regularity about the form of the forgiveness function, and (b) identifying correlates of individual differences in that function—particularly a new predictor based on evolutionary theorizing (McCullough, 2008).

Forgiveness as Logarithmic Change

Forgiveness is a process of temporal change by which people's feelings and motivations toward people who have harmed them become more positive and less negative (Enright et al.,1992; Exline & Baumeister, 2000; McCullough et al.,1997). Because forgiveness seems to be a process of monotonic change (and because we scaled our dependent variables so that smaller values implied more forgiveness), we tested a variety of two-parameter linear and nonlinear models that can depict monotonic decay (Wixted & Ebbesen, 1997). By doing so, we discovered evidence consistent with the idea that forgiveness is a logarithmic function of time since the transgression. A logarithmic function underlies the Weber-Fechner law governing stimulus-perception relations (Fechner, 1966). Applied here, the Weber-Fechner law implies that as temporal distance from a stimulus (in this case, a transgression) increases geometrically, forgiveness increases linearly.

Although most researchers concede that the Weber-Fechner law has been superseded by the power law (Stevens, 1971) for describing most stimulus-perception relations, one implication of a logarithmic forgiveness function, as with the power function, is that time (or, more precisely, some psychological process that continues through time) in some sense *retards* the progress of forgiveness (Wixted, 2004b; Wixted & Ebbesen, 1997): As time passes, the rate of change becomes smaller. This can be seen by differentiating the logarithmic function with respect to time: In the first derivative, time since the offense appears in the denominator, as it does in the power and exponential-power functions (Wixted & Ebbesen, 1997).

In memory research, one common way to conceptualize the temporally unfolding process that impedes forgetting is to invoke the concept of *consolidation*. Wixted (2004b), for instance, interprets the power law of forgetting as evidence for consolidation, and he invokes neuroscientific evidence suggesting that consolidation is largely the work of the hippocampus. Although researchers have barely scratched the surface of forgiveness in relation to the hundred years of research on the forgetting function (Rubin & Wenzel, 1996), it seems possible that the relatively good fit of a logarithmic forgiveness function means that people's negative feelings toward their transgressors become consolidated at the same time that they are being dissipated by another mechanism that works in the other direction, the net result of which is an ever more stubborn bolus of negative affect and motivation that is, nevertheless, ineluctably worn down over time. Science knows little about the psychological processes that might lead to consolidation in the context of forgiveness—much less about the neural substrates of those processes—but evidence that ruminating about an offense deters forgiveness might be a productive starting point for conceptualizing what consolidation might look and feel like (McCullough, Bono, et al., 2007). In any case, more fine-grained experimental research, perhaps combined with neuropsychological methods, might help to determine whether a consolidation process, combined with a mechanism that promotes decay, is responsible for the logarithmic appearance of the forgiveness function.

By interpreting the logarithmic function as the result of a process of decay plus a process of consolidation, it seems to follow that interventions for influencing forgiveness might be most effective if they are administered relatively early after transgressions have occurred because relatively little consolidation will have occurred at that point in time—just as the formation and decay of memories can be best influenced by processes that occur early in time after initial learning occurs (Wixted, 2004b). It might also be posited that "informal interventions" such as apologies, appeasement gestures, and expressions of contrition (McCullough, 2008) will be most effective if received early after a transgression occurs. These seem like easy ideas to test through experimental and intervention research. For example, in Study 1 we found that forgiveness rates were uniquely correlated with the extent to which offenders apologized and made amends within a few days after the transgression occurred. Do apologies have equally potent effects after one's feelings about an offense have had time to consolidate?

A second implication of a logarithmic model for the forgiveness function is the prediction, due originally to Jost [1897, cited in Wixted (2004a)], that if a person's feelings about two separate transgressions are equally negative at a given point in time, the transgression that happened further in the past will be forgiven less quickly than will the transgression that occurred more recently. This insight might be difficult for clinicians to believe, many of whom have told us over the years that their intuition is that people forgive quite slowly when transgressions have occurred in the recent past, but that forgiveness gets easier as people have time to put the transgression into perspective. Our findings suggest that exactly the opposite is true. A third implication of the present findings is that if two people experience the same initial level of outrage because of an offense but have different rates of forgiveness, then the difference in their levels of forgiveness at any point in time will become ever larger as time passes.

A fourth and final implication of a logarithmic forgiveness function is that the proportionate increase in a stimulus needed to produce a noticeable change in perception at a given background level of the stimulus is constant across all possible background levels. In other words, if someone who reaches a certain level of forgiveness 10 days after a transgression needs to wait another five days to experience a noticeable increase in forgiveness (i.e., after a 50% increase in time), then the same person who reaches a certain level of forgiveness after 100 days will have to wait 50 more days to experience a noticeable increase in forgiveness (i.e., after another 50% increase in time). Applying the Weber-Fechner law to forgiveness, then, implies that people will perceive themselves to make relatively large strides in forgiveness early in the process. As the transgression recedes further and further into the past, however, ever larger amounts of time must pass to obtain similar perceived progress in forgiveness. Whether these implications are correct remains to be evaluated, but explicit tests of these implications would go far in providing further evidence for the logarithmic model of forgiveness that these data suggest.

How Much Change Over Time?

By interpreting the parameters resulting from the logarithmic model, it appears that our participants made rather remarkable progress in forgiving: Within 3 months, the typical person in this study became approximately 7 (7.61 in Study 1; 6.82 in Study 2) times less "able" to endorse a negatively worded item at any given level of difficulty regarding his or her transgressor. Another way of putting this is that after 3 months, it became approximately seven times more difficult for the typical person in our sample to "strongly agree" (vs. "agree") that he or she wanted to see his or her transgressor "hurt and miserable." Stated in this fashion, we think it is clear that a lot of forgiving goes on within the first few months following a transgression (at least within the context of the types of transgressions we have studied here). Indeed, if the logarithmic function is true, someone would have to wait approximately 23 years before they obtained the second 2.03-logit reduction through the processes that generated the first 2.03-logit reduction during the first 3 months in Study 1.

Construct Validity for Forgiveness as Logarithmic Change

In both studies, we found that individual differences in forgiveness, measured as logarithmic change, were correlated with the "robust predictors" of forgiveness that have been identified in previous forgiveness research (Exline et al., 2004). For example, we found that people high in Big Five Agreeableness had higher rates of logarithmic decay than did their less agreeable counterparts. In addition, people were more forgiving of transgressors to whom they felt close and committed. Also, as might be expected, transgressions that were perceived to be painful or for which the transgressor was held responsible were associated with less forgiveness. Finally, people whose transgressors made an effort to apologize and make amends for their behavior experienced relatively fast progress in forgiving (McCullough et al., 1997). In the context of the present study, these findings lend confidence to our interpretation of rates of logarithmic change in our self-report measure as a process of forgiveness. They also lend credence to previous conclusions drawn from cross-sectional and two-wave longitudinal studies regarding the correlates of forgiveness (Finkel et al., 2002; McCullough & Hoyt, 2002; McCullough et al., 1997).

Perceived Relationship Value and Forgiveness

In addition to examining the robust predictors of forgiveness, in Study 2 we also tested the "valuable relationships" hypothesis. This hypothesis, which originates in the assumption that humans' tendencies to forgive arose out of pressures for the evolution of reciprocal altruism (Axelrod, 1984; Trivers, 1971) and possibly kin altruism (Hamilton, 1964), specifies that two individuals who have been in conflict will be motivated to forgive and return to more positive relations to the extent that they view their relationship as retaining long term-value (Aureli & de Waal, 2000; Koski et al., 2007; McCullough, 2008; Watts, 2006). Indeed, recent evolutionary simulations suggest that when relationships with nonkin have very high long-term value, natural selection favors the evolution of agents that forgive their close relationship partners after most defections (Hruschka & Henrich, 2006). The evolution of these high rates of forgiveness in valuable relationships is due to the fact that maintaining and repairing well-established reciprocal relationships can often yield more favorable benefit-cost ratios than can severing those relationships and reestablishing new ones in their place.

Many studies now show that measures of closeness and relationship commitment are key predictors of forgiveness (Finkel et al., 2002; McCullough et al., 1998), and it is implicitly assumed that commitment obtains its association with forgiveness by way of variables such as perceived relationship value. In Study 2, we found that a measure of perceived relationship value did indeed predict forgiveness, even when controlling for measures of relationship closeness and commitment. These results are consistent with McCullough's (2008) contention that forgiveness is the result of an evolved psychological mechanism that turns on computations of relationship value. We do not wish to imply that these results are definitive evidence for any evolutionary hypothesis about the mental computations that govern forgiveness, much less that they demonstrate causal relations. Nevertheless, we do think these results provide a reasonable impetus for future work on the role that perceived relationship value might play in activating humans' tendencies to forgive.

Limitations and Future Directions

A limitation of the present work is that the harms people experienced were quite heterogeneous (ranging, as they did, from insults to parental rejection to sexual infidelity), and we were not able to control for all of the ways in which these experiences differed across persons. It is important to note also that we were unable to control for the nature of people's interactions with their transgressors following the transgression. Later acts of apology and contrition, for example, might have distorted the forgiveness process away from the natural decay process that we were trying to observe; conversely, negative interactions with their transgressions probably exerted effects in the opposite direction. Indeed, the fact that approximately 5% of participants became significantly less forgiving over time suggests that events going on in people's lives were influencing their forgiveness trajectories in ways that we could not control.

Even though people reported that their transgressions were, in general, quite painful (in Study 1, 4.02, and in Study 2, 4.95, on a 0–6 scale, where 3 = *somewhat painful* and 6 = *the worst pain I ever felt*), they were obviously much less severe than the sorts of harms that other researchers have studied (e.g., sexual abuse, intimate partner violence, political persecution, genocide, etc.). Whether these results would generalize to a more severe set of interpersonal harms is unknown. Future work would benefit from a more intensive look at naturally occurring, more severe, and more uniform transgressions.

Finally, we think it would be useful to explore whether our results generalize to other methods with which forgiveness might be measured (e.g., implicit, behavioral, or physiological). In a related vein, it would be most useful to know whether the individual differences in rates of forgiveness that we have observed in this study are correlated with individual differences in the measures of social behavior, health, psychological well-being, and relationship functioning that have been associated with forgiveness in previous cross-sectional and experimental work (Finkel et al., 2002; Karremans & Van Lange, 2004; Karremans, Van Lange, & Holland, 2005; Karremans et al., 2003; Witvliet, Ludwig, & Vander Laan, 2001).

Conclusion

The logarithmic model of forgiveness we have discussed herein has a mechanistic interpretation: that a process, or combination of processes, creates decay in people's negative emotions and motivations regarding a transgressor, and that this process becomes less effective over time. Exactly *what* those processes are that create this form of change remains to be evaluated. Throughout this paper, we have referred to memory research, and perhaps a more explicit integration of memory research with forgiveness theorizing would be fruitful. The processes responsible for forgiveness and the processes responsible for forgetting may have more in common than scientists have heretofore appreciated. For example, if the negative cues that stimulate people to feel avoidant and vengeful toward their transgressors become less salient over time, it seems likely that forgiveness would result. Similarly, if *some* of those cues become stronger through rehearsal (e.g., rumination; McCullough, Bono, et al., 2007), thereby generating a consolidation of the memory of the offense, it seems like this countervailing process might produce the diminishing returns that these data imply.

On the other hand, it is possible that the resemblance of the forgiveness curve to the forgetting curve is purely coincidental. Perhaps if we had scaled our forgiveness variable so that higher scores implied more forgiveness (so that scores gradually increased with the passage of time), we would have tied our results to concepts such as growth, recovery, or development (Singer & Willett, 2003). Finer-grained research could reveal whether the apparent similarity of forgiving and forgetting is deep and substantive, or merely metaphorical. But irrespectively of whether a decay conceptualization or a growth conceptualization is ultimately most apposite, we think that new theorizing about forgiveness that incorporates mechanisms that can produce such changes, and studies that attempt to identify such mechanisms empirically, can do much to elucidate the forgiveness process. At the very least, we hope this paper will be viewed alongside other recent efforts (e.g., Carnelly et al., 2006; Hemenover, 2003; Verduyn et al., 2008) to model affective change and to explore the mechanisms that create it, and efforts from a very different quarter to identify the evolutionary processes that gave rise to humans' capacities to forgive and the proximate mechanisms upon which those capacities rely (Axelrod, 1984; de Waal & Pokorny, 2005; Dreber, Rand, Fudenberg, & Nowak, 2008; Hruschka & Henrich, 2006; McCullough, 2008).

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Appendix

The Perceived Relationship Value Scale

When people remember a negative life event that happened to them, they often have other thoughts in response. We are interested in the thoughts that occurred to you today whenever you thought about the person who hurt you. Please use a number between 1 ("strongly disagree") and 5 ("strongly agree") to indicate whether you had the following thoughts today whenever you thought about the painful event you experienced or the person who hurt you.

1 = Strongly disagree

2 = Somewhat disagree

3 = Neither agree/disagree

4 = Somewhat agree

5 = Strongly agree

1. I thought about the things I still like about our relationship.
2. I realized that there are many good things in our relationship still.
3. I focused on the positives in our relationship.
4. I tried to think about the good times we have shared.
5. I thought of how nice it would be for us to have a strong relationship again.
6. I imagined us having a positive friendship.
7. I thought about his/her strong points.
8. I focused on the good things about him/her.
9. I tried to think about all of the things I like about him/her.
10. I tried to focus on the nice things he/she has done in the past.

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