Social sharing modulates the dynamics of affective arousal

Abstract

Social sharing of emotional experience is nearly universal, yet whether it produces genuine affective recovery or merely interrupts an ongoing experience remains unknown. We applied DynAffect-C, a dynamical systems model that separately estimates endogenous regulatory pull and exogenous perturbation, to experience-sampling data from four independent datasets (N = 382). Social sharing had no effect on valence dynamics. For arousal, sharing simultaneously elevated activation ($\omega_S = 0.029$, $p = .003$) and strengthened the attractor pull returning arousal toward baseline ($\beta_S = 0.029$, $p = .023$), a clean dissociation between perturbative and regulatory channels. To formalize this tradeoff, we introduce the Net Affective Benefit of Sharing (NABS), a person-level index quantifying whether sharing-induced regulatory strengthening outweighs perturbative cost. Individual NABS estimates were broadly distributed around zero ($M = 0.038$, $p = .482$), though one dataset showed reliably positive NABS. No dispositional trait predicted NABS after correction, suggesting that the balance is situational rather than dispositional.

Emotional experience is fundamentally social. Across cultures, event types, and emotional valences, the overwhelming majority of emotional episodes elicit an almost immediate impulse to share with someone what happened and how it felt (Rimé, 2009). This impulse is not incidental: the need to form and maintain meaningful interpersonal attachments is among the most fundamental motivational forces shaping human behavior (Baumeister & Leary, 1995), and its chronic frustration carries well-documented consequences for physical health and mortality (Holt-Lunstad et al., 2010). And yet, despite decades of research on emotional disclosure, we do not have a rigorous answer to what is arguably the most basic question one could ask: when someone shares an emotional experience, does it actually help them recover? Not whether they feel better in the moment of telling, but whether the underlying emotional trajectory resolves more quickly, returns to baseline more cleanly, or whether sharing merely interrupts the experience temporarily while leaving the regulatory architecture untouched. These are not the same thing, and the difference matters enormously. A person who feels calmer during a conversation but spends the following hours at an elevated arousal baseline has not regulated their emotion; they have been briefly distracted from it. Clinical practice, therapeutic tradition, and everyday intuition have long operated on the assumption that disclosure heals, but that assumption has never been subjected to a test capable of distinguishing recovery from interruption, or of identifying the conditions under which sharing tips the balance one way rather than the other. DynAffect-C (Prince et al., 2026), a unified dynamical model of endogenous and exogenous influences on affective change, provides that test for the first time.

The Social Life of Affect

The impulse to share emotional experience is among the most robust findings in the psychology of emotion. Field studies and laboratory experiments alike show that virtually every emotional episode, regardless of valence, intensity, or cultural context, elicits the desire to tell someone about it, and that most people act on this desire within hours of the precipitating event (Rimé, 2007, 2009). This universality reflects something deeper than a preference for conversation. Emotional disclosure is one of the primary mechanisms through which social bonds are formed and sustained: people disclose more to those they already like, disclosers tend to be better liked in return, and the act of disclosure itself generates liking for the listener (Collins & Miller, 1994). Even minimal social contact, far short of full emotional disclosure, reliably elevates positive affect and belonging. People who exchanged a few words with a barista rather than transacting efficiently reported better mood afterward (Sandstrom & Dunn, 2014a), and days characterized by more frequent interactions with acquaintances, however brief, were associated with greater happiness and felt connection (Sandstrom & Dunn, 2014b). These effects reflect the broader capacity of social interaction to regulate affective states, a process Zaki and Williams (2013) formalize as interpersonal emotion regulation, encompassing social modeling, co-regulation, and support provision. That sharing carries these benefits is not in dispute. What is less clear is whether those benefits are large enough, and sustained enough, to outweigh whatever arousal the act of disclosure itself introduces.

When sharing concerns positive experience, its benefits compound. Gable and colleagues (2004) showed that sharing good news with an enthusiastic listener, a process they termed capitalization, amplifies positive affect beyond what the event itself would produce, with the quality of the listener's response mattering as much as the disclosure itself. For negative experience, the evidence is more layered. Landmark laboratory work established that writing about traumatic events produced lasting improvements in physical health and psychological adjustment (Pennebaker & Beall, 1986), an effect replicated across hundreds of studies and linked to cognitive restructuring and the relief of inhibitory effort (Pennebaker, 1997). In daily life, however, sharing's consequences are far less uniform. Experience-sampling studies find that emotion-contingent sharing sometimes attenuates negative affect and sometimes does not, with effects that vary across persons, contexts, and the emotional content being disclosed (Brans et al., 2013). The availability of a responsive listener shapes which regulatory strategies people deploy and how effectively they work (Pauw et al., 2022). Most revealingly, sharing and rumination interact in their downstream consequences: sharing predicts enhanced emotional differentiation when rumination is low, but attenuated differentiation when it is high, suggesting that disclosure and perseverative self-focus operate as competing regulatory forces whose interaction determines the quality of emotional processing (Sels et al., 2024). The pattern that emerges across this literature is one of a process whose benefits are real but conditional, as though sharing contains within it both a regulating force and a destabilizing one, and whether a given person in a given moment ends up on the right side of that balance is something the existing literature cannot predict. The heterogeneity of effects is not noise; it is a signal that something important about the mechanism is not yet understood.

Part of what makes the mechanism hard to study is that people are poor judges of what sharing will feel like before they do it, which means the decision to share is itself shaped by systematic error. Commuters instructed to speak with strangers on their morning train anticipated the experience negatively but reported markedly greater positive affect than those who sat in solitude, a finding that held even when participants were explicitly told that strangers would be willing to talk (Epley & Schroeder, 2014). Epley and colleagues (2022) situate this pattern within the broader phenomenon of undersociality, a pervasive tendency for miscalibrated social cognition to inhibit connection. People overestimate how shallow a meaningful conversation will feel before it happens (Kardas et al., 2022a) and underestimate the pleasure that sustains a conversation as it continues (Kardas et al., 2022b). They learn substantially more from casual strangers than they anticipate (Atir et al., 2022), find spoken communication more humanizing and mind-revealing than equivalent text (Schroeder et al., 2017), and consistently underestimate the reward of simply initiating contact with another person (Schroeder et al., 2022). Misperception extends into the aftermath of completed interactions: people systematically underestimate how much their conversation partner liked them (Boothby et al., 2018), and conversations rarely end when either participant actually wants them to, because each person is uncertain about the other's preferences (Mastroianni et al., 2021). Together these findings establish that the social world is more affectively rewarding and harder to read than intuition suggests. They also establish something with direct bearing on the question of recovery versus interruption: if people routinely misread the emotional consequences of social contact before, during, and after it occurs, then self-report measures taken at any single point in time are an unreliable guide to what sharing is actually doing to the affective system. The experience of a conversation may feel clarifying or cathartic in the moment, and still tip the balance of the affective trajectory in either direction once it ends. What is needed is a method that tracks the trajectory itself.

Individual Differences in the Temporal Dynamics of Affect

Tracking that trajectory requires a precise account of what emotional trajectories look like and what governs them. Emotions do not exist as discrete episodes; they unfold as continuous movements through the two-dimensional space of valence and arousal, the core properties of subjective feeling (Russell, 1980, 2003; Barrett, 2006). Each person's trajectory through that space is organized around a characteristic home base, a stable attractor toward which momentary states continually return, reflecting the default level of operation of the individual's affective system (Kuppens et al., 2010b). Where that home base sits reflects enduring features of personality and adjustment: a more pleasant valence baseline tracks extraversion and positive affectivity, while a more unpleasant one tracks neuroticism and depression risk (Kuppens et al., 2010a). How clearly a person reads their own position in that space matters too. People who make finer-grained distinctions among their co-occurring emotional states respond more selectively to what happens around them; those lower in this capacity for emotion differentiation show blunter, less context-sensitive affective trajectories (Erbas et al., 2018; Erbas et al., 2022; Kalokerinos et al., 2019). Both parameters, where affect is anchored and how precisely it is tracked, are potentially responsive to the act of sharing, which involves narrating, interpreting, and receiving feedback on experience in ways that could plausibly shift the home base or alter the granularity with which the aftermath is differentiated. Whether those shifts tip the balance of the trajectory toward faster recovery or toward prolonged arousal is precisely what a trajectory-level framework is designed to detect, and what snapshot measures cannot.

Beyond where affect is anchored, people differ in how much it moves. Elevated affective variability carries reliable associations with neuroticism, lower self-esteem, and depressive symptomatology, and meta-analytic work confirms that these dynamic signatures carry information about wellbeing beyond what mean affect levels alone reveal, though selectively and in interaction with context (Houben et al., 2015; Dejonckheere et al., 2019). Critically, affect dynamics and behavior are coupled in real time: in large-scale experience-sampling research, current affective state systematically shaped which activities people selected next, including whether those activities were mood-enhancing or mood-decreasing (Taquet et al., 2016). Sharing is one of the most common of those daily choices, which means the decision to disclose is not made from a neutral starting point. It is made from within a particular affective state, and whatever effect sharing has on that state feeds back into the dynamics that prompted it. This bidirectional coupling matters for the balance question: a person in a highly aroused state who shares and feels briefly calmer may simply be returning to a trajectory that was already descending, while a person in a stable state who shares and feels briefly more activated may have introduced a cost that takes time to resolve. Disentangling these possibilities requires modeling the full trajectory, not sampling it at a point.

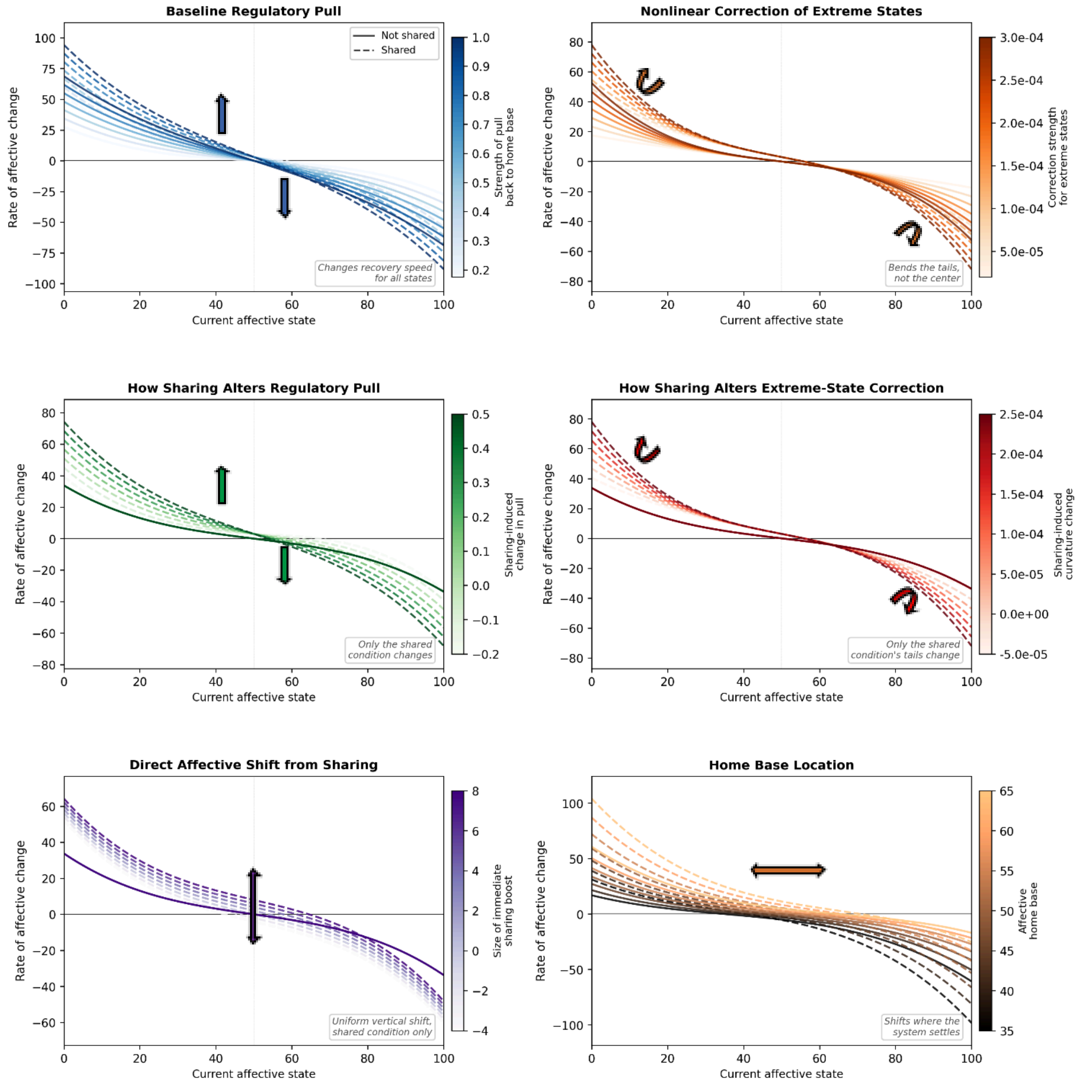

Figure 1. Theoretical illustration of how distinct regulatory processes leave qualitatively different signatures on the dynamics of emotional recovery. Each panel displays the rate of affective change as a function of the current affective state under a dynamical systems model in which affect is continuously drawn back toward an individual's home base. Solid lines represent unshared episodes; dashed lines represent shared episodes. Within each panel, one process is varied (indicated by color intensity) while all others are held constant. The top row shows baseline processes that operate regardless of sharing: the strength of regulatory pull back to the home base (left) and the nonlinear correction that selectively accelerates recovery from extreme states (right). The middle row shows how sharing can alter each of these, changing the slope or curvature of the recovery function for shared episodes only. The bottom row shows a direct affective shift from sharing that uniformly raises or lowers the recovery curve without changing its shape (left) and the home base location that anchors the affective spectrum (right). Critically, each process produces a unique geometric signature that cannot be mimicked by adjusting any other parameter, providing the theoretical basis for their joint identification within a single model.

The central question that a trajectory-level framework must answer is this: after something happens to a person, including the act of sharing itself, how quickly does the affective system return to baseline? That capacity for recovery is governed by attractor strength, the regulatory pull that continuously draws affect back toward the home base (Hayes & Strauss, 1998; Gottman et al., 2002). When this pull is strong, emotional perturbations resolve; when it is weak, affect persists, a phenomenon termed emotional inertia that prospectively predicts the onset of depressive disorder and indexes affective dysregulation more broadly (Kuppens et al., 2010a; Kuppens et al., 2012; Koval et al., 2013; Koval et al., 2016; Koval & Kuppens, 2012). The processes that modulate attractor strength are therefore among the most consequential determinants of emotional wellbeing. Rumination weakens regulatory pull, keeping attention locked on negative content and prolonging emotional states well beyond the events that triggered them (Nolen-Hoeksema et al., 2008; Koval et al., 2012). Cognitive reappraisal strengthens it, with favorable consequences that extend across subjective experience, physiological responding, and social functioning (Gross, 1998a, 1998b, 2015; Gross & John, 2003; Aldao et al., 2010; Butler et al., 2006; Gross & Levenson, 1997; Nezlek & Kuppens, 2008; Houben et al., 2024; Koval et al., 2015). Social sharing sits alongside these as a third major candidate, something people routinely turn to in the aftermath of emotional experience, with plausible mechanisms for both strengthening regulatory pull through co-regulation and normalization, and weakening it through the reactivation of emotional content. The critical point is that both forces are real, and the question is not whether sharing helps or hurts but which force dominates, for whom, and under what conditions. Answering that question requires a model that formally separates them.

DynAffect-C: Endogenous and Exogenous Forces in Affective Change

The dynamical systems approach to affect, applied in psychology through differential equation models of continuous-time change (Hayes & Strauss, 1998; Gottman et al., 2002; Scheffer et al., 2009; Oravecz et al., 2011), provides the natural formal framework for making exactly this distinction. The DynAffect account (Kuppens et al., 2010b) captures affect trajectories as a diffusion process governed by three person-specific parameters: affective home base, noise-driven variability, and the linear attractor strength that pulls states back toward the home base. A key limitation of DynAffect is that external events enter only as undifferentiated stochastic noise, meaning that real-world events that leave structured, lingering emotional traces are confounded with internal regulation. This creates what Prince et al. (2026) call the attribution problem of emotional inertia: the same observed affective persistence can reflect slow internal return-to-baseline or the lingering emotional impact of a meaningful external event, with standard indices unable to distinguish between them. Drawing on the insight that mood may function as a representation of recent environmental momentum (Eldar et al., 2016), on empirical modeling of momentary wellbeing as a weighted function of external value signals (Rutledge et al., 2014), and using sparse identification of nonlinear dynamical systems to discover governing equations directly from data (LaFollette et al., 2025), Prince et al. (2026) introduced DynAffect-C, a unified model that places both endogenous and exogenous forces within a single differential equation:

$$\frac{d\theta(t)}{dt} = \beta(\mu - \theta(t)) + \alpha[\mu - \theta(t)]^3 + \rho dC(t) + \sigma\varepsilon(t)$$

where β and α are the linear and nonlinear attractor strengths governing endogenous regulatory pull, $dC(t)$ is the first difference of a weighted composite of external control variables, ρ is the exogenous force or coupling between those signals and affective change, and $\varepsilon(t)$ is residual stochastic noise.

Social sharing occupies an unusual position among possible inputs to this model because it plausibly operates through two mechanistically distinct channels simultaneously, and those channels pull in opposite directions. On one hand, disclosure is an event with its own valenced and arousing qualities: the act of telling, being heard, and receiving a response perturbs the speaker's affective state in ways that depend on the content disclosed and the listener's reaction. This is the exogenous perturbation channel, captured in DynAffect-C's $dC(t)$ term, and it may introduce arousal costs that persist into the hours after a conversation ends. On the other hand, engaging in emotional disclosure may alter the regulatory architecture itself, strengthening or weakening the attractor pull that returns affect toward baseline after any perturbation, through mechanisms such as reappraisal, co-regulation, or the normalization of experience. This is the attractor modulation channel, operating through β and α, and it is the mechanism that would produce genuine recovery rather than mere interruption. By treating social sharing as the control variable in DynAffect-C, both channels become simultaneously estimable within a single identifiable framework, making it possible for the first time to ask not just whether sharing changes how a person feels, but whether it changes how their affective system regulates itself, and whether the regulatory gain is sufficient to offset the perturbative cost.

The Present Research

DynAffect-C was applied to experience-sampling data from four independent datasets in which participants reported core affect and social sharing at multiple time points across daily life, a methodology uniquely suited to capturing affective trajectories as they unfold in natural context (Csikszentmihalyi & Larson, 1987; Myin-Germeys et al., 2018). The three datasets, Brans et al. (2013), Koval and Kuppens (2012), Kuppens et al. (2010b), and Erbas et al. (2018), provided samples with varying EMA protocols and densities, enabling assessment of model robustness across contexts. Population-level parameters were pooled across datasets via inverse-variance fixed-effects meta-analysis, and individual difference moderators of the sharing parameters were examined to clarify for whom sharing is most dynamically consequential. Together these analyses provide the first formal test of whether emotional disclosure produces genuine recovery or mere interruption, address why sharing's documented consequences are so heterogeneous across persons and contexts (Sels et al., 2024), and shed light on why people so reliably underestimate what they stand to gain from social contact even as they consistently seek it out (Rimé, 2009; Epley et al., 2022).

Because sharing operates through two channels simultaneously, a simple summary of its effect requires integrating across both. The perturbation channel and the attractor modulation channel need not move in the same direction: sharing might strengthen regulatory pull while simultaneously elevating arousal, dampen both, or amplify both, and the net consequence for the affective trajectory will depend on whichever force proves larger and more durable. Whether sharing tips the balance toward genuine recovery or toward prolonged arousal therefore cannot be read off from either parameter alone. To formalize this tradeoff, we introduce the Net Affective Benefit of Sharing, or NABS, a signed quantity derived from the DynAffect-C parameters that captures whether the regulatory strengthening attributable to sharing outweighs its perturbative arousal cost. A positive NABS indicates that sharing accelerates return to baseline by more than it temporarily excites. A negative NABS indicates the reverse, that the cost of sharing outlasts any regulatory benefit. By examining NABS and its individual difference moderators, it becomes possible to move beyond asking whether sharing helps on average and toward identifying the conditions under which it tips the balance toward recovery, the conditions under which it does not, and the person-level features that determine which outcome a given individual is likely to experience.

Method

Datasets and Participants

Four independently collected experience-sampling datasets were included, each containing repeated within-person assessments of core affect and social sharing in daily life. Together the datasets contributed data from N = 382 participants providing tens of thousands of EMA observations, enabling both stable parameter estimation at the person level and cross-context generalizability through meta-analytic pooling.

Brans et al. (2013) recruited undergraduate and community participants in Belgium for a two-week EMA protocol. Assessments were triggered by a combination of random time-based signals and emotion-event prompts. At each prompt, participants reported current affect and indicated whether they had engaged in social sharing of their emotional experience since the prior assessment, alongside a battery of other emotion regulation strategies. Koval et al. (2013) enrolled participants in an EMA protocol designed to examine affect dynamics in the context of daily social experience and stress. Participants completed multiple daily assessments over approximately two weeks, reporting current valence and arousal alongside contextual variables including social sharing. Kuppens et al. (2010b) constitutes the original dataset from which the DynAffect account was developed and validated. Participants completed intensive repeated assessments of core affect over an extended diary period, with contextual variables including social sharing recorded at each prompt. Erbas et al. (2018) was an EMA study focused on emotion differentiation in daily life. Participants completed multiple daily assessments of both core affect dimensions and social sharing over several weeks.

Measures

Core affect. At each assessment, participants rated current valence and arousal on Likert-type scales. Ratings were z-scored within person prior to all analyses to place parameters on a common standardized scale and remove between-person differences in mean level and range of use.

Social sharing. At each assessment, participants indicated whether they had engaged in social sharing of their emotional experience since the prior prompt. This binary indicator constituted the control variable $S_p(t)$ in all model specifications, taking a value of 1 when sharing was reported and 0 otherwise.

Trait measures. Subsets of datasets included self-report trait measures administered at baseline. These comprised the Behavioral Inhibition and Activation Scales (BIS and BAS Drive, Fun Seeking, and Reward Responsiveness subscales), the Center for Epidemiological Studies Depression Scale (CESD, along with subscales for depressed affect, positive affect, somatic complaints, and interpersonal problems), the Rosenberg Self-Esteem Scale (RSE), the Satisfaction with Life Scale (SWL), the Affect Intensity Measure (AIM), and participant age. These were used as candidate moderators of NABS and its components across datasets with available data (pooled $N = 382$).

The DynAffect-C Model

DynAffect-C (Prince et al., 2026) extends the original DynAffect account (Kuppens et al., 2010b) by formally separating the endogenous regulatory forces that govern how affect returns to baseline from the exogenous influence of identifiable real-world events. The original DynAffect model captures affect trajectories as an Ornstein-Uhlenbeck diffusion process governed by three person-specific parameters: an affective home base μ_p toward which states return, a noise-driven variability parameter σ_p, and a linear attractor strength β_p that governs the rate of that return. A key limitation of this formulation is that all external influences enter only as undifferentiated stochastic noise. Real-world events that leave structured, lingering emotional traces are therefore confounded with the internal regulatory process itself, making it impossible to determine from observed affect alone whether a person is recovering slowly or was simply hit hard by something external. DynAffect-C resolves this attribution problem by adding an explicit control variable term, allowing external inputs to be estimated separately from endogenous regulation.

Applied here with social sharing as the control variable, the full DynAffect-C transition equation for person p at time t is:

$$\frac{d\theta_p(t)}{dt} = \beta_{eff,p}(t)\left(\mu_p - \theta_p(t)\right) + \alpha_{eff,p}(t)\left(\mu_p - \theta_p(t)\right)^3 + \omega_{S,p} \times S(t) + \xi_p(t)$$

$$\beta_{eff,p}(t) = \left(\beta_p + \beta_{S,p} \times S(t)\right); \quad \alpha_{eff,p}(t) = \left(\alpha_p + \alpha_{S,p} \times S(t)\right)$$

Each term carries a precise theoretical interpretation. The expression $\left(\mu_p - \theta_p(t)\right)$ is the signed displacement of current affect from the home base. The first term scales this displacement by the effective linear attractor strength $\beta_{eff,p}(t)$. When no sharing occurs ($S(t) = 0$), this reduces to the baseline attractor strength β_p, which governs how forcefully the system draws current states back toward equilibrium. When sharing occurs, the parameter $\beta_{S,p}$ captures any modification of this pull: a positive value indicates that sharing strengthens regulation, accelerating return to baseline, while a negative value indicates weakening. The second term introduces nonlinearity: the baseline cubic parameter α_p governs curvature of the attractor function, capturing whether regulatory pull accelerates disproportionately for large departures from equilibrium, and $\alpha_{S,p}$ captures any modulation of this curvature by sharing. The third term, $\omega_{S,p} \times S(t)$, is the exogenous perturbation channel. It shifts the affective state directly by $\omega_{S,p}$ units per unit of sharing, independent of current displacement from the home base and independent of regulation. A positive $\omega_{S,p}$ means sharing immediately elevates arousal above what intrinsic dynamics alone would produce. Finally, $\xi_p(t)$ is residual stochastic noise with person-specific standard deviation σ_p, capturing unmeasured influences.

For practical estimation the continuous-time equation was approximated in discrete time using an Euler scheme:

$$\theta_p(t+1) = \theta_p(t) + \beta_{eff,p}(t)\left(\mu_p - \theta_p(t)\right) + \alpha_{eff,p}(t)\left(\mu_p - \theta_p(t)\right)^3 + \omega_{S,p} \times S(t) + \sigma_p \times \varepsilon_p(t)$$

where $\varepsilon_p(t) \sim N(0, 1)$. The model was estimated separately for valence and arousal, and person-level parameters $\left\{\mu_p, \beta_p, \alpha_p, \beta_{S,p}, \alpha_{S,p}, \omega_{S,p}, \sigma_p\right\}$ were obtained for each participant by maximizing the Gaussian likelihood of the observed time series given the model.

Meta-Analytic Pooling

To obtain stable population-level estimates while preserving the independence of the four datasets, person-level parameter estimates within each dataset were averaged to produce dataset-level summary statistics, which were then pooled using inverse-variance weighted meta-analysis. Both fixed-effects (FE) estimates and DerSimonian-Laird random-effects (RE) estimates are reported. All analyses were conducted separately for valence and arousal, and heterogeneity was assessed via the I^2 statistic.

Results

The central empirical question is whether social sharing modulates the regulatory architecture of the arousal system, perturbs it exogenously, or both. The results were strikingly dimension-specific (see Figure 2). For valence, none of the three social sharing parameters differed from zero. The exogenous perturbation parameter ω_S yielded a pooled fixed-effects estimate indistinguishable from zero (FE = 0.004, 95%CI = [–0.016, 0.024], p = .698, I^2 = 5%). The linear attractor modulation parameter β_S was similarly null (FE = 0.013, 95%CI = [–0.014, 0.041], p = .350, I^2 = 2%), as was the nonlinear modulation parameter α_S (FE = –0.001, 95%CI = [–0.017, 0.016], p = .950, I^2 = 0%). Near-zero I^2 values across all three parameters confirm that this null pattern is consistent across datasets rather than reflecting cancellation of opposing effects. Social sharing did not systematically shift how pleasant or unpleasant people felt, nor did it alter the pace at which valence returned to baseline.

For arousal, a qualitatively different picture emerged. All three sharing parameters were positive and reliably distinguishable from zero. Social sharing produced a reliable exogenous elevation in arousal beyond what intrinsic trajectory dynamics would predict (FE = 0.029, 95%CI = [0.010, 0.049], p = .003, I^2 = 0%). This suggests that the act of sharing activates the arousal system. Critically, sharing also strengthened linear attractor pull (FE = 0.029, 95%CI =

[0.004, 0.054], p = .023, I^2 = 0%), indicating that the same episodes of sharing that elevate arousal also increase the rate at which arousal returns toward the home base. Cubic attractor modulation was likewise positive and significant (FE = 0.019, 95%CI = [0.007, 0.030], p = .002, I^2 = 23%), indicating that sharing additionally steepens the nonlinear component of the attractor function, amplifying the restorative force particularly for large departures from equilibrium. Random-effects estimates closely tracked fixed-effects values throughout, consistent with the low between-dataset heterogeneity observed.

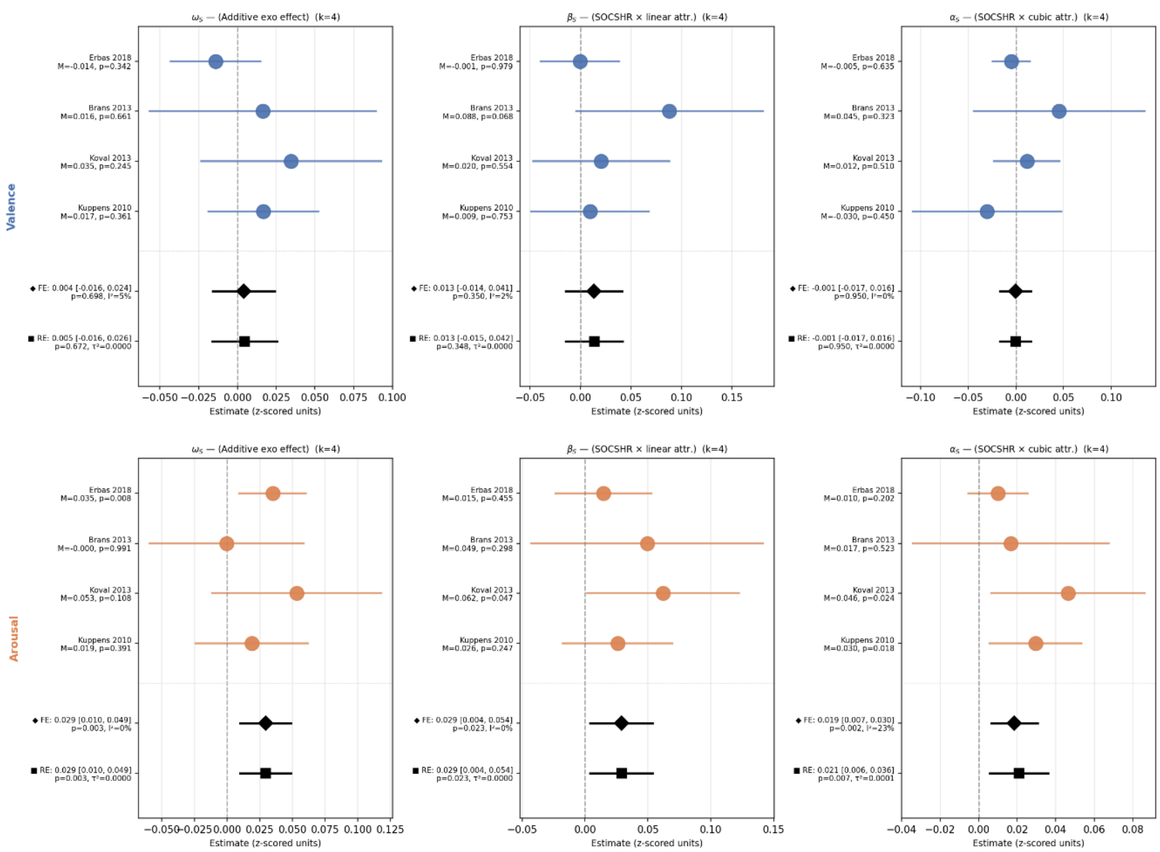

Figure 2. Meta-analytic estimates of DynAffect-C social sharing parameters across four EMA datasets. Each row shows results for valence (blue) and arousal (orange) separately. Columns correspond to the three sharing parameters: the additive exogenous effect (ω_S), the sharing effect on linear attraction (β_S), and the sharing effect on nonlinear attraction (α_S). Within each panel, circles represent per-study estimates with 95% confidence intervals. The diamond and square at the bottom of each panel show fixed-effects (FE) and DerSimonian-Laird random-effects (RE) pooled estimates, respectively, each with 95% CI, omnibus p-value, and heterogeneity statistics (I^2 for FE; τ^2 for RE). Valence and arousal parameters were pooled independently. k = 4 studies per cell.

This dissociation between valence and arousal warrants emphasis. Social sharing leaves the hedonic dimension of affective experience essentially untouched while simultaneously perturbing and strengthening regulation of the activation dimension. The act of narrating emotional experience and being heard is intrinsically activating, and its regulatory consequence is not a direct improvement in hedonic tone but rather an acceleration of the decay of that activation back toward equilibrium. All subsequent analyses therefore focus on arousal, where all three channels of sharing's influence are estimable and interpretable.

How Social Sharing Reshapes Arousal Dynamics

To understand what these parameter estimates mean for the actual shape and behavior of the affective system, it is helpful to examine their consequences under canonical conditions. Using median parameter values across all arousal participants ($N = 409$: $\beta = 0.651$, $\beta_{S,p} = 0.029$, $\alpha_{S,p} = 0.019$), the effective linear attractor strength increases reliably with sharing level, following the relationship $\beta_{eff}(t) = 0.651 + 0.029 \times S(t)$ with tight bootstrap confidence intervals (see Figure 2A). Each standard-deviation increase in sharing is associated with a roughly uniform increase in the rate at which arousal is pulled back toward the home base.

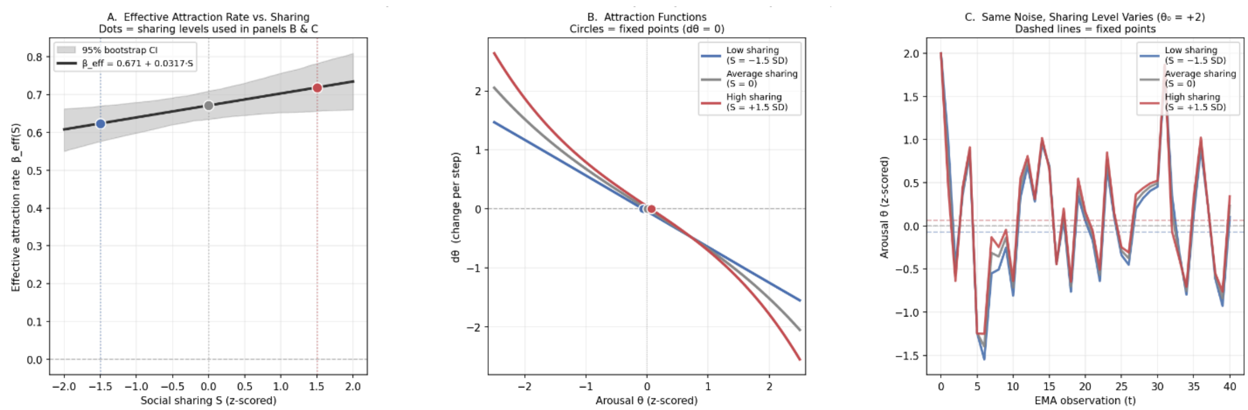

Figure 3. DynAffect-C arousal dynamics as a function of social sharing. All sample dynamics and trajectories are based on median arousal parameters estimated via fixed-effects meta-analysis across all participants (analytical $N = 409$; $\beta = 0.651$, $\beta_S = 0.0288$, $\alpha_S = 0.0185$). Panel A shows the effective attraction rate $\beta_{eff}(t) = \beta + \beta_S \times S(t)$ as a function of social sharing (z-scored), with a 95% bootstrap confidence interval across participants. Colored dots mark the three sharing levels examined in panels B and C (low: S = −1.5 SD; average: S = 0; high: S = +1.5 SD). Panel B shows the rate of change in arousal (dθ) as a function of current arousal (θ) for each sharing level. Circles mark the fixed point (dθ = 0) for each condition, reflecting the arousal level toward which the system gravitates. Panel C shows simulated arousal trajectories beginning from an elevated state ($\theta_0 = +2$) under each sharing condition, with identical noise sequences applied across conditions. Dashed horizontal lines indicate the fixed point for each sharing level. Together, the panels illustrate that higher social sharing both strengthens the regulatory pull back toward equilibrium and modestly shifts the arousal fixed point upward.

Importantly, sharing strengthens this regulatory pull without shifting where the system rests at equilibrium. Attractor functions computed at low, average, and high sharing levels all cross zero at the same fixed point: the home base is invariant to sharing (see Figure 2B). What changes is the magnitude of the endogenous force for any given displacement from that point. A person sharing at high levels experiences stronger corrective pressure toward their characteristic arousal baseline than the same person sharing at low levels, and this difference grows with the magnitude of displacement, reflecting the additional contribution of nonlinear modulation.

These parameter-level differences translate into observable differences in the affective trajectory. Holding the sequence of stochastic perturbations constant and varying only the level of sharing, arousal trajectories starting from an elevated state recover at meaningfully different rates depending on sharing level (see Figure 2C). The differences at any single observation are modest, but they are cumulative, compounding across successive time points in a way that a snapshot measure taken once before and once after disclosure cannot detect. This is precisely the form of evidence that motivates a continuous-trajectory approach to studying the consequences of sharing: the regulatory benefit of sharing is not a single event but a process that unfolds across time.

The Net Affective Benefit of Sharing

The results thus far establish that social sharing simultaneously activates the arousal system and strengthens its capacity to self-regulate. These two forces work in opposite directions: one elevates arousal above where it would otherwise be, and the other accelerates the rate at which that elevation decays. Whether sharing is on balance beneficial to the affective trajectory depends on which force is larger and how quickly the regulatory benefit translates into actual recovery. Neither parameter alone is sufficient to answer this question.

To formalize the tradeoff, we define a Net Affective Benefit of Sharing (NABS) as:

$$NABS_p = \frac{\sigma_p \times \beta_{S,p} / \beta_p}{\beta_{eff,p}} - \frac{\omega_{S,p}}{\beta_{eff,p}}$$

where $\beta_{eff,p} = \left(\beta_p + \beta_{S,p} \times S\right)$, evaluated at $S = 1$. The numerators contrast the two opposing forces. The term $\sigma_p \times \beta_{S,p}/\beta_p$ is the endogenous regulatory benefit: it captures how much sharing strengthens attractor pull relative to baseline strength, weighted by the noise level σ_p that the regulatory system must manage. A larger $\beta_{S,p}$ means stronger sharing-induced acceleration of return-to-baseline, and scaling by σ_p/β_p expresses this benefit in units of regulatory efficiency gain relative to the system's inherent demands. Subtracting $\omega_{S,p}$ from this benefit yields the net regulatory advantage after accounting for the direct arousal cost of social sharing. Dividing both benefit and cost by $\beta_{eff,p}$ normalizes the net balance relative to the total regulatory capacity of the system under sharing conditions.

A positive NABS indicates that the regulatory benefit outweighs the perturbative cost: sharing accelerates return to baseline by more than it temporarily elevates arousal. A negative NABS indicates the reverse: the arousal cost of sharing outpaces its regulatory dividend, leaving the trajectory worse off than it would have been without sharing. A NABS near zero indicates approximate balance between the two forces. NABS was computed individually for each participant using their person-level parameter estimates, yielding a distribution that characterizes where each person tends to fall in the recovery-versus-interruption continuum.

Parameter Sensitivity

Before examining how NABS distributes across participants, it is important to understand how it responds to variation in each of its constituent parameters. Holding three parameters fixed at their median population levels and sweeping the fourth across a plausible empirical range reveals the functional dependencies that govern when sharing tips the balance toward regulation versus disruption (see Figure 4).

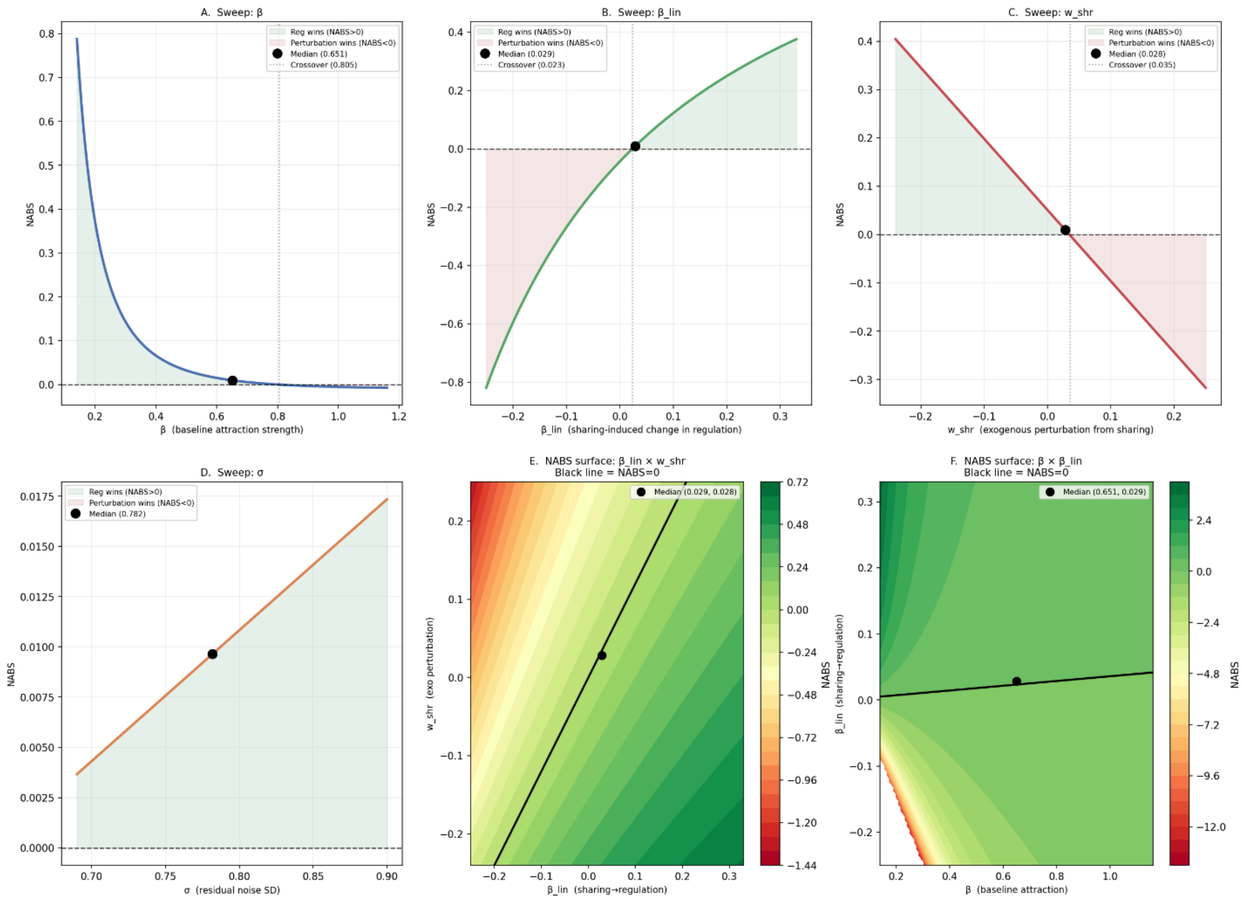

Figure 4. Parameter sensitivity of the Net Affective Benefit of Sharing. Each panel varies one or two parameters while holding the others at their median values. Panels A–D show univariate sweeps across baseline attraction strength (β), sharing-induced change in regulation (β_S), exogenous perturbation from sharing (ω_S), and residual noise SD (σ), respectively. In each sweep panel, the dashed horizontal line marks NABS = 0 (the crossover from net cost to net benefit), the filled circle marks the meta-analytic median, and shaded regions distinguish the parameter space where sharing produces net regulatory benefit (green) from net cost (red). Panels E and F show bivariate NABS surfaces: Panel E maps NABS as a joint function of β_S and ω_S, and Panel F as a joint function of β and β_S. In both surface panels, the black line traces the NABS = 0 contour and the filled circle marks the meta-analytic median parameter pair. Color scales range from red (large net cost) to green (large net benefit). Taken together, the panels show that NABS is most sensitive to β_S and ω_S, that the median parameter estimates place the typical participant near the crossover boundary, and that individual variation in these parameters is sufficient to produce meaningful heterogeneity in whether sharing confers a net benefit or net cost.

NABS decreases monotonically as baseline attractor strength β_p increases, such that individuals whose affective systems are already strongly self-regulating derive less marginal benefit from the additional regulatory strengthening that sharing provides. For individuals with weaker baseline regulatory capacity, the same sharing-induced increment in $\beta_{S,p}$ translates into a proportionally larger improvement in regulatory strength and therefore a more positive NABS.

NABS increases steeply and nonlinearly with $\beta_{S,p}$, crossing from net cost to net benefit at approximately $\beta_{S,p} = 0.023$. The population median of 0.029 sits just above this threshold, placing the typical participant marginally in the net-beneficial zone. The proximity of this crossover to the median is theoretically important: the population does not occupy a regime where sharing's regulatory benefit is so large as to produce clearly positive NABS regardless of other parameters. Small individual differences in how strongly sharing modulates attractor pull are sufficient to move a person across the boundary. Further, NABS decreases linearly with the exogenous perturbation cost $\omega_{S,p}$, and increases linearly with residual noise σ_p, because noisier affective systems have more regulatory inefficiency for sharing's attractor boost to correct.

The joint parameter surfaces make this sensitivity vivid (see Figure 4E-F). Across all parameter combinations examined, the canonical participant sits close to the NABS = 0 boundary, with the balance surface falling steeply in both directions. Sharing is not robustly helpful or robustly harmful at population-average parameter values. It is poised at the margin, with individual variation in any of the underlying parameters sufficient to tip the balance in either direction.

NABS Results

Consistent with the sensitivity analyses, individual NABS estimates were broadly distributed around zero, with a pooled mean of 0.038 that did not differ significantly from zero ($t(381) = 0.70$, $p = .482$; see Figure 5A). The spread of the distribution, however, is far from trivial. Individual NABS values ranged across approximately ten standardized units, reflecting genuine between-person differences in the interplay between sharing's perturbative and regulatory consequences. The slight positive skew of the distribution suggests that cases of net benefit modestly outnumber cases of net cost at the extremes, though neither pattern dominates the center of the distribution. Decomposing NABS into its endogenous benefit and exogenous cost components and plotting them against each other for each participant confirms that both sources of variability contribute to between-person spread in the overall measure (see Figure 5B).

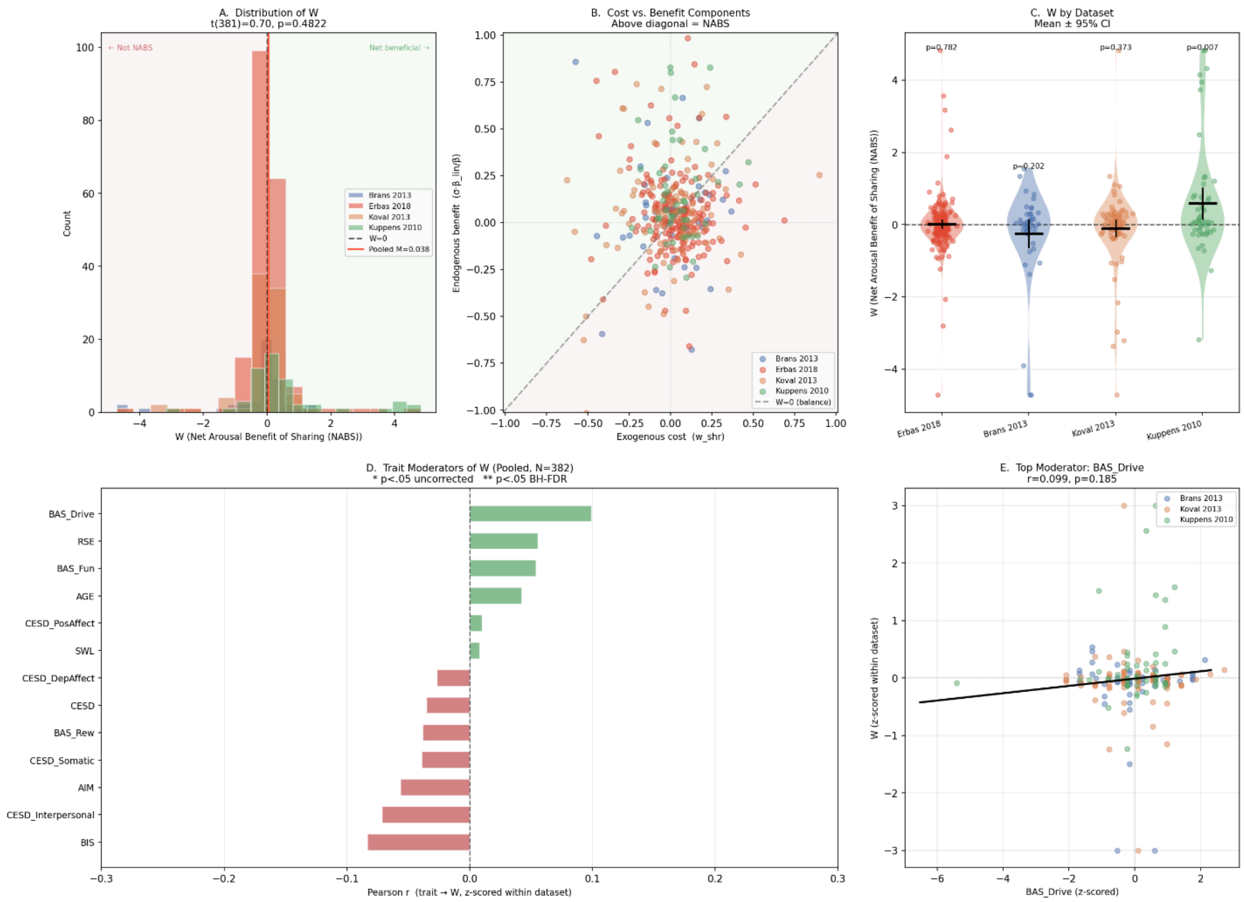

Figure 5. Distribution, decomposition, and trait moderators of NABS. Panel A shows the pooled distribution of individual NABS scores, color-coded by dataset, with the dashed vertical line at NABS = 0 and the pooled mean annotated (M = 0.038, t(381) = 0.70, *p* = .482). Shading distinguishes the net-cost (red) from net-benefit (green) regions. Panel B plots each participant's endogenous regulatory benefit ($\sigma_p \times \beta_{S,p}/\beta_p$) against their exogenous perturbation cost ($\omega_{S,p}$), with the diagonal representing NABS = 0; points above the diagonal indicate net benefit. Colors denote dataset. Panel C shows NABS by dataset as violin plots with individual participant jitter and mean ± 95% CI crosshairs; one-sample t-test p-values against zero are annotated above each distribution. Kuppens 2010 is the only dataset with a mean significantly above zero (*p* = .007). Panel D shows Pearson correlations between 12 trait measures and NABS (pooled, z-scored within dataset), with bars colored green (positive) or red (negative); single asterisks denote p < .05 uncorrected and double asterisks denote p < .05 after BH-FDR correction. No trait survives correction. Panel E plots the relationship between the strongest positive moderator (BAS Drive) and NABS across datasets (r = 0.099, *p* = .185), with a pooled regression line.

At the dataset level, three of the four samples showed mean NABS values that did not differ significantly from zero: Erbas et al. (2018; *p* = .782), Brans et al. (2013; *p* = .373) and Koval et al. (2013; *p* = .202). The Kuppens et al. (2010b) dataset was the exception, with a mean NABS that was significantly positive (*p* = .007) and a distribution clearly shifted into the net-beneficial region (see Figure 5C). This between-dataset heterogeneity is evidence that the balance between sharing-induced regulation and disruption is context-sensitive, and that in at least one well-characterized naturalistic setting the regulatory benefit of sharing outweighed its perturbative cost at the population level. What features of that sample or its EMA protocol tipped the balance remains an open question.

To identify person-level features that predict where on the NABS distribution individuals fall, pooled correlations between baseline trait measures and individual NABS scores were computed across all datasets with available trait data ($N = 382$; see Figure 5D). Moderators of the endogenous benefit and exogenous cost components were also examined separately to clarify whether any trait associations operate primarily through the regulatory or perturbative channel (see Figure 6). No trait moderator survived correction for multiple comparisons using the Benjamini-Hochberg false discovery rate procedure. The uncorrected pattern was nonetheless directionally interpretable. BAS Drive showed the largest positive association with total NABS ($r = .099$, $p = .185$), with self-esteem and BAS Fun Seeking showing the next largest positive trends. At the other end, behavioral inhibition showed the largest negative association, with higher threat sensitivity nominally linked to less favorable NABS. Decomposing by component, somatic symptoms of depression showed the only nominally significant association in the full analysis, with higher somatic burden linked to lower exogenous arousal activation from sharing ($r = -0.121$, $p = .013$), an effect that did not survive false discovery rate correction. All other trait associations were null at both uncorrected and corrected thresholds.

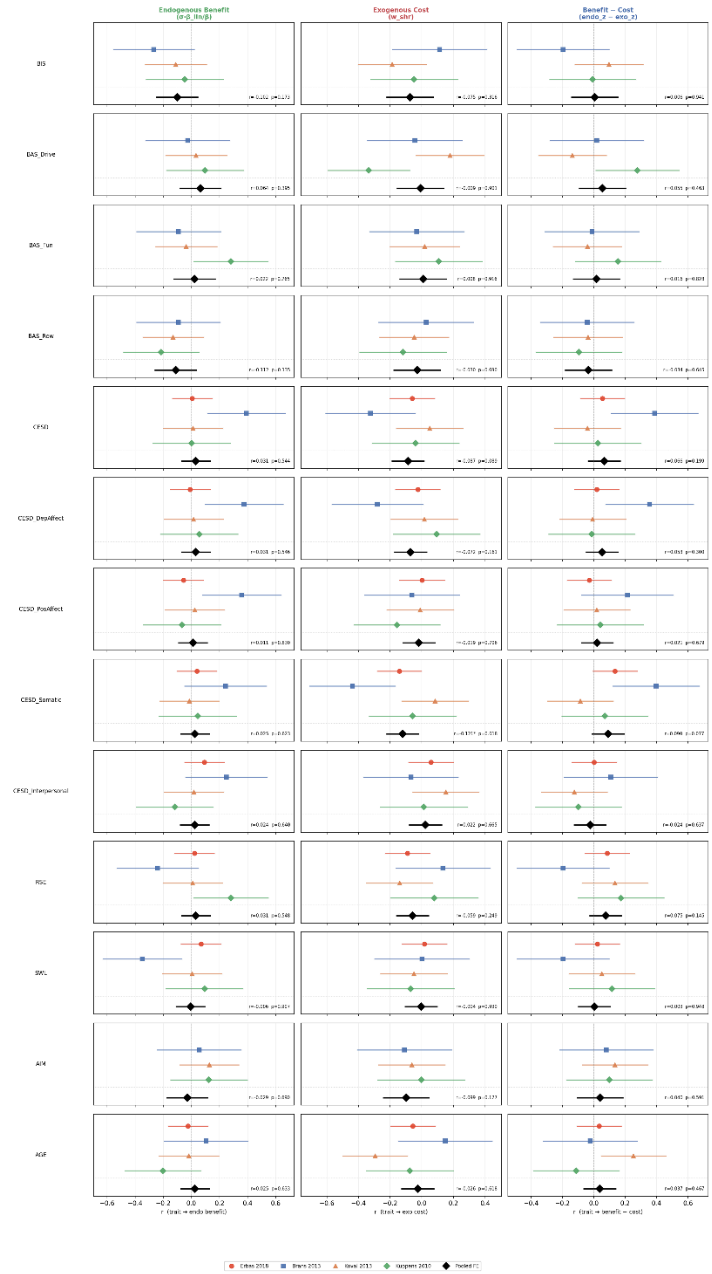

Figure 6. Trait associations with the endogenous benefit and exogenous cost components of NABS. Each row corresponds to one of 13 trait measures (BIS, BAS Drive, BAS Fun, BAS Reward, CESD total, CESD Depressive Affect, CESD Positive Affect, CESD Somatic, CESD Interpersonal, RSE, SWL, AIM, Age). Columns correspond to the two NABS components and their difference: endogenous regulatory benefit ($\sigma_p \times \beta_{S,p}/\beta_p$; left), exogenous perturbation cost ($\omega_{S,p}$; center), and their difference, benefit minus cost (right). Within each cell, colored markers show dataset-specific Pearson correlations with 95% CIs (circles = Erbas 2018; squares = Brans 2013; triangles = Koval 2013; diamonds = Kuppens 2010), and the black diamond at the bottom shows the pooled fixed-effects estimate. Correlation values and p-values for the pooled FE estimate are annotated at lower right of each cell. Single asterisks denote p < .05 uncorrected; double asterisks denote p < .05 after BH-FDR correction. The only nominally significant pooled association is between CESD Somatic symptoms and exogenous cost (r = −0.121, p = .013), which does not survive correction. No trait reliably predicts any NABS component after correction for multiple comparisons.

The pervasive null pattern across trait moderators is itself informative. Stable personality and wellbeing measures assessed once at baseline appear poorly positioned to explain who benefits from sharing and who does not, despite the observed heterogeneity in NABS. This finding is consistent with the sensitivity analysis: because the typical participant sits close to the balance point, the factors that tip any given person toward recovery or interruption are more likely to be situational than dispositional. Who one shares with, what one shares about, how the listener responds, and the affective state from which sharing is initiated are all time-varying contextual features that cross-sectional trait inventories cannot capture but that EMA designs combined with DynAffect-C are well-positioned to recover in future work.

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