When stressed, you might get depressed – but will you also commit crime? Revisiting a fundamental criminological question

ABSTRACT:

We all "know" stress is bad and chronic stress is worse for our mental and physical well-being. But does stress generally cause negative emotions and crime? Grounded in stress process theories and leveraging modern analytic tools (e.g., directed acyclic graphs; Bayesian ordinal multilevel modeling), we revisit this foundational question by describing the prevalence of subjective stress and item-level associations between subjective stress, negative emotions, and criminal intentions in two-wave panel data from adults in Dhaka, Bangladesh (n = 978 responses; 489 participants). Between-person findings are largely consistent with *stress deficit* expectations; respondents reporting more stress also are more likely to report criminal intentions and negative emotions. However, within-person results show changes in stress are reliably associated only with changes in negative emotions and not with criminal intentions. Residents of low-SES urban communities report more stress, but analyses exploring community heterogeneity in within-person correlations are weakly consistent with *stress amplification* expectations only for theft intentions and no other offenses. Between-person, but not within-person, indirect effect estimates from mediation models appear consistent with strain theory expectations. Overall, while the results are generally supportive of the link between stress and negative emotions documented in sociological research, the question of whether stress causes crime remains unsettled.

1 | INTRODUCTION

Four decades ago, Pearlin and colleagues (1981) developed the foundation for a stress process model that remains widely used in sociology today (cf. McLeod, 2012; Aneshensel, 2015; McEwen and McEwen, 2017) and boasts paradigmatic status across an array of social and health-related disciplines (Wheaton, 2009; Wheaton, Young, Montazer, and Stuart-Lahman, 2013; Pearlin and Bierman, 2013). A central thesis is that exposure to stressors, if not mitigated by social supports or other intervening processes, can result in the subjective experience of stress. "Stressors" include the "broad array of problematic conditions and experiences that can challenge the adaptive capacities of people," and they may take the form of "disruptive events" or "more persistent hardships and problems built into the fabric of social life" (Pearlin, 2010: 208). Meanwhile, consequent subjective "stress" may manifest itself in a host of observable detrimental outcomes at various levels, ranging from the cellular to neurobiological, systemic, psychological, and behavioral levels (Pearlin et al., 1981; Pearlin, 2010).

Meanwhile, the claim that stress specifically can cause criminal behaviors, and that chronic stress is especially problematic, is disseminated broadly by public health websites (cf. CDC, 2020; Crisis House, 2022; Jones, 2022). Agnew's general strain theory, which draws from the stress process model, provides an explanatory framework that posits criminal behavior as a behavioral coping reaction to stress-induced negative emotions. General strain theory is widely taught across criminological curricula; it is also frequently subjected to empirical testing, with published results typically reporting at least qualified support for its core predictions (Dooley and Goodison, 2020).

With that said, the evidence base for general strain theory appears somewhat mixed, with numerous studies identifying issues or reporting qualified support for the theory (e.g., Tittle, Broidy, and Gertz, 2008; Botchkovar, Tittle, and Antonaccio, 2009), and others routinely claiming support across a range of contexts and outcomes (e.g., Baron, 2004; Agnew, 2006b; Link, Cullen, Agnew, and Link, 2016). Furthermore, despite its status as a staple in textbooks, many scholars and the public alike remain skeptical of the causal relevance of stress and of general strain theory to explaining criminal behavior (cf. Cooper, Walsh, and Ellis, 2010; Gabbidon and Boisvert, 2012). Additionally, the mechanistic links between stress and negative emotional outcomes like depressive symptoms appear rather well-established, whereas the direct causal pathways from stress to criminal behavior remain somewhat less clear. Thus, after decades of research, a clear consensus on whether stress causes crime remains elusive.

In this study, we revisit the question of whether subjective stress causes negative emotions and criminal behavior. We begin by briefly reviewing theoretical and empirical expectations from stress process theories. Then, framed by research questions derived from these theoretical expectations, we present an overview of key findings from descriptive analyses of two waves of survey data collected from adults in Bangladesh aimed at addressing this core question.[1] Specifically, we document item-specific, multivariate, between- and within-person correlations between self-reported subjective perceptions of stress, negative emotions, and criminal intentions with the hopes of gaining new insights into this old question.

2 | THEORETICAL EXPECTATIONS FROM STRESS PROCESS THEORIES

2.1 | Stress clustering and proliferation

[1] Additional materials, including detailed information regarding our analytical approach (e.g., modeling and measurement procedures) and more supplementary results, can be found in an online supplement accompanying this manuscript.

A central tenet of stress process theories is that stressors are not randomly distributed but tend to cluster in time and social space. Exposure to one stressor often leads to stress proliferation or subsequent secondary stressors. Those who are socially and economically disadvantaged face the greatest risks of exposure to both the clustering of stressful events and chronically stressful conditions (Pearlin, 2010; Pearlin and Bierman, 2013). This clustering helps explain the socioeconomic stratification of health and psychosocial outcomes, as disadvantaged groups experience increased stress exposure while having fewer effective coping resources.

General strain theory similarly identifies certain social locations as environments where stressors are especially likely to accumulate. Agnew (2001: 325, 343-7) argues that certain stressors, including problematic family and peer relationships, financial hardships, work-related problems, and criminal victimization, are especially likely to trigger potent negative emotions that can cause criminal behavior. This is because such stressors are presumably especially likely to be subjectively experienced as high in magnitude, to be perceived as unjust, and to be associated with the proliferation of stressful experiences or with chronic exposure to stress (Agnew, 2013). The theory particularly emphasizes lower-SES urban areas as vulnerable social locations where chronic stress exposure may be especially prevalent (Agnew 1992: 60-61; 2001: 334; see also Kaufman, Rebellon, Thaxton, and Agnew, 2008; Botchokar, Tittle, and Antonaccio, 2013).

2.2 | Stress deficit

The stress process model and general strain theory overlap substantially (cf. Van Gundy, 2002; Slocum, 2010), with both positing that exposure to external stressors (aka, objective strains), if not mitigated by social supports or other intervening processes, results in the subjective experience of stress (aka, subjective strain) and subsequent stress-induced *deficits* in functioning. Put simply, when stress gets “under the skin” it triggers a host of processes that can detrimentally affect emotions, decision-making, and behavioral outcomes.

Specifically, subjective experiences of stress operate by triggering a series of physiological and psychological responses, often called the "stress response system" (Schwartz et al., 2023). This "fight-or-flight" response involves the release of hormones like adrenaline (epinephrine) and cortisol, leading to increased heart rate, blood pressure, and breathing, heightened sensory awareness, and suppressed immune function. This activation also involves increased activity in the brain's sensory networks, while temporarily reducing activity in areas responsible for higher-order cognitive processing, such as impulse control and thoughtfully reflective decision-making. While this acute stress response is generally adaptive, it can become maladaptive under certain conditions, such as in post-traumatic stress disorder, where the stress response system becomes dysregulated. Moreover, chronic stress can lead to a disruption of the body's hormonal balance systems (i.e., HPA-axis dysregulation; McEwen, 2004; Miller, Chen, & Zhou, 2007; Juster, McEwen, & Lupien, 2010), resulting in allostatic overload (or a state of wear and tear on the body due to prolonged stress) with detrimental outcomes including energy depletion, a weakened immune system, and impaired cognitive function (McEwen et al., 2015; Sandi & Haller, 2015). Stress can also induce alterations in the brain's Default Mode Network (DMN) activation, with increased connectivity facilitating rumination (i.e., repetitive, negative thinking) and contributing to depressive symptoms (Qin et al., 2009; Hamilton, Chen, and Gotlib, 2013).

As indicated above, the precise mechanisms through which stress might cause negative emotions such as depressive symptoms are relatively well-established. However, the direct causal pathways by which stress might cause criminal intentions or behaviors appear more indirect and less well-understood. General strain theory specifically argues that negative emotions often create pressure for corrective action and that some individuals reactively engage in criminal behavior as a means of coping with the negative emotions caused by subjective stress. Based on stress responses research, it is also plausible that stress indirectly increases risks of criminal intentions or behaviors by increasing impulsivity (Buchanan & Preston, 2014; Starcke & Brand, 2016), affecting risk assessment (Porcelli & Delgado, 2017; Ethridge et al., 2020), and amplifying negative emotions. Additionally, certain stressors may elicit instrumental motives to cope in specific ways - for instance, financial hardships may trigger motives or intentions to engage in economic crimes like theft, whereas relational stress may cause violent intentions (Mazerolle and Piquero, 1998; Agnew 2006b; Felson et al., 2012). With that said, a historically vexing challenge for strain theories has been explaining the relative rarity of crime coupled with high prevalence rates for stress and stress-induced negative emotions.

2.3 | Stress amplification versus desensitization

Another seemingly unresolved question in the literature concerns whether chronic exposure to stressors typically amplifies or attenuates stress responses in disadvantaged communities. The *stress amplification* expectation, found in both the stress process model and general strain theory, suggests that the concentration of stressors should intensify stress and its consequences. Agnew, citing Bernard (1990), presents an example when suggesting "that poor, inner-city residents have higher rates of violence not only because they experience more objective strains but also because they are more sensitive to such strains" (2001: 322). He references Thoits' (1995) review of evidence concerning "differential vulnerability" in which she states "that members of disadvantaged social groups are especially vulnerable or emotionally reactive to stressors" (p.55). Likewise, Agnew (2001: 334) draws from Anderson's (1999) urban ethnographic research to highlight how "seemingly trivial strains like a negative remark or a stare often generate much distress among inner-city residents, partly because they signal future conflicts of a more serious nature."

However, competing evidence suggests the possibility of countervailing processes. For instance, some research indicates that chronic exposure to violence in these environments may lead to *desensitization* and attenuated associations between stress and emotional distress (Farrell and Bruce, 1997), depressive symptoms (Fitzpatrick, 1993), or risks of criminal behavior (Zimmerman and Messner, 2011; Ludwig et al., 2013; Wright & Fagan, 2013). Individual differences in stress response (Bartolomucci et al., 2005; Miller, Chen, & Zhou, 2007), habituation (Herman, 2013; Natelson et al., 1988), and variations in subjective experiences of stress may also significantly influence the effect of stressors. These factors, along with individual and cultural differences in social and situational interpretations of stress (Starcke & Brand, 2016), on average may mitigate rather than amplify causal effects of stress on specific individual outcomes in some contexts.

In either case, this tension between *amplification* and *desensitization* expectations highlights the importance of examining heterogeneity in stress effects across social locations and contexts. Documenting such patterns may have crucial implications for theories about the causal effects of stress on negative emotions and criminal behavior, particularly in disadvantaged communities where stressors tend to cluster.

3 | RESEARCH QUESTIONS

Our theoretical review of stress process theories generated several research questions related to expectations about social distributions and correlates of stress that we hope to answer with our descriptive analyses of survey data. Our primary goal here is to describe stress/outcome correlations in survey data precisely and transparently with the hopes of documenting robust phenomena that might encourage future theoretical elaborations, precise predictions, and severe tests of those predictions (for a discussion of the importance of *robust phenomena*, see Eronen and Bringmann, 2021).

3.1 | RQ1: Stress clustering

The first question asks about the relative frequencies of subjective stress reports. It is separated into two parts to differentiate between overall subjective stress distributions and differences in relative frequencies across social locations (*stress clustering*). We will answer these questions by examining ordinal distributions of specific subjective stress items.

RQ1A (Stress distributions): How often did participants report stressing or worrying about financial, relational, occupational, or victimization issues?

RQ1B (*Stress clustering*): Do reported levels of subjective stress vary systematically across rural/urban communities with high/low aggregate SES? Specifically, do residents of low-SES urban communities report more frequently stressing or worrying about these various potential sources of stress?

Ample research suggests that residents of socioeconomically disadvantaged communities are (1) more chronically exposed to potent stressors such as poverty, physical decay, social disorder, and victimization; (2) display more physiological indicators of allostatic overload, have poorer health, and report higher levels of subjective distress, and (3) are at greater risk of experiencing depression, crime, and other psychopathological outcomes (e.g., Sampson, Morenoff, and Gannon-Rowley, 2002; Silver, Mulvey, and Swanson, 2002; Matheson et al., 2006; Shulz et al., 2012; Robinette et al. 2016). We begin by assessing whether similar patterns are observed in a sample of Bangladesh adults.

3.2 | RQ2: Stress deficit

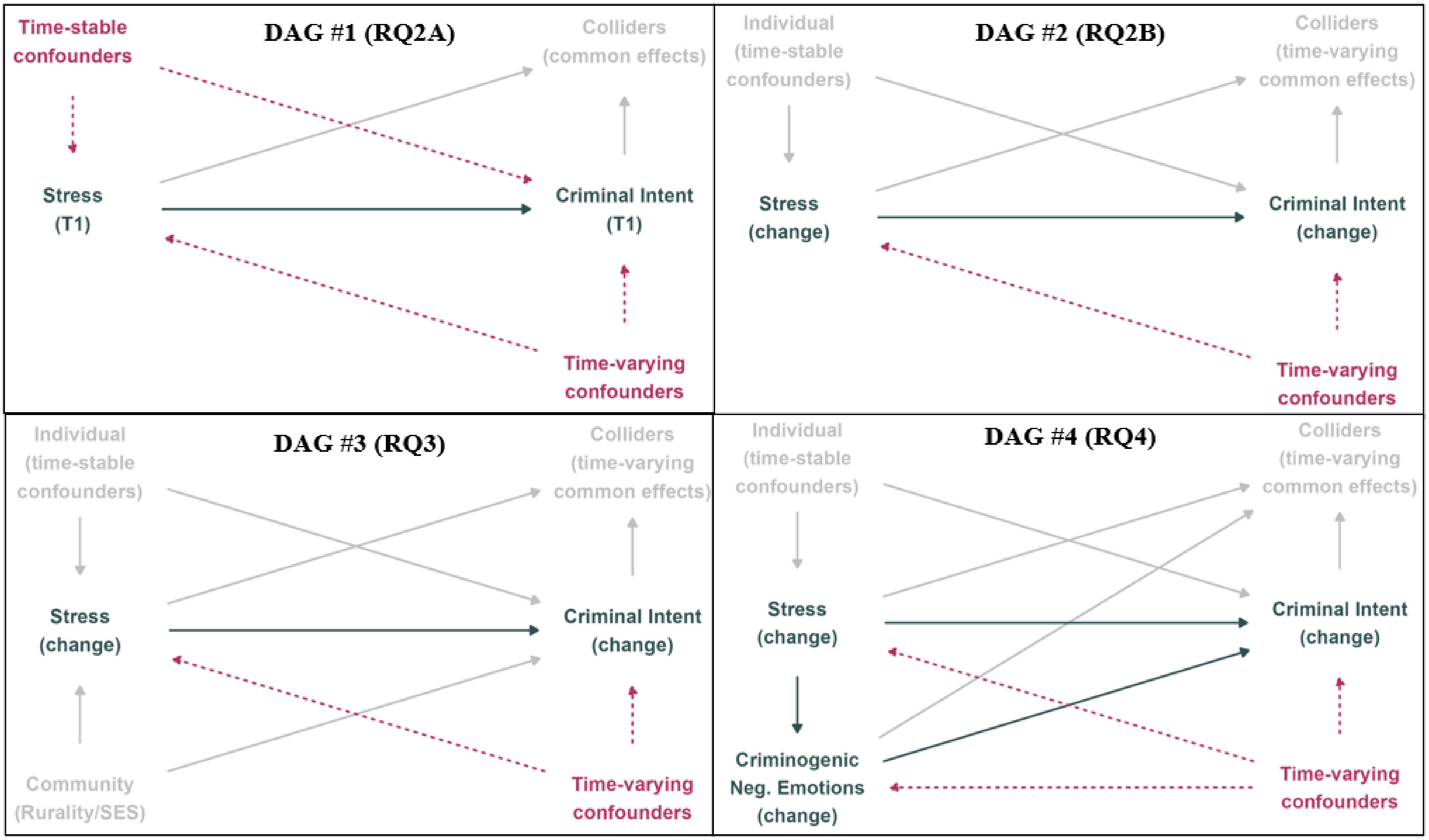
The second question asks whether there is a positive bivariate association between subjective stress and two theorized outcomes – criminal intent and negative emotions. We described this as the *stress deficit* expectation, which asserts subjective stress monotonically increases undesirable outcomes under certain moderating conditions. Given logical inconsistencies (Proctor and Niemeyer, 2019: 244-9), potential endogeneity (Paternoster and Mazerolle, 1994), and mixed empirical evidence (Tittle, Broidy, and Gertz, 2008; Willits, 2019) concerning posited effect moderators, we do not focus on those different conditions. Rather, we generate estimates of unadjusted and community-specific differences (aka, "total effects") averaged across the various conditions experienced by participants.

RQ2: Is subjective stress positively associated with self-reported criminal intent and negative emotions?

Note the question asks about criminal intent instead of criminal behavior. While our survey data contain items measuring criminal intentions and behaviors, the intention items provide better leverage over answering the causal question of interest. Pairing items measuring recent stress feelings with intent items measuring probabilistic projections of future criminal behaviors more accurately specifies temporal ordering and contemporaneous nature of presumed causal relationships (see Agnew, 2002) than pairing with response items measuring retrospective reports of past criminal behaviors. Likewise, intentions are widely modeled as an important part of decision-making generally (e.g., Kim and Hunter, 1993; Webb and Sheeran, 2006) and as an ancillary to criminal behavior specifically (e.g., Aiken et al., 2024; Barnum, Nagin, and Pogarsky, 2021), including within general strain research (e.g., Tittle, Broidy, and Gertz, 2008; Skrzypiec, 2017; Willits, 2019; Herman et al., 2024).

Much of general strain theory's voluminous evidence base is built on between-person estimates from cross-sectional or lagged longitudinal designs. Yet, to summarize Felson and colleagues (2012: 347), we know criminal offenders have difficult lives, but we also have reasons to suspect that the (between-person) relationship between crime and suffering is spurious. Therefore, they explain "[m]ethods that examine within-individual change are more appropriate for studying contemporaneous effects" (p.348) such as those posited in stress process and general strain theories. Likewise, our study adds to a large body of research on stress and depression (cf. Kessler, 1997; Hammen, 2006, 2015) and to a small but growing body of research estimating within-person change correlations between stress and crime (e.g., Brezina, 2010; Felson et al., 2012; Herman et al., 2024). Some of this crime literature focuses on "objective" or experienced strains (e.g., victimization) while lacking more proximal measures of subjective stress (e.g., Slocum, Simpson, and Smith, 2005; Lee, Kim, and Song, 2022; Slocum et al., 2022). Restricted samples of past crime-involved participants are also common (e.g., Felson et al., 2012; Slocum et al., 2005; Slocum et al., 2022), which risks "selection distortion" biases in estimates (see Brauer and Day, 2023). Also, while researchers studying depression long have recognized the need to focus on specific stressors (e.g., Kessler, 1997), criminological studies documenting correlations between changes in specific types of subjective stress and specific emotional and behavioral outcomes are rare despite theoretical reasons to expect certain stressors to elicit specific coping responses (but see Felson et al., 2012; Herman et al., 2024).

FIGURE 1: Directed Acyclic Graphs (DAGs) Depicting Causal Modeling Assumptions by Research Question



NOTE: Solid dark slate paths represent focal estimand(s). Solid light grey arrows represent paths blocked by design or analysis. E.g., within-person "fixed effects" estimate from "between-within" design adjusts for time-stable confounders; colliders are adjusted by default without explicit stratification; stratification on community blocks confounding and permits assessment of effect heterogeneity. Maroon dashed arrows represent unblocked backdoor paths. DAGs illustrate the need for precise theorizing; unprincipled adjustment on time-varying covariates may introduce collider bias or result in improper stratification on a mediator.

Despite focus and design differences, we seek to contribute to this accumulation of within-person change observations pertaining to stress and crime. With access to two waves of panel survey data, we use a multilevel modeling procedure to separately estimate "between-person" and "within-person" change associations (Allison, 2009). This "between-within" multilevel modeling approach permits adjustment by design for all time-invariant sources of confounding in estimating within-person change contrasts. Likewise, we separate this question into two parts that ask about associations for each estimation procedure:

RQ2A: (*Stress deficit*; Between-person): Do individuals who report higher levels of subjective stress at Time 1 (T1) also have a higher probability of reporting criminal intentions or negative emotions compared to those reporting less stress at T1?

RQ2B: (*Stress deficit*; Within-person): Are within-person increases in subjective stress from T1 to T2 (i.e., T2-T1) associated with within-person increases (T2-T1) in the probability of reporting criminal intent or negative emotions?

The directed acyclic graphs (DAGs) in the top row of Figure 1 communicate the simplistic causal assumptions underlying the between-person (DAG #1) and within-person change (DAG #2) estimates. Comparison of these DAGs communicates the within-person change estimates' (DAG #2) adjustment by design for all "Individual" (measured or unmeasured) sources of time-stable, between-person confounding (for similar representation of fixed effects in DAGs, see Huntington-Klein, 2018; 2021, Ch.16). Meanwhile, the unadjusted between-person estimates (DAG #1) are at greater risk of transmitting biasing information from these varied individual-specific sources of confounding.[2]

[2] Most between-person analyses in existing literature attempt to adjust for confounding by adding measured covariates (e.g., demographics; prior crime), but causal interpretations from such designs require strong causal assumptions that the covariate set blocks all backdoor paths without opening backdoor or forking paths. Meanwhile,

In our observational data analyses, both estimates are potentially biased by unmeasured time-varying confounders. Identification of and adjustment for potential confounders or their causal descendants can reduce confounder bias (Silver, Lonergan, and Nedelec, 2022), but unprincipled stratification on covariates without strong causal identification strategies or precise causal models can introduce bias in estimates (e.g., by stratifying on a collider; cf. Wysocki, Lawson, and Rhemtulla, 2022; Brauer and Day, 2023). A lack of precise theory and robust descriptions of basic empirical patterns leaves us unprepared for complex, fully adjusted models, as adding variables without coherent causal justifications can cause problems such as open backdoor or forking paths (Pearl and Mackenzie, 2018). Given our descriptive aims, we present visualizations of unadjusted average contrasts as empirical estimands representing our target theoretical estimands (Lundberg, Johnson, and Stewart, 2021), leaving the task of developing more elaborate and plausible causal models and assessing consequences of accounting for additional mechanisms (e.g., confounders; colliders; moderators) to subsequent research.

3.3 | RQ3: Stress amplification

The third question asks about potential heterogeneity across communities in the estimated associations between stress and its theorized outcomes. Recall, the *stress amplification* theoretical expectation posits stronger positive associations in (e.g., urban, low SES) areas where residents report more chronic experiences with stress.

> RQ3 (*Stress amplification*): Are within-person change (fixed effects) correlations between subjective stress and posited outcomes - self-reported criminal intent and negative emotions - positive and strongest in low-SES urban communities?

imprecise theorizing contributes to inconsistent selection of covariate sets (and sample characteristics) across studies, thereby collectively undermining causal assumptions and limiting knowledge accumulation.

"Community (Rurality/SES)" depicted in DAG #3 is a measured time-stable (T1) covariate, so average within-person change effect estimates adjust by design for time-stable confounding due to community. However, we separately depict it because RQ3 models will include interactions between stress and community to assess heterogeneity across communities in focal estimates of effects of stress changes on criminal intent and negative emotions.

3.4 | RQ4: Emotion mediation

The negative emotions items used for effect magnitude benchmarking include measures of potentially "criminogenic" emotions – feeling like *your life circumstances were unfair*, *mistreated by others*, or *betrayed by people you care about* – presumed by general strain theory to motivate criminal coping responses to stress under certain conditions. Under the very strong causal assumption that the simplified model in DAG #4 accurately depicts the data-generating process underlying our survey response data, the final question asks whether observed change correlations are consistent with general strain theory's *emotion mediation* expectation.

> RQ4 (*Emotion mediation*): Are the change correlation patterns consistent with a simple causal mediation data-generating process in which increases in overall stress indirectly cause increases in self-reported criminal intent through increases in "criminogenic" negative emotions?

4 | DATA AND MEASURES

4.1 | Sample context and data

In a previous tri-country study, the lead author documented sizeable correlations between coercive experiences, mental health symptoms, and criminal behavior in Dhaka, Bangladesh (AUTHOR CITE). Notably, rates of self-reported involvement in criminal behavior were also relatively low in the Dhaka sample despite high aggregate risks of exposure to stressors like high population density, high poverty rates, and substantial inequality (e.g., about 20% of Bangladesh's population in 2016 experienced deprivation on the Multidimensional Poverty Measure; see World Bank, 2024). Yet, Bangladesh also is characterized predominantly as a collectivist, South-Asian, Islamic culture emphasizing high interdependence, harmonious social relationships, and strong moral and religious values that may restrain crime (AUTHOR CITE). Curious to better understand the low prevalence rates of criminal behaviors despite apparently high risks of chronic exposure to potent stressors in this context, the lead author conducted a two-wave panel survey of Bangladesh residents in 2013 (T1) and 2015 (T2) that focused on examining theorized associations between stress, morality, negative emotions, and crime.

Thus, the data analyzed for this study are primary data collected via face-to-face interviews with adults aged 19 and older in the Dhaka District of Bangladesh. Sampling and interviews were conducted by Org-Quest, a professional survey organization in the region with prior criminological research experience. The organization used stratified random sampling with random replacement to interview 600 participants at T1: from 350 urban households in 35 mahallas/paras within 18 (of 100) wards in Dhaka municipality, and from 250 rural households in 13 villages within 3 (out of 13) unions in the Dhaka District. At wave 1, the sample was comprised of participants about 32 years old on average (ranging from 19 to 75 years), about 50% of whom were males, with an average of approximately 10 years of formal education (ranging from 1 to 20 years), and about three-quarters were married. For more information about sampling, interview procedures, or sample characteristics at T1, see AUTHOR CITE.

TABLE 1. Response and attrition rates for two-wave panel survey in Dhaka

2013 (T1)	Total Contacts	Completed Interviews		Refusal		Not Available							
	n	n	%	%	n	n	%						
Urban	533	350	65.7	14.1	108	75	20.3						
Rural	316	250	79.1	7.3	43	23	13.6						
Total	849	600	70.7	11.5	151	98	17.8						
2015 (T2)	**Total Contacts**	**Completed Interviews**		**Refusal**		**Untraceable Address Chg.**		**Migrated Elsewhere**		**Out of Country**		**Died**	
	n	n	%	n	%	n	%	n	%	n	%	n	%
Urban	350	252	72.0	13	3.7	59	16.9	22	6.3	3	0.9	1	0.3
Rural	250	237	94.8	1	0.4	0	0	9	3.6	2	0.8	1	0.4
Total	600	489	81.5	14	2.3	59	9.8	31	5.2	5	0.8	2	0.3

Overall response rate at T1 was 70.7% (see Table 1). Attrition rate was 18.5%, with 489 of the original 600 participants completing interviews at T2. As observed with response rates at T1, attrition rates were lower in rural than urban areas, with 94.8% and 72% successful completion rates at T2 among rural and urban participants, respectively. The most common reason for attrition across the two-year panel interval was an untraceable address change among urban residents, accounting for over half of all unsuccessful follow-up attempts (59/111, or 53.2%). Otherwise, examination of item response distributions did not reveal systematic differences in stress, criminal intent, or emotions by survey completion or attrition status.[3]

4.2 | Measures

Criminal intent. Our focal response variables consist of six *criminal intent* items asking participants to estimate the future likelihood that they will engage in six different acts: *theft less than 5BAM* (approximately equivalent purchasing power in 2013 as $5USD); *theft greater than 5BAM*; *threats to use violence on someone*; *physically harming someone else on purpose*; *using*

[3] As an additional data quality check, we investigated both waves of data for exact and near duplication across all survey items. We did not find any exact duplicate entries and near duplication based on Kuriakose and Robbins' (2016) "maximum proportion match" method was not common and distributionally consistent with conventional and presumably non-fraudulent surveys. For more information about (and future reporting of these) near duplicate checks, see AUTHOR CITE.

marijuana or other illegal drugs; and *attempting to access another person's private information (e.g., bank account; computer files) without permission*.[4] Response categories originally were provided on a 5-point ordinal response scale (1=*No chance* to 5=*High probability*). As is typical with self-report crime items, a substantial majority of respondents reported "1" (*No chance*) and responses exceeding "2" (*Little chance*) are extremely uncommon for these items. Due to the lack of variability, a desire to minimize problems caused by empty cell frequencies, and a desire to generate a manageable number of interpretable response contrasts, each item is dichotomized as "0" (=*No chance*) or "1" (=*Little chance or greater*).[5] A seventh binary item assessing "any criminal intent" is coded as "0" for participants with "0" (*No chance*) scores on all six items and "1" for those with a score of "1" (=*Little chance or greater*) on at least one item.

Negative emotions. For benchmarking and mediation modeling, we also modeled responses to seven binary items related to experiences with negative emotions. These items asked participants how often in the past week they: *felt you could not get going*; *felt everything was an effort*; *felt lonely*; *felt you could not shake the blues*; *felt like your life circumstances were unfair*; *felt mistreated by others*; and *felt betrayed by people you care about*. The first four are items measuring depressive symptoms ("depressed affect"; "somatic complaints") modified from Radloff's CES-D scale (1977; see also Moullec et al., 2011). The remaining three items are

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[4] Wave 1 also included a "selling drugs" item that, due to lack of variation, was replaced in Wave 2 with a "commit any crime" item. These items were not included because we cannot examine within-person changes.

[5] These data also contain items indicating how often participants reportedly engaged in past criminal behavior in the past two years (1=Never to 5=Very often). As noted previously, we focus on *criminal intent* items because examining associations between current reports of stress in the past week and criminal behavior in the past two years would fail to establish proper causal ordering among variables implied by strain or stress process theories, whereas current reports of stress in the past week and future behavioral intentions in theory provides more appropriate causal ordering. Yet, there is high stability in past crime and criminal intent responses, with an average polychoric correlation of rho=0.84 and range from rho=0.8 to rho=0.9 between the original T1 ordinal item pairs. Additionally, supplemental figures (See online Supplement sections 4.2 and 5.2.4) illustrate similar item response distributions and highly comparable stress-crime associations at T1.

designed to measure a different type of negative emotions that are theorized to be subjective consequences of coercive or criminogenic stress, namely the affective sense that one is unfairly treated or betrayed (aka, “alienation”; see Caspi et al., 1994; Brauer, Tittle, and Antonaccio, 2019). For all items, the five original response categories were recoded so that “0” indicates infrequently (*Never*; *Rarely*; *Sometimes*) and “1” indicates frequently (*Often*; *Very often*) experiencing these depressive symptoms or feelings in the past week.[6]

Subjective Stress. Our focal predictors are seven ordinal items asking participants how often they stress or worry about financial issues (*having enough money to buy necessities*; *having reliable daily transportation*), relational issues (*earning respect from those around you*; *being treated fairly by others around you*), occupational issues (*getting a job that you really enjoy*), or victimization issues (*other people stealing from you*; *other people mugging or assaulting you*). Each item was measured with a five-category ordinal response scale ranging from 1=*Never* to 5=*Very often*. Item-specific analyses generate separate estimates for each ordinal item. Mediation models use a standardized stress scale created as the sum of all seven items. Supplemental results in Appendix 1 provide ordinal item-specific estimates generated using a standardized sum scale and a latent item-response theory (IRT) theta stress scale.

Community Location. We assess heterogeneity in stress distributions and effect estimates across participants residing at T1 in rural or urban areas characterized by low or high aggregate levels of socioeconomic status (SES). *Rural/urban residence* was identified and coded during stratified sampling procedures at T1 (see “Data” section above). Participant SES was measured as the sum of six items assessing how often the participant feels like they have enough money to afford necessities or luxuries for them and their families (*groceries*; *medications*;

[6] Prevalence rates for each of the crime and negative emotion items are provided in online Supplement section 4.2.

clothes; *transportation*; *education*; *traveling for leisure*). Each item was measured on a 5-point response scale ranging from "1"=*Never* to "5"=*Very often*. Participants were then grouped into 18 urban ward or 13 rural village areas, and aggregate "*L2 SES*" was measured as the standardized group mean of participant SES in each ward or village. Communities at or below the median L2 SES were coded as "Low SES" and as "High SES" if above the median L2 SES score. The final *community location* variable is a four-category factor indicating the participant resided at T1 in a *Rural/Low SES* (n=113), *Rural/High SES* (n=124), *Urban/Low SES* (n=144), or *Urban/High SES* (n=108) area.[7]

5 | ANALYTIC APPROACH

For transparency and reproducibility purposes, our workflow, code, and all published and supplemental results related to this paper are provided in an online Supplement.[8] Before presenting specific descriptive results, we introduce core features of our analytic approach that may be unfamiliar to some readers.

5.1 | Item-specific analysis

Given a set of items presumably measuring an underlying unidimensional phenomenon (e.g., *subjective stress*; *criminal intent*), criminologists often adopt numerous composite indexing

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[7] Dichotomizing continuous data is a controversial decision, as discretizing a variable may discard potentially useful information. We chose to dichotomize L2 SES to simplify a complex multifaceted analysis after observing what appeared to be a "natural" split in the distribution at approximately the median and mean L2 SES scores. However, additional models using a standardized sum stress scale included three-way interactions between rural residence, standardized L2 SES, and each stress estimator (between & within) assessed whether key conclusions are affected by the decision to use a community-level SES median split for community identification. Supplemental results from these models are presented in Appendix 2.

[8] Online supplement containing code and results is available at: WEBSITE. R files used to generate supplement are available at: GITHUB. Online supplement (& supplemental review) are accessible for anonymous peer review at: https://osf.io/ejpvk/?view_only=fd83d1fe353745c9960c861f5b4e9c0a

or scaling procedures to measure underlying latent constructs (e.g., variety; summed; average; factor; IRT theta; cf. Osgood, McMorris, and Potenza, 2002; Sweeten, 2012). However, when working with imprecise theories, nascent evidentiary bases, and multi- or non-dimensional constructs, item-specific analyses may be more informative and generate fewer inference errors when describing distributions, relationships between phenomena, and between-item heterogeneity in those distributions or relationships (Fried and Nesse, 2015; McNeish, 2024). Latent measurement approaches are useful where appropriate, and we rely on a standardized summed stress scale in our mediation models (and show supplemental results with an IRT scale in Appendix 1). Yet, we think composite scaling approaches should not be adopted by default without prerequisite item-specific descriptive analysis and subsequently strong theoretical and empirical justification.[9] Likewise, the approach we adopt is to start with documenting basic item-specific descriptive estimates before moving toward scaling, where deemed appropriate. Moreover, item-specific analyses permit us to assess whether correlational patterns are consistent with theoretical claims that certain stressors are more likely to cause negative emotions and criminal intentions or that certain stressors elicit instrumental motives to cope in particular ways.

5.2 | Ordinal modeling of IVs and DVs

Ordinal (e.g., Likert-type) items or composite measures created from ordinal items often are analyzed as metric continuous variables. Unfortunately, this practice is known to cause magnitude and even sign (directionality) inference errors, meaning it increases the risks of false positives, false negatives, and effect inversions (Liddell and Kruschke, 2018; Bürkner and

[9] Of course, most researchers know not to arbitrarily combine items. Yet, it is common to rely on Cronbach's alpha or factor loadings to determine the appropriateness of combining items into composite scales. Unfortunately, doing so may result in an arbitrary (or worse) combination of items, and common composite scaling (e.g., sum; IRT) or variety indexing procedures cannot be counted on to automatically generate valid measures of assumed latent theoretical constructs. For rich discussions and cautions about uncritical construction of composite measurements, see Rhemtulla, van Bork, and Borsboom (2020) and Revelle (2024); for a classic take, see Merton (1940).

Vuorre, 2019). In contrast, ordinal approaches to modeling dependent and key independent variables measured using ordinal Likert-type survey items can improve model recovery of underlying data distributions while minimizing errors and increasing precision in descriptive inferences. One relatively parsimonious solution is to use a cumulative probit or logit link to estimate effects of or on ordinal increases across discrete ordinal category thresholds. Here, we use the `brms` (Bayesian regression model using Stan) R package for modeling, which offers ordinal response modeling and offers built-in estimation of cumulative monotonic effects of ordinal predictors with its `mo()` function (Bürkner, 2017; Bürkner and Charpentier, 2020).

5.3 | Multilevel B/W modeling

Another core feature of our analytic approach is the implementation of "between/within" (B/W; aka, "hybrid" or Mundlak) multilevel modeling, which improves estimation precision by separating unique sources of variation stemming either from between-person differences or within-person changes (cf. Mundlak, 1978; Allison, 2009; Rohrer and Murayama, 2023). Here, we use it to separately estimate the degree to which between-person differences and within-person changes in subjective stress are correlated with differences or changes in the probability of reporting criminal intent or negative emotions. As explained earlier, an important advantage of this modeling technique is that within-person estimates are adjusted by design for all time-invariant sources of confounding. This includes time-invariant effects of between-person characteristics that criminologists frequently include as measured covariates, such as sex, ethnicity, self-control, or genetic influences.

5.3.1 | Unadjusted cross-sectional vs. change estimates (RQ2)

In addressing RQ2, we first estimated multivariate cross-sectional models simultaneously regressing all criminal intent ("any criminal intent" was modeled separately) or all negative emotions outcome items at T1 separately on each stress item at T1. Descriptively, these cross-sectional T1 models permit estimation of between-person differences in expected outcome probabilities across participants (N=489 individuals) reporting different ordinal responses to stress items. Though comparable to the "between" (cross-time average) estimates from our multilevel models, we initially present these T1 estimates to clearly contrast the descriptive between-person inferences one might generate from modeling cross-sectional data with those generated from within-person estimation.

Then, we leveraged our second wave of data to estimate multivariate B/W multilevel models that simultaneously regressed all criminal intent (again, except "any criminal intent") or all negative emotions outcome items on an individual-specific cross-time average stress score – the "between-individual" estimator – and a time-specific deviation from an individual's cross-time average – the "within-individual" estimator (N=978 observations nested within N=489 individuals). Adapting Kurz's (2023b) and McElreath's (2020) notation for ordinal and multilevel modeling, we represent these more complex B/W models in Equation 1.

Equation 1.

$$\begin{aligned}
\boldsymbol{outcome}_{\boldsymbol{yit}} &\sim \text{Binomial}\left(\boldsymbol{n} = \mathbf{1}, p_{\boldsymbol{yit}}\right) \\
\text{logit}\left(p_{\boldsymbol{yit}}\right) &= \alpha_{ID_{yt}} + \beta_1(\text{mo}[stress_{jit} - \overline{stress}_{ji}, \delta_1]) + \beta_2(\text{mo}[\overline{stress}_{ji}, \delta_2]) \\
\alpha_{ID} &\sim \text{Normal}(\alpha, \sigma) \\
\alpha &\sim \text{Normal}(0,2) \\
\sigma &\sim \text{Student} - t(3,0,2.5) \\
\beta_1 &\sim \text{Normal}(0,0.25) \\
\beta_2 &\sim \text{Normal}(0,0.125) \\
\delta_1 &\sim \text{Dirichlet}(2,2,2,2) \\
\delta_2 &\sim \text{Dirichlet}(2,2,2,2,2,2,2,2)
\end{aligned}$$

In all T1 and B/W models, we specified a Bernoulli distribution with a logit link for each `y` outcome item observed for individual `i` at time `t`. An outcome- and ID-specific random intercept ($\alpha_{ID_{yt}}$) with diffuse priors on α and σ allows estimated outcome probabilities to vary across individuals.[10] Each model was estimated with 4 chains and 4000 total post-warmup posterior draws per outcome using `brms::mvbind()` function, which offers "multivariate" or simultaneous response modeling (Bürkner, 2024). The `mo[]` terms indicate each of our `j` ordinal stress items have undergone monotonic transform, while the δ term indicates a vector of simplex parameters representing normalized differences between consecutive categories of these ordinal variables. The beta coefficient for these monotonic transformed variables is comparable to those representing "effects" of metric covariates in regression equations, with the numeric estimates interpreted as the average difference in the latent-mean scale of criminal intent or negative emotions between two adjacent categories of the ordinal predictor variable.

Though we do not focus on them until the mediation models, the cross-time "between-person" estimator ($\beta_2(\text{mo}[\overline{stress}_{ji}, \delta_2])$) in these models produce cross-sectional estimates that are interpretively similarly to those generated by the T1 regression models. Instead, we compare T1 results with contrasts from the within-person "fixed effects" or "FE" estimator in these models ($\beta_1(\text{mo}[stress_{jit} - \overline{stress}_{ji}, \delta_1])$), which describes average correlations between within-person changes in stress and changes in outcome responses.

With nine and five response categories for cross-time average and within-person deviation stress scores resulting in eight and four estimated thresholds respectively, the hyperparameters for their `mo()` transformed betas were determined by dividing the SD of a weakly informative (Normal[0,1]) beta prior distribution by the total number of estimated response thresholds (between: 1/8 = 0.125; within: 1/4 = 0.25). Specifying a weak uniform

[10] We omitted a fixed effect for time (i.e., latent growth curve estimator) to avoid inappropriately adjusting out any causal effects of systematic changes in stress across waves that might be absorbed by an estimator for population-level outcome trends over time. For example, a widespread economic or crime-related "shock" between waves might confound estimates or, alternatively, might systematically increase negative emotions or criminal intent *through* its systematic effects on population-level changes in subjective stress. In any case, inclusion of a time fixed effect only very slightly attenuated some estimated change associations.

Dirichlet prior distribution (α=2 for every threshold) for the cumulative monotonic simplex parameters (δ) allows each estimated threshold probability to vary substantially from one another (cf. McElreath, 2020: 393; Bürkner & Charpentier, 2020).

5.3.2 | Community-specific change estimates (RQ3)

After comparing unadjusted cross-sectional T1 and within-person FE estimates, we restrict our focus to FE estimates in RQ3 to assess whether within-person change correlations between subjective stress and posited outcomes are positive and strongest in low-SES urban communities. This is accomplished by adding our community factor variable indicating residence in one of four types of communities (rural or urban; low or high aggregate SES) to our B/W regression model along with an interaction between our FE estimator and the community factor variable (see Equation 2 below). The `k` subscript references the k=4 factor levels of the community variable and denotes separate parameters were estimated for k-1 factor levels.

Equation 2.

$$
\begin{aligned}
\boldsymbol{outcome_{yit}} &\sim \text{Binomial}\left(\boldsymbol{n}=\boldsymbol{1}, p_{\boldsymbol{yit}}\right)\\
\text{logit}\left(p_{\boldsymbol{yit}}\right) &= \alpha_{ID_{yt}} + \beta_1(\text{mo}[stress_{it} - \overline{stress}_i, \delta_1]) + \beta_2(\text{mo}[\overline{stress}_i, \delta_2])\\
&\quad + \beta_{3_k}(\text{community}_k) + \beta_{4_k}(\text{mo}[stress_{it} - \overline{stress}_i] \times \text{community}_k, \delta_{3_k})\\
\alpha_{ID} &\sim \text{Normal}(\alpha, \sigma)\\
\alpha &\sim \text{Normal}(0,2)\\
\sigma &\sim \text{Student} - t(3,0,2.5)\\
\beta_1 &\sim \text{Normal}(0,0.25)\\
\beta_2 &\sim \text{Normal}(0,0.125)\\
\beta_{3_k} &\sim \text{Normal}(0,1)\\
\beta_{4_k} &\sim \text{Normal}(0,1)\\
\delta_1 &\sim \text{Dirichlet}(2,2,2,2)\\
\delta_2 &\sim \text{Dirichlet}(2,2,2,2,2,2,2,2)\\
\delta_{3_k} &\sim \text{Dirichlet}(1)
\end{aligned}
$$

5.3.3 | "Practically large" marginal effects

Naïve interpretation of model beta coefficients is rarely useful and can result in substantial inference errors, particularly in regression models with interactions and/or those specifying nonlinear link functions to predict limited dependent variables. Thus, we transform and visualize model betas as "marginal effects" on outcome scales to help translate findings into interpretable effect magnitudes (Mize, 2019; Long and Mustillo, 2021).

With a nonbinary focal predictor, it is common to generate (conditional or average) marginal effects as predicted contrasts between those scored as "0" or "1" on a raw or standardized variable, thus representing an estimated (conditional) average effect of a one-unit predictor increase on outcome changes in the response scale. However, alternatives are possible and perhaps desirable depending upon one's descriptive or causal inferential aims. For example, McElreath (2020: 391-6; see also Kurz, 2023a: Sec. 12.4) illustrates the utility of estimating "maximum" effects representing predicted response contrasts across the highest and lowest scores of a predictor variable. In general, we prefer "maximum" contrasts to scale-specific "one-unit change" contrasts for numerous reasons.[11] Yet, it is also important to thoughtfully select one's theoretical and empirical estimands (Lundberg et al., 2021), avoiding temptations to rely on standardized metrics, and instead carefully considering whether software package or academic field defaults represent the most appropriate, plausible, or meaningful estimates or contrasts in the research context.

Likewise, after estimating models, examining fit summaries, and performing posterior predictive checks (see Supplement), we compared various alternative (e.g., 1-category; maximum) predicted contrasts that might effectively summarize model results for readers. In doing so, we considered meaningful effect contrasts that reflect plausible real-world limits to the

[11] For instance, the minimum and maximum values on imprecisely measured ordinal predictor scales may be more concretely defined and represent more valid contrasts than those implied by an average one-unit increase (e.g., consider "never/always" vs. "sometimes/often" contrasts). Maximum contrasts also serve as bounds on the total expected effect of a predictor, such that they intuitively represent the expected effect of "dialing up" the predictor from its lowest to its highest possible value. Likewise, unlike "one-unit increase" contrasts, the magnitudes of maximum contrasts for ordinal or continuous predictors are readily comparable to estimated effects of dichotomous "treatment" or factor ("dummy") predictors that also contrast lowest (0) and highest (1) values.

types of large yet actually occurring changes that might be observed in nature. In the case of subjective stress reports, we found that anything larger than a two-category change in subjective stress from T1 to T2 rarely if ever occurred in these data regardless of stress type. So, we transformed our model estimates into what we call “practically large” marginal effect (PLME) estimates of a two-Likert category increase in stress item responses on predicted outcome probabilities, calculated as predicted probability difference distributions averaged over all between-person two-unit response category predictive contrasts at T1 (e.g., “5-3”; “4-2”; “3-1”) or for within-person two-category stress increases from T1 to T2 averaged over all between-person stress levels. Conceptually, a two-unit difference or change in subjective stress item response categories represents a plausible yet practically large counterfactual expected effect associated with a “real-world maximum” increase in subjective stress.

These effects, in turn, are usually interpreted as expected differences or changes in the probability of an outcome (e.g., of reporting a “1” instead of a zero on a binary criminal intent or negative emotions item). These probability contrasts are equivalent to absolute risk or prevalence estimates, which we often convert to percentage-point increases in the text. The median of a Bayesian posterior distribution is typically used for point estimates, and uncertainty around estimates is often communicated with traditional 95% credible interval (95% CrI) thresholds. However, we also rely frequently on alternative summaries of posterior distributions, such as overlaying 50% or bold highlighting 80% quantile intervals. These decisions reflect our core aim of describing the data rather than severely testing hypotheses. Overall, our approach is intended to effectively generate valid descriptive inferences while communicating degrees of uncertainty around those inferences.

5.4 | Emotion mediation (RQ4)

We address RQ4 by exploring whether multivariate correlational patterns are consistent with the prediction that presumedly "criminogenic" emotions mediate associations between subjective stress and criminal intent. Unfortunately, estimating mediation models with every multivariate combination of stress item, criminogenic emotion item, and criminal intent outcome item compounds the number of potential estimates, making summary and visualization untenable. Thus, for this exploratory descriptive analysis, we will reduce the number of potential estimates by, first, relying on a standardized sum stress composite scale and, second, collapsing our negative emotions items into a variety index.[12,13]

At this time, there is a lack of accessible options for multilevel mediation modeling that can accommodate between- and within-unit estimation and specification of a cumulative probit or logit function for ordinal predictors. So, we generated estimates from multilevel between/within Bayesian models in `brms` (similar to those presented earlier) with the composite stress and negative emotions variables, then used the `mediate()` function from the `easystats::bayestestR` R package (Lüdecke et al., 2022) to estimate mediation pathway coefficients (e.g., direct and indirect effects).[14] These mediation models specify stress (X) and

[12] We adopt a sum stress scale because alternative approaches like factor-based or IRT scaling typically enforce strong assumptions about the unidimensionality of an underlying latent construct (Sijtsma, Ellis, and Borsboom, 2024). In doing so, they often weight items according to underlying theta or factor loadings, which may overrepresent effect estimates corresponding to upweighted component items while suppressing those corresponding to down-weighted items. In this case, while a general "stressed" construct might be partly driving reporting on each component stress item, multidimensionality cannot be ruled out - that is, one can imagine experiencing high financial stress, low relational stress, high job-related stress, and low victimization stress - or any other possible combination of stress levels. Likewise, absent compelling and contrary theoretical reasoning, we adopt an unweighted (simple sum) composite measure, as it should be more effective in capturing and describing any effects of underlying multidimensional components (see Appendix 1).

[13] For robustness purposes, the online Supplement (section 12) also presents results of mediation models using a sum scale instead of variety index for criminogenic emotions.

[14] Since this package generates average causal mediation estimates from posterior distributions, our hope was that this approach would be flexible enough to apply to our models with ordinal predictors. Unfortunately, that was not the case (see https://github.com/easystats/bayestestR/issues/576).

criminogenic emotions (M) as metric continuous variables (linear M models) and criminal intent (Y) as a binary outcome (logistic Y models). We then supplemented estimates from these models with within-person "X to M" and "X to Y" effect plots generated using `bmlm` R package (Vuorre and Bolger, 2018), which is designed to estimate within-unit mediation processes.

Ultimately, we present exploratory mediation estimates generated from these complementary approaches to assess whether our data plausibly might have been generated by the posited causal processes – that is, whether descriptive patterns are consistent with (among other plausible alternatives) the existence of indirect linear causal effects of differences or changes in stress (sum scale) on criminal intent (binary items) through differences or changes in "criminogenic" negative emotions items.

6 | RESULTS

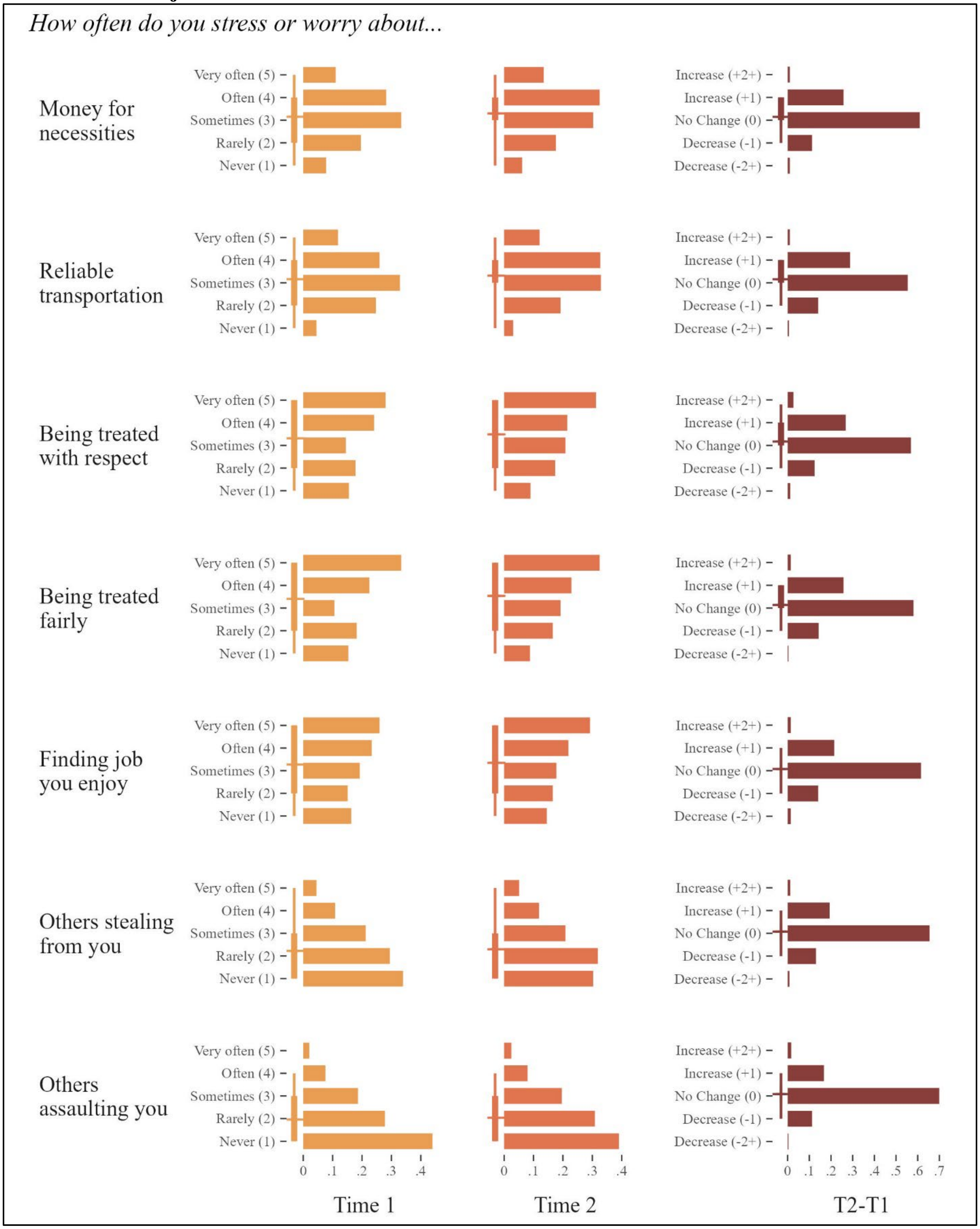
6.1 | Sample stress distributions (RQ1A)

RQ1A asks how often participants in our sample reported stressing or worrying about financial, relational, occupational, or victimization issues. We investigated this by examining the ordinal response distributions of all seven subjective stress items and within-person changes in these distributions across waves, for all participants with valid data at both observation periods (N=978 observations from 489 participants). Figure 2 displays observed proportions reporting in every ordinal response option for each stress variable at T1 and T2, as well as the observed degrees of change in item response categories across the two waves for each stress variable (T2–T1). The figure also displays interval plots showing the item mean with 50% and 95% intervals.

The observed response patterns for the first two financial stress items are approximately normally distributed in both waves, with the majority of respondents reporting somewhat or often stressing about money (T1: 61.6%; T2: 62.8%) or transportation (T1: 58.9%; T2: 65.6%) and relatively few reportedly never stressing about these things (range: 3.1% to 7.8%). In comparison, the observed item distributions for relational and job-related stress items do not exhibit symmetric decay about the midpoint characteristic of normal distributions. Rather, approximately half of our Bangladeshi participants reportedly often or very often stress about being treated with respect (T1: 52.2%; T2: 52.8%), being treated fairly (T1: 55.8%; T2: 55.4%), and finding a job they enjoy (T1: 49.3%; T2: 51.1%), while a sizeable proportion report never experiencing these types of stress (range: 8.8% to 16.4%). Finally, response distributions for subjective stress about criminal victimization exhibit high positive skew, with the majority of respondents reporting never or rarely stressing about others stealing from them (T1: 63.4%; T2: 62.2%) or assaulting them (T1: 71.8%; T2: 69.9%). Very few respondents report very often stressing about such victimization (range: 2.0% to 5.1%), which might be expected given the relative rarity of crime and criminal victimization. Of course, frequency and potency of stress are distinct characteristics, and general strain theory suggests that victimization-related stress may be especially potent and criminogenic despite being comparatively rare.

One additional pattern in Figure 2 is particularly noteworthy. The third column shows that very few respondents reported stress reductions or increases across the two waves greater than two units (on Likert-type stress items ranging from 1 to 5), despite a theoretical maximum possible change ranging from “-4” (1-5) to “4” (5-1). In fact, even two-unit changes in either direction across the two waves were quite rare. Thus, the few observed increases or decreases greater than two ordinal categories were recoded to a maximum change of (+/-)2.

FIGURE 2. Subjective Stress Distributions



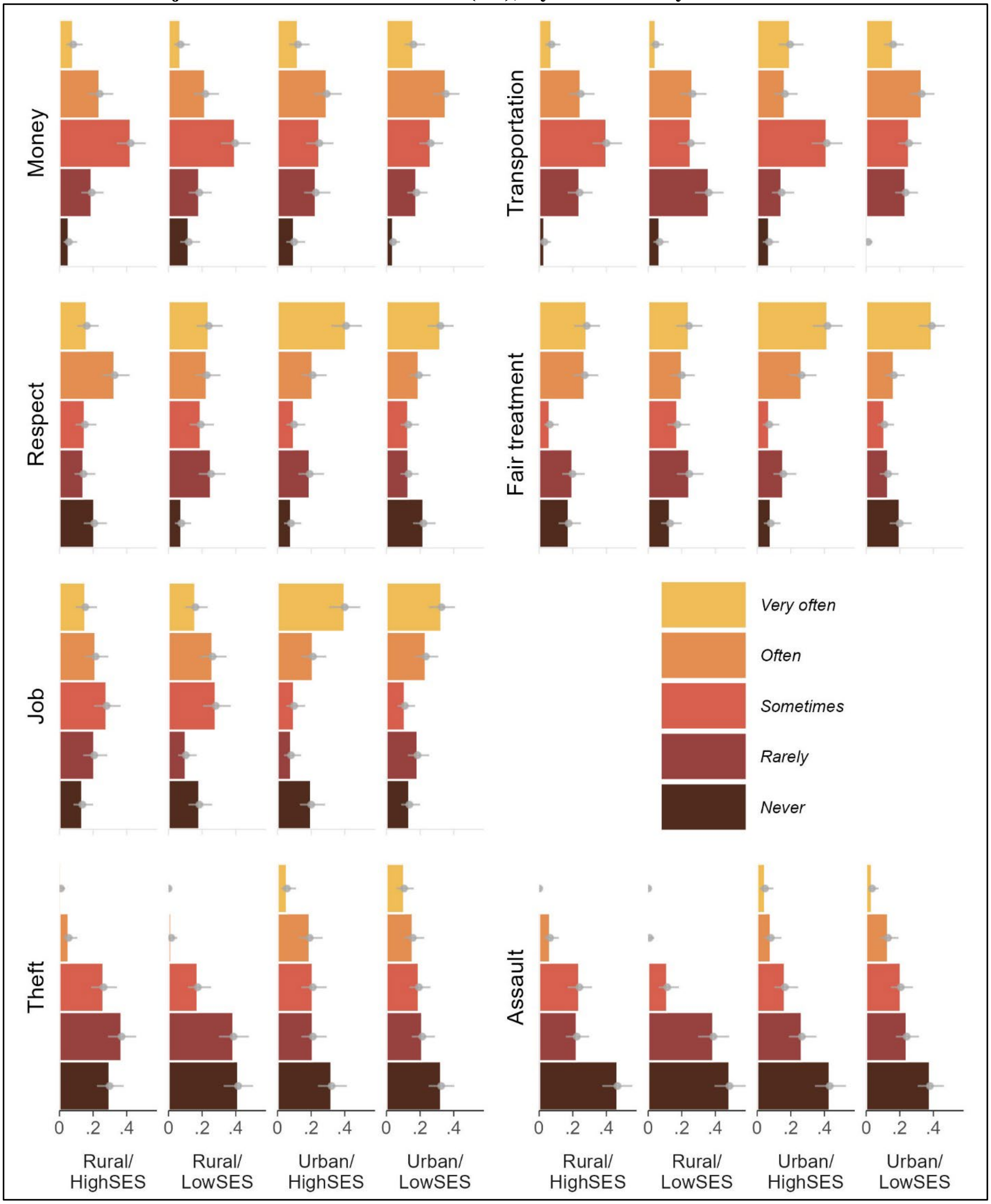
Note: N=489 respondents participating at both survey waves. Interval plots show item mean (horizontal tick), 50% (thick vertical bar), and 95% (thin vertical bar) intervals. Bars display the proportion of full sample reporting each item response category (T1; T2) or degrees of change in item response categories (T2–T1).

6.2 | Stress clustering (RQ1B)

RQ1B asks about heterogeneity in subjective stress distributions across social locations and, specifically, whether residents of low-SES urban communities report more frequently stressing or worrying about these sources of stress (*stress clustering*). To answer this question, we examined community-specific stress item response distributions for participants residing in each of the four rural or urban communities identified as having low or high aggregate SES. Figure 3 summarizes our findings. Unlike Figure 2, which plotted *observed* response distributions, the community-specific response distributions in Figure 3 are posterior estimates (medians and quantile intervals) generated by Bayesian sequential ordinal probit models for each stress item. This approach permits communicating population uncertainty surrounding recovered sample proportions, which we visualize using 95% credible intervals around the estimated proportions for every subjective stress response category.

Our primary aim with this plot is to help readers visualize stress response distributions and community differences in these distributions and, ultimately, to determine whether levels and sources of stress vary across rural/urban communities with high/low aggregate SES. The largest distributional difference is between those respondents residing in urban versus rural areas: Urban respondents reported more frequently experiencing stress from all sources - financial, interpersonal, job, and victimization. Also, consistent with *stress clustering* expectations, residents of low SES urban areas report more frequently stressing about financial and victimization issues. Thus, residents in these areas might more chronically experience stress and, if *stress amplification* expectations are correct, participants from these communities may be more susceptible to its posited deleterious consequences.

FIGURE 3. Subjective Stress Distributions (T1), by Community



Note: N=489 respondents participating at both survey waves. Bar charts display T1 stress item response distributions by community (rural/urban; high/low SES), calculated as the median of the posterior predictive distribution (PPD) for each response category within a community from sequential ordinal models specifying category-specific effects of community. Grey interval plots display PPD median (dot) and 95% uncertainty interval (line). Median estimates accurately recover observed proportions for each response category within each group.

6.3 | Stress deficit (RQ2)

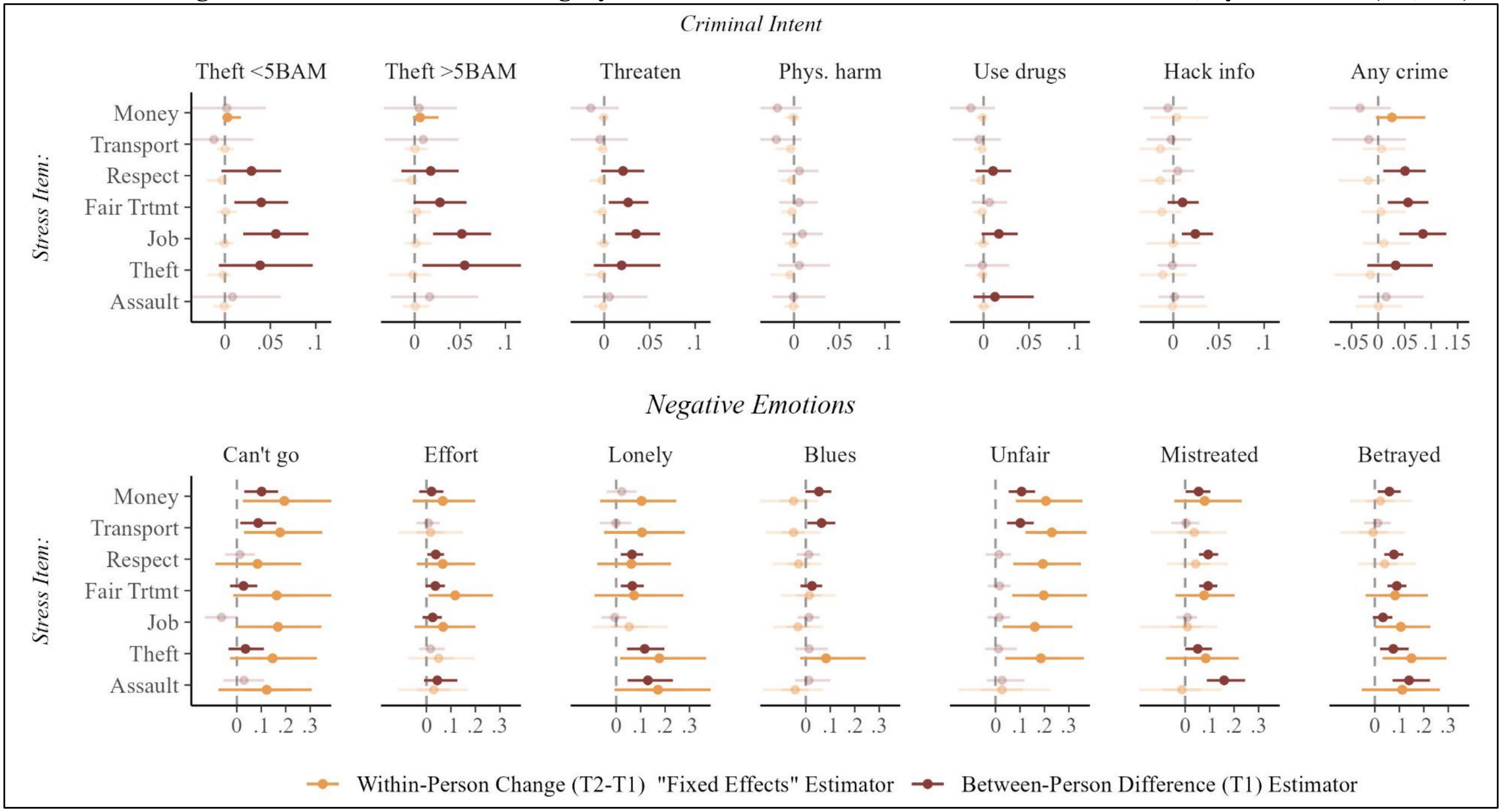
With RQ2, we move from describing stress distributions to examining stress as a theoretically posited predictor of criminal intent and depressive symptoms. Specifically, the question asks whether between-person differences (RQ2A) and within-person changes (RQ2B) in subjective stress are correlated with differences or changes in the probability of reporting criminal intent and negative emotions.

Figure 4 displays these "practically large" marginal effects (PLME) estimates and 95% credibility intervals, highlighting with bold point-intervals for easier visibility all contrasts with at least an 80% posterior probability of being greater than zero (i.e., at least 80% of the posterior estimates for a contrast are greater than zero; for a brief explanation of Bayesian credible intervals, see Makowski et al., 2019). These "plausibly positive" bold estimates are in line with monotonic *stress deficit* expectations from stress process and general strain theories, whereas null or negative estimates are inconsistent with *stress deficit* expectations.

Examining specific criminal intent item estimates first (Columns 1-6 in top panel), Figure 4 reveals 17 of the 42 between-person (T1) estimates are plausibly positive (i.e., 80% posterior probability of being greater than zero).[15] Overall, these between-person results reveal substantial heterogeneity across stress and response items. Perhaps the most robust between-person differences involved interpersonal, work-related, and victimization stress: Examination of T1 bold interval estimates indicate participants who reported more frequently stressing or worrying about respect, fair treatment, getting a job they enjoy, or being a victim of theft also were somewhat more likely to report at least some future chance of stealing less than 5BAM (first column), stealing more than 5BAM (second column), and threatening others (third column).

[15] Median posterior PLME estimates and 95% credible intervals plotted in Figure 4 for all of the crime and negative emotion items are provided in tables in the online Supplement (section 7.6.1).

FIGURE 4. Marginal Effects of Ordinal 2-Category Increase in Stress Item on Outcome Probabilities, by Estimator (T1; FE)



Note: N=489 respondents participating at both survey waves. Each of the 196 intervals displayed represents the estimated marginal effect of a "practically large" ordinal 2-category increase in stress on an outcome probability derived from 196 distinct Bayesian logistic regression models. Of these, 182 estimates are from multivariate models simultaneously regressing (using `brms:: mvbind()`) the six specific criminal intent outcomes or the seven negative emotions outcomes on each of the seven stress types (T1: 13*7=91 models; multilevel "between/within" or B/W: 13*7=91 models). The other 14 estimates are from seven T1 or seven B/W models separately regressing "any criminal intent" on each stress item. In B/W models, stress items were separated into a L2 cross-time average (Xbar_i) between-person predictor and a L1 within-person change (X_it - Xbar_i) "fixed effects" estimator. In all models, stress predictors (L1 & L2) were specified as monotonic ordinal predictors with a cumulative probit link function. Models were estimated in brms with 4 chains and 4000 total post-warmup posterior draws per outcome. Marginal effect contrast distributions were estimated from the expectation of the posterior predictive distribution for each model as predicted probability difference distributions, either averaged over all 2-category stress differences (T1), or for 2-category stress increases (T1 to T2 change) averaged over all between-person stress levels. Median posterior density estimates with 95% intervals displayed. Bold point-intervals indicate at least 80% of posterior contrast estimates are greater than zero.

The between-person "any crime" estimates (last column) essentially reproduced these three crime-specific patterns, with the four bold (80% plausibly positive) unadjusted PLME estimates ranging from 0.03 (stress about theft victimization: PLME = 0.03, 95% CrI = [-0.02, 0.10]) to 0.08 (stress about job: PLME = 0.08, 95% CrI = [0.04, 0.13]). Put differently, participants who report (two-ordinal categories) higher subjective stress about respect, fair treatment, getting a job they enjoy, or being a victim of theft are 3- to 8-percentage-points more likely to report some future chance of engaging in at least one type of crime compared to those reporting (two-ordinal categories) lower stress.

The item-specific within-person results, which adjust by design for time-stable individual differences, reveal starkly different patterns. All 17 of the plausibly positive T1 estimates were estimated as null or near-null associations by the within-person fixed effects estimator. In fact, of the 42 possible specific crime item associations examined, the fixed effects estimator shows only two stress-crime item change correlations that were positive with at least 80% plausibility: Reporting a two-category increase in stress about money from T1 to T2 is associated with an extremely small unadjusted increase in the predicted probability of reporting any future intent to engage in theft less than 5BAM (PLME = 0.003, 95% CrI = [-0.003, 0.018]) and theft greater than 5BAM (PLME = 0.006, 95% CrI = [-0.002, 0.026]). A plausibly positive within-person unadjusted estimate for stress about money was observed in the model predicting "any crime" as well. Participants who report an increase (of two-ordinal categories) in stress about money from T1 to T2 are about 3-percentage-points (PLME = 0.026, 95% CrI = [-0.004, 0.089]) more likely than they were at T1 also to report some future chance of engaging in at least one type of crime.

With respect to negative emotions, 29 out of 49 outcome-specific marginal effect contrasts at T1 were positive with 80% plausibility, whereas the within-person fixed effects estimator generated 32 (of 49) plausibly positive stress-emotions change correlations. With that said, there is systematic heterogeneity in estimates across outcomes, with some outcomes showing some or even all (e.g., "blues") null estimates. Moreover, in most negative emotions models, the unadjusted within-person estimator generated larger marginal effect contrasts than did the between-person estimator.

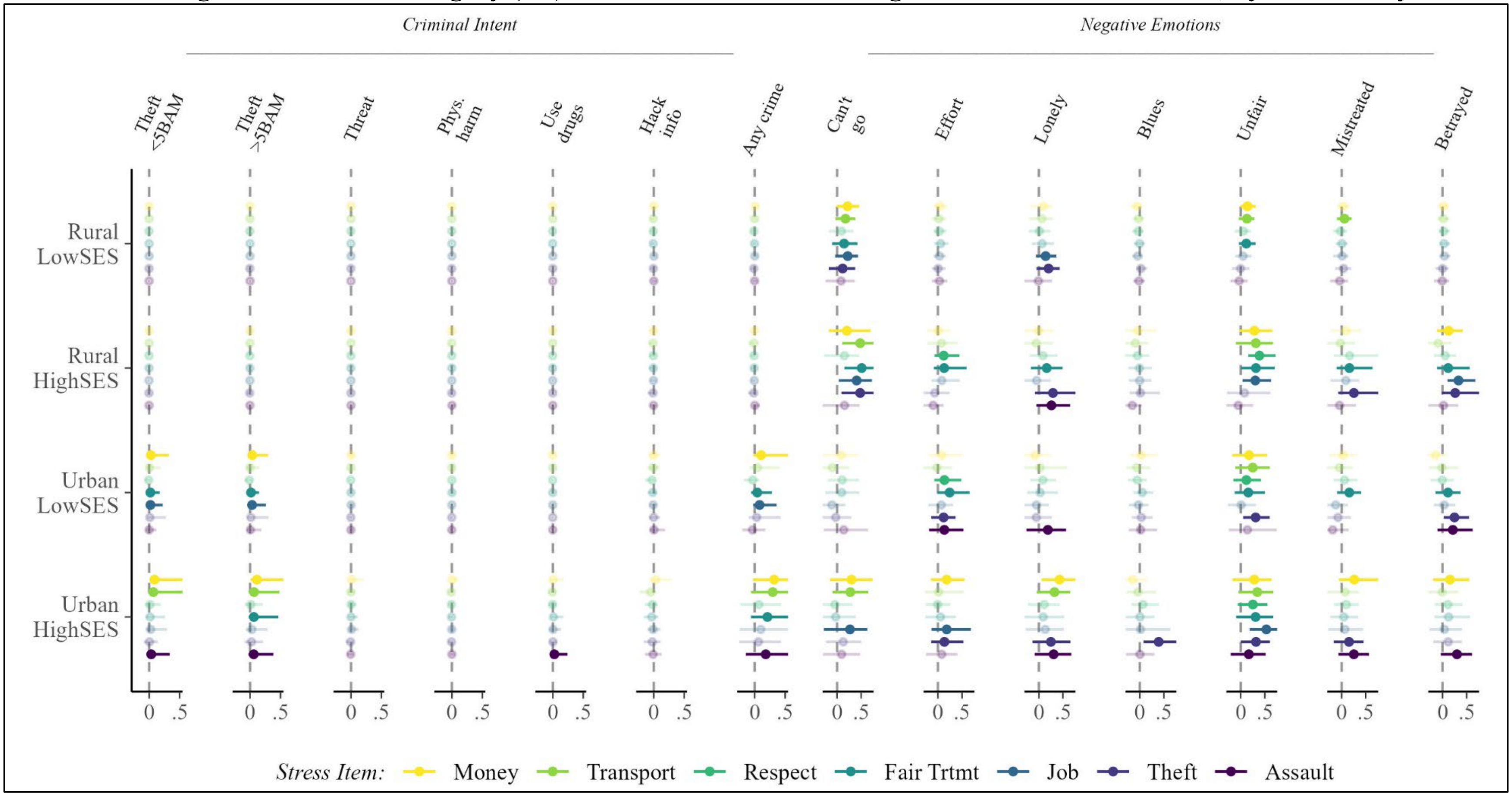
We can quantify this difference by comparing the median and quantile intervals of stacked distributions of posterior PLME T1 or change estimates, which is conceptually akin to comparing an unweighted meta-analytic effect of a two-unit stress increase (T1) or change (T2-T1) across between-person or within-person models. The median of all posterior PLME estimates for negative emotions T1 models is 0.04 (80% CrI = [-0.01, 0.11]), whereas the comparable median of all posterior estimates for negative emotions change models is twice as large at 0.08 (80% CrI = [-0.05, 0.23]). Put differently, 50% of all two-category ordinal stress contrast estimates from between-person negative emotions models predict at least a 4-percentage-point between-person difference in the probability of reporting negative emotions, with the upper quintile of estimates predicting at least an 11-percentage-point difference. In comparison, 50% of all within-person change estimates from negative emotions models predict at least an 8-percentage-point within-person increase in the probability of reporting negative emotions associated with a two-category stress increase – a magnitude that is twice as large as the median between-person estimate on an absolute risk or prevalence scale. Wider credible intervals indicate greater uncertainty due to increased plausibility of larger within-person estimates, with the upper quintile of estimates predicting at least a 23-percentage-point increase in the probability of negative emotions associated with a two-category stress change.

Additionally, these magnitudes on absolute risk or prevalence scales are much more likely to be positive and tend to be substantially larger for models predicting negative emotions compared to those predicting criminal intent. The median of stacked posterior PLME estimates are 0.01 (80% CrI = [-0.02, 0.05]) for between-person criminal intent models and -0.00 (80% CrI = [-0.01, 0.01]) for within-person criminal intent models. Overall, the unadjusted model estimates plotted in Figure 4 appear to be largely consistent with *stress deficit* expectations when predicting negative emotions, while models predicting criminal intent generate much smaller absolute risk difference or change estimates that are quite tightly centered at or near zero.

6.4 | Stress amplification (RQ3)

RQ3 asks whether within-person change correlations between subjective stress and posited outcomes (criminal intent; negative emotions) are positive and strongest in low-SES urban communities. Figure 5 displays community-specific PLME estimates and 95% credibility intervals, again bold highlighting all contrasts with at least 80% posterior probability of being greater than zero. Comparable to the “within” estimates in Figure 4, this plot visualizes community-specific predicted probability difference distributions associated with two-category within-person stress increases from T1 to T2 averaged over all between-person stress levels. As before, “plausibly positive” bold estimates are in line with monotonic *stress deficit* expectations from stress process and general strain theories, whereas null or negative estimates are inconsistent with *stress deficit* expectations. Moreover, the *stress amplification* expectation anticipates observing the largest estimates in low-SES urban communities.

FIGURE 5. Marginal Effect of 2-Category (FE) Increase in Stress on Change in Outcome Probabilities, by Community



Note: N=489 respondents participating at both survey waves. Each of the 392 intervals displayed represents the estimated marginal effect of a "practically large" ordinal 2-category increase in stress on an outcome probability derived from a fixed effects (FE) estimator in 98 distinct Bayesian multilevel between/within logistic regression models (98 models*4 community estimates). Of these, 364 estimates are from 91 multivariate models simultaneously regressing (using `brms:: mvbind()`) the six specific criminal intent outcomes or the seven negative emotions outcomes on each of the seven stress types (13*7=91 models). The other 28 estimates are from seven models separately regressing "any criminal intent" on each stress item. Stress items were separated into a level 2 (L2) cross-time average (Xbar_i) between-person predictor and a level 1 (L1) within-person change (X_it - Xbar_i) "fixed effects" or FE estimator. Both L1 and L2 stress variables were specified as monotonic ordinal predictors with a cumulative probit link function. Models also included a factor variable for community and a multiplicative interaction between FE stress estimator and community. Models were estimated in brms with 4 chains and 4000 total post-warmup posterior draws per outcome and per community group. Marginal effect contrast distributions were estimated from the expectation of the posterior predictive distribution for each model as predicted probability difference distributions for 2-category stress increases (T1 to T2 change) by community, averaged over all between-person stress levels. Median posterior density estimates with 95% intervals displayed. Bold point-intervals indicate at least 80% of posterior contrast estimates are greater than zero.

As with the unadjusted estimates in Figure 4, nearly all of the community-specific within-person estimates from criminal intent models in Figure 5 are tightly centered around zero. Though these patterns might have been generated by weak or negligible population associations between changes in measured subjective stress and changes in criminal intent, they could alternatively reflect insufficient data to detect population signals due to a combination of outcome rarity and small subsample sizes (ranging from n=108 to 144 participants per group).

Regarding exceptions, the 21 “plausibly positive” within-person associations (out of 196) observed between stress and criminal intent again are confined mostly to the two theft outcome items (n=13 estimates) and to the aggregate “any crime” item (n=7). Consistent with *stress amplification* expectations, these plausibly positive estimates are observed solely in low SES (n=9) and high SES (n=12) urban communities where aggregate stress levels are highest. Moreover, while these positive community-specific estimates are noisier (as expected given smaller subsample sizes), they also are larger in magnitude than the unadjusted estimates.

For example, recall the unadjusted within-person PLME estimates in Figure 4 predicted a 3-percentage-point increase in the probability of “any” criminal intent associated with a two-category increase in stress about money. In comparison, the community-specific estimates in Figure 5 predict the same two-category increase in stress about money is associated with a 32-percentage-point increase (PLME = 0.32, 95% CrI = [-0.03, 0.82]) in the probability of “any” criminal intent in urban high SES communities and an 11-percentage-point increase (PLME = 0.11, 95% CrI = [-0.02, 0.56]) in urban low SES communities. The wide but mostly positive credibility intervals in these communities indicate that increases in subjective stress are associated with changes in the probability of criminal intent ranging from negligible to large and positive in magnitude, with comparable magnitudes even to negative emotions benchmarks.[16]

Regarding negative emotions, 69 of 196 within-person estimates from negative emotions models in Figure 5 indicate plausibly positive and potentially large community-specific associations between subjective stress and negative emotions. As before, there is some systematic heterogeneity in estimates across outcomes. Most notably, within-person changes in reports of feeling the "blues" are largely uncorrelated with changes in subjective stress.

Inconsistent with *stress amplification* expectations, estimated associations between subjective stress and negative emotions in Figure 5 do not appear to be systematically strongest in urban low SES areas, nor do they even appear to be consistently stronger in urban areas compared to rural areas. If anything, the within-person PLME estimates might be stronger in high SES compared to low SES communities. Again, one way to quantify these differences is by comparing the median and quantile intervals of stacked distributions of posterior PLME change estimates across communities, which is akin to comparing an unweighted average meta-analytic effect of a two-unit stress increase on negative emotions across community-specific models. The median of all posterior PLME estimates from negative emotions models is 0.03 (80% CrI = [-0.08, 0.20]) for rural low SES areas and 0.05 (80% CrI = [-0.18, 0.30]) for urban low SES areas; the comparable average estimates are more than twice as high at 0.10 (80% CrI = [-0.15, 0.46]) and 0.14 (80% CrI = [-0.12, 0.46]) for rural high SES and urban high SES areas, respectively.

In comparison, the median of stacked posterior PLME estimates for criminal intent models are -0.002 (80% CrI = [-0.018, 0.001]) for rural high SES, -0.001 (80% CrI = [-0.012, 0.005]) for rural low SES, 0.006 (80% CrI = [-0.040, 0.193]) for urban high SES, and -0.001

[16] Median posterior PLME estimates and 95% credible intervals plotted in Figure 5 for all of the crime and negative emotion items are provided in tables in the online Supplement (section 9.2.1).

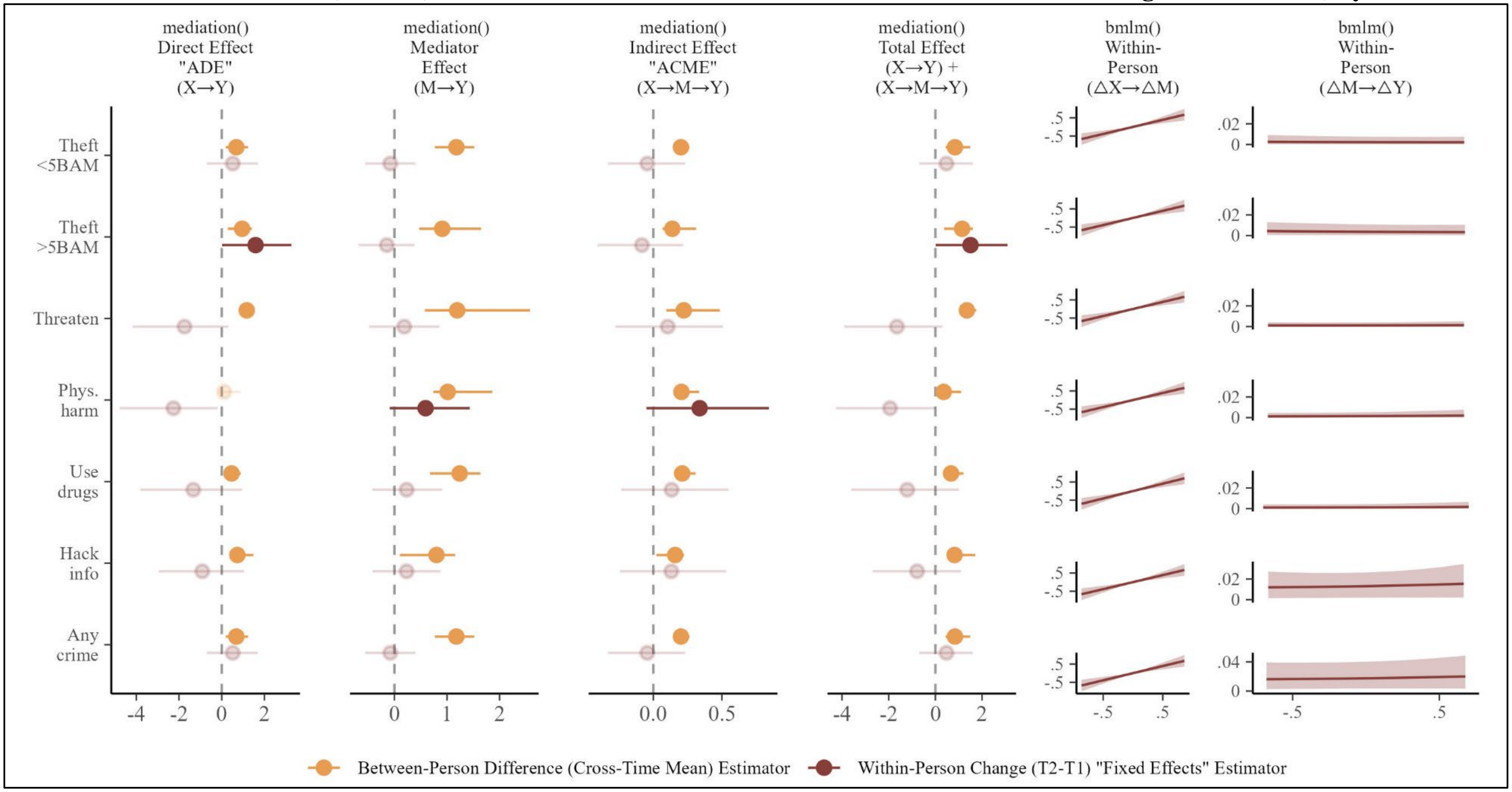
(80% CrI = [-0.025, 0.062]) for urban low SES communities. Overall, and similar to conclusions from unadjusted model estimates in Figure 4, a substantial portion of the community-specific estimates in Figure 5 appear to be consistent with *stress deficit* expectations when predicting negative emotions but, when predicting criminal intent, only a small fraction of models for select outcomes (e.g., theft; any crime) appear consistent with *stress deficit* expectations.

6.5 | Mediation expectation (RQ4)

RQ4 asks whether the correlational patterns in these data are consistent with a simple causal mediation data generating process in which increases in overall stress indirectly cause increases in self-reported criminal intent through increases in presumedly "criminogenic" negative emotions. Figure 6 summarizes results from our two complementary modeling approaches to addressing this question.

The first four columns in Figure 6 display between-person and within-person estimates of direct (X to Y), mediator (M to Y), indirect (X to Y via M), and total (direct plus indirect) effects, respectively. These estimates were generated using `bayestestR::mediation()` R package from Bayesian multilevel B/W models regressing binary criminal intent outcomes on between-person and within-person measures of "overall" subjective stress (standardized sum scale) and criminogenic negative emotions (variety index). Overall, between-person estimates in these columns appear largely consistent with strain theory's *mediation* expectations. Participants reporting higher overall subjective stress are more likely to report criminogenic emotions (not shown), and those who report higher levels of overall subjective stress and experiencing more criminogenic emotions also generally are more likely to report all types of criminal intent, except perhaps for physical harm.

FIGURE 6. Estimated Total, Direct, & Indirect Effects of Stress on Criminal Intent via Criminogenic Emotions, by Estimator



Note: N=489 respondents participating at both survey waves. COLUMNS 1-4: Multilevel b/w Bayesian models predicted binary criminal intent outcomes (7 logistic "Y" models) and a between- or a within-person mediator (2 Gaussian "M" models). All models included a standardized sum stress scale separated into L2 between-person (Xbar_i) and L1 within-person change (X_it - Xbar_i) "fixed effects" estimators ("X"). "Y" models also included both L2 (between) and L1 (change) measures of differences/changes in the number of criminogenic emotions reported. Untransformed posterior mediation estimates generated from fitted models using `bayestestR::mediation()` R package. Median posterior density estimates with 95% equal-tailed (ETI) credible intervals displayed. Bold point-intervals indicate at least 80% of posterior estimates are greater than zero. COLUMNS 5-6: Comparable within-person mediation models were fit using `bmlm::mlm()` R package to generate model-implied posterior effect estimates averaged over random effects for plotting in original item metrics. Column 5 (X→M) displays estimated effect of changes in X (X = -0.5 to X = 0.5 equates to 1 SD unit increase in stress) on changes in M (M = -0.5 to M = 0.5 equates to increase of 1 additional criminogenic emotion reported). Column 6 (M→Y) displays estimated effect of changes in M on changes in the probability of Y (e.g., increase from Y = 0 at M = -0.5 to Y=0.02 at M = 0.5 implies an increase of one reported emotion causes a 2-percentage-point increase in the probability of criminal intent). These estimates also reflect any indirect effect of X on Y through M, while x-axis range displays model-implied degree of change in M (emotions) caused by change in X (stress).

With that said, within-person estimates in Columns 1 to 4 of Figure 6 largely are inconsistent with strain theory's *mediation* expectations, again with the possible exception of physical harm: Participants who report increases in overall subjective stress also report increases in criminogenic emotions and, indirectly, report increases in physical harm intent (see Row 4, Columns 2 and 3). Yet, even if our DAG #4 and this possible empirical exception were valid, any potential within-person indirect causal effect of changes in subjective stress on physical harm intent through criminogenic emotions would appear to be wholly offset by stronger countervailing direct negative effects of changes in subjective stress on physical harm intent (see Row 4, Columns 1 and 4).

The last two columns in Figure 6 present plots of within-person marginal effects on outcome scales. These were generated from within-person mediation models fit using `bmlm::mlm()` R package, which plots model-implied posterior effect estimates converted to original item metrics averaged over random effects. In general, results from this alternative approach to estimating within-person mediation effects largely are consistent with findings in Columns 1 to 4 and confirm within-person results from earlier item-specific models (i.e., Figures 4 and 5). The plot in Column 5, which is the same for all seven criminal intent outcomes, indicates that reporting a one standard-deviation unit within-person increase in overall subjective stress from T1 to T2 is associated with an estimated increase of approximately one additional criminogenic emotion reported. In contrast, the seven plots in Column 6 show that an increase of one reported emotion – the degree of change implied by a one-SD unit change in stress – is associated with a negligible or null increase in the probability of reporting criminal intent, with expected change magnitudes ranging from 0- to approximately 2-percentage-points at most. Note that these plotted marginal effect estimates also capture any indirect effect of overall subjective stress on criminal intent through emotions. Thus, within-person increases in subjective stress are associated with increases in criminogenic emotions, but both appear to be largely irrelevant to changes in criminal intent.

7 | DISCUSSION

We set out seeking to revisit a fundamental criminological question: Does subjective stress causes negative emotions and criminal behavior? Our descriptive analyses were guided by specific research questions about *stress clustering*, *stress deficit*, *stress amplification*, and *mediation* expectations derived from stress process theories. To answer these questions, we documented univariate distributions, unadjusted and community-specific correlations, and multivariable mediation-style (direct and indirect) results to describe associations between subjective stress, negative emotions, and criminal intent in two waves of survey data from adults in Bangladesh. Relying on several modern analytic techniques to strengthen the precision and accuracy of our descriptive inferences (e.g., DAGs for causal clarity; item-specific analysis; ordinal modeling to match item response distributions; practically large marginal effects; benchmark comparisons), we aimed to assess whether descriptive results were consistent with theoretical expectations. A few things seem clearer after these efforts.

First, stress predictably clustered in social space in these data. Urban respondents reported more frequently stressing about financial, interpersonal, job, and victimization issues, while residents of low SES urban areas in particular reported more frequently stressing about financial and victimization issues (see Figure 3). These findings align with a large body of evidence documenting that residents of socioeconomically disadvantaged communities are more chronically exposed to potent stressors, display more physiological indicators of allostatic overload, have poorer health, report higher levels of subjective distress, and are at greater risk of experiencing depression, crime, and other psychopathological outcomes (i.e., *stress clustering* expectation; cf. Sampson, Morenoff, and Gannon-Rowley, 2002; Silver, Mulvey, and Swanson, 2002; Matheson et al., 2006; Shulz et al., 2012; Robinette et al. 2016).

Second, overall findings from both between-person and within-person estimates showed a substantial number of positive associations between subjective stress and negative emotions. Based on the median of within-person posterior estimates across all unadjusted negative emotions models, a two-category change in subjective stress was associated with an 8-percentage-point increase on average in the probability of reporting negative emotions. Again, these findings are consistent with a large literature documenting robust relationships between stressful experiences, perceived stress, negative affect, and depression (i.e., *stress deficit* expectation; cf. Hammen, 2015; Cristóbal-Narváez, Haro, and Koyanagi, 2020; Maciejewski et al., 2021).

Third, perhaps the most notable finding was the stark differences observed across within-person and between-person estimates for subjective stress and criminal intent associations. Unadjusted between-person estimates (Figure 4) seemed largely consistent with strain theory's *stress deficit* expectations, as respondents who reported more stress also were more likely to report criminal intentions and negative emotions. In contrast, the mostly null within-person estimates of stress-criminal intent associations, with intervals tightly centered around zero, indicate that changes in subjective stress were largely unrelated to changes in the probability of reporting criminal intentions in this sample, with few exceptions. Similarly, unlike the between-person estimates, the within-person indirect effect estimates from mediation models largely were inconsistent with theoretical expectations.

Recall from our DAGs (Figure 1) that within-person “FE” estimates are generally preferred over between-person estimates when inferring causality from correlations because they adjust for (measured and unmeasured) time-invariant sources of confounding that otherwise bias between-person estimates generated from the same data (Allison, 2009; Quintana, 2021). Given this, the between-person (T1) estimates of stress-criminal intent associations might spuriously reflect various sources of confounding, whereas the within-person estimates might be more valid estimates of the average (null) effects of stress on criminal intent.

Interpreted at face value, these results indicate: (1) Many people in this sample report experiencing various types of subjective stress, and some are at greater risk of reporting high subjective stress due to their social locations; and (2) People who report experiencing increased levels of subjective stress over time also tend to report experiencing more depressive symptoms and “criminogenic” negative emotions but not more criminal intentions over that same time frame.

Yet, despite the clear advantages they offer over between-person estimates, within-person change estimates from observational data also should be interpreted descriptively and should not be used to make strong causal inferences in most circumstances (cf. Rohrer and Murayama, 2023). One reason is that neither the between-person nor within-person estimators rule out time-varying sources of confounding, nor do either necessarily adjust for selection or reverse causality processes. For example, involvement in crime may cause more difficulties in interpersonal and work relationships, and criminal lifestyles or activity routines might expose people to greater victimization risks (Bjerk, 2009). Likewise, the link between stress and depression is known to be complex and bidirectional, as individuals with histories of depression are more likely to select into and to perceive more stressful circumstances that may then cause or maintain depressive symptoms (Hammen, 2006; 2015). Thus, as with cross-sectional analyses of observational data, the between-person and within-person estimates of stress "effects" on negative emotions or crime that are consistent with theoretical expectations might have been generated by theorized causal processes, and/or they may have been generated by one or more alternative and possibly contradictory processes (e.g., confounding, selection, or reporting biases; complex bidirectional processes) that were not sufficiently ruled out by our research design.

Another issue is that analysis of rare events requires large samples and within-person change estimates require sufficient variation over time to ensure an adequate signal-to-noise ratio in the data. Despite having a relatively large sample (n=978 observations from 489 individuals participating in both waves), an overwhelming majority of respondents reported no criminal intentions of any type in both waves and, thus, no within-person changes. Additionally, consider that the within-person estimator describes average within-person change correlations over a very specific time lag – in this case, contemporaneous correlations between changes over a two-year panel interval. This substantial time interval was designed to increase the chances of observing sufficient within-person changes in subjective stress, negative emotions, and crime. The fact that both between-person and within-person estimates revealed a large number of positive associations of substantial magnitude for certain negative emotions items suggests that the design may have been sufficient to detect theoretically expected correlations between changes in subjective stress and changes in the probability of reporting negative emotions.

For these reasons, we strongly caution against interpreting these results as evidence against general strain theory due to the high potential risks of Type II errors (e.g., Brauer, Day, and Hammond, 2021). Rather, we encourage future follow-up research designed with much larger samples and perhaps more precise measures to maximize the chances of detecting potential average stress effects on crime of very small magnitudes. For instance, typical designs like ours should plan for detecting a “smallest effect size of interest” of potentially less than 2-percentage-point differences in very low baseline predicted probabilities of criminal intentions on absolute risk scales (see Riesthuis, 2024).

Regarding community heterogeneity in estimates for criminal intentions, some “plausibly positive” within-person estimates were documented and, consistent with *stress amplification* theoretical expectations, these conditional associations were observed and estimated to be much larger in magnitude in urban communities where reported stress levels were highest. Examination of the item-specific criminal intent estimates suggests that patterns consistent with *stress amplification* expectations were isolated only to correlations between stress about money and theft outcomes. That is, urban participants who reported increases in financial stress from T1 to T2 also were more likely to report intentions to steal at T2 compared to T1. This pattern aligns with findings from prior research and appears consistent with claims that criminal intentions to steal in part reflect instrumental motives to cope with perceived financial stress (e.g., Brezina, 2000; Agnew, 2006b; Felson et al., 2012). However, given the mostly null associations for other stress and criminal intent items, and considering that small subsamples resulted in relatively noisy and imprecise interval estimates, we again recommend follow-up research with larger samples.

Findings showed substantial heterogeneity in estimates across specific types of stress, negative emotions, and communities. However, inconsistent with *stress amplification* expectations, community-specific estimates did not show a clearly distinguishable trend towards stronger associations between subjective stress and negative emotions among residents of communities with higher aggregate stress levels (e.g., urban, low-SES). The one glaring exception was the observation of virtually all null estimates for the "*felt you could not shake the blues*" item. This unexpected pattern might indicate the *blues* item, which is used widely in stress process research, is a poor indicator of depressive symptoms in this sample; alternatively, this specific symptom may be largely uncorrelated with changes in subjective stress for unknown reasons in this context.

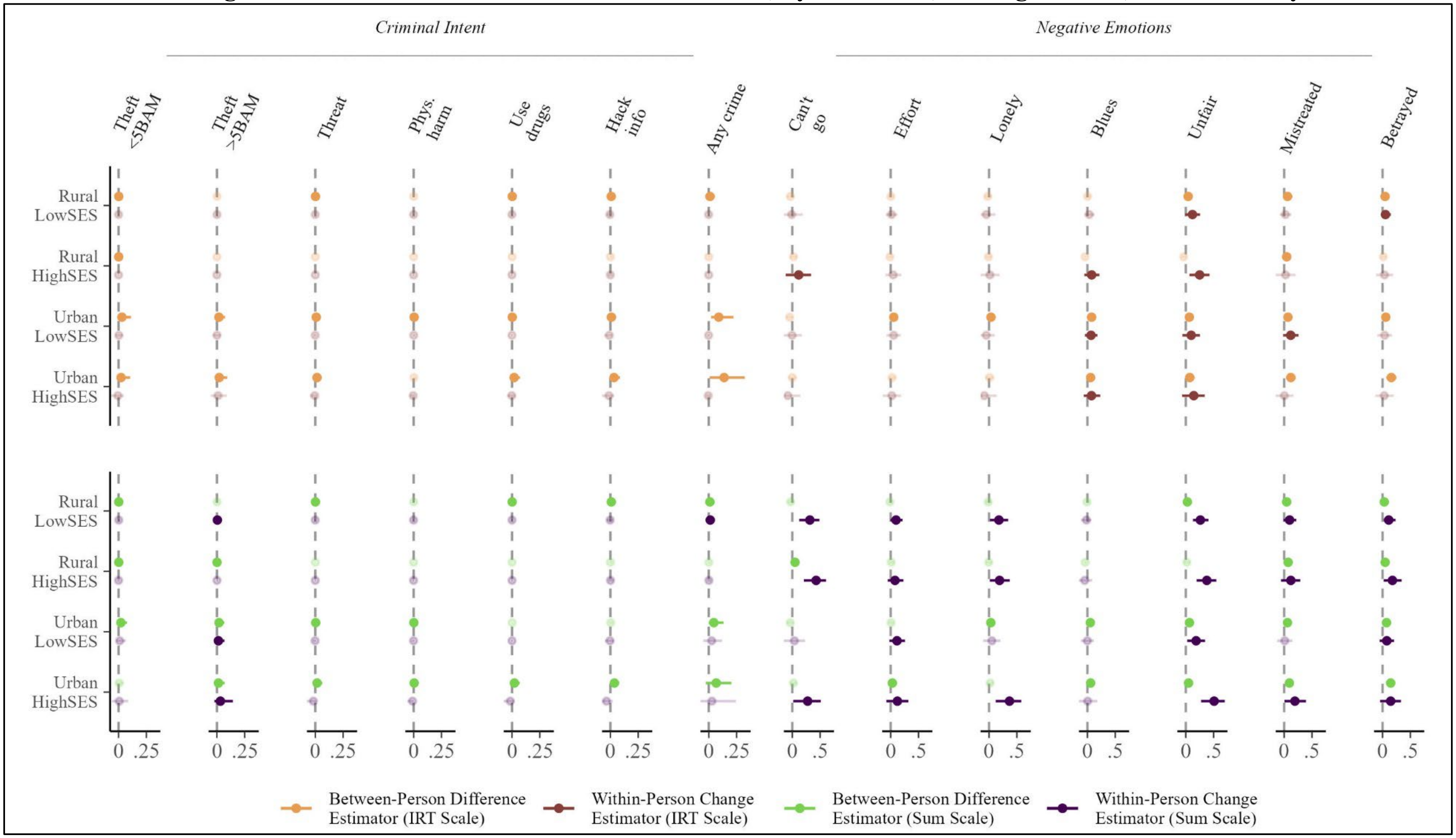
Results of mediation models again confirmed a strong positive within-person association between changes in "overall" subjective stress (sum scaled) and changes in "criminogenic" negative emotions symptoms (variety index). However, increases in these apparently stress-responsive and presumedly "criminogenic" emotions were largely unrelated to changes in criminal intent. Thus, these multivariable correlational findings were largely inconsistent with theoretical *mediation* expectations. They suggest that increases in subjective stress are correlated with increases in negative affective feelings of being unfairly treated or betrayed (cf. Brauer, Tittle, and Antonaccio, 2019) but that such feelings might not be very "criminogenic" after all, at least on average. It remains possible that larger samples and more focused research designs could uncover evidence of these theorized causal mediation processes, perhaps with conditional estimates representing response contrasts over shorter time intervals and across various theoretically specified conditions (e.g., for individuals with particular predispositions; in situations lacking alternative noncriminal coping opportunities; in the presence of social pressures to cope with crime; see Agnew, 2006a).

8 | CONCLUSION

Overall, our results appear consistent with the claim that stress causes negative emotions, but the foundational question of whether stress causes crime remains unsettled. However, the descriptive results raise additional interesting questions and point to pathways for future research. For example, it is important to know whether the descriptive patterns we document here generalize to other samples and contexts. Specifically, follow-up studies with larger samples will help determine more precisely whether average (unadjusted) within-person associations between subjective stress and criminal intent indeed are quite small on an absolute risk scale and whether within-person conditional estimates replicate with larger magnitudes in socioeconomically disadvantaged and high-stress communities. Additionally, focused experimental designs, perhaps with vignettes, virtual reality, or lab methods aimed at observing short-term causal effects triangulated across multiple precise measurement items, might investigate whether increases in financial stress indeed cause instrumental motives or intentions to cope with economic crimes. Finally, descriptive research might point out promising pathways or potential dead-ends but, whether we start or end with theory, ultimately we need to move towards improving the precision of our scientific theories and designing severe tests of precise and risky predictions, ideally about specific mechanisms, from those theories.

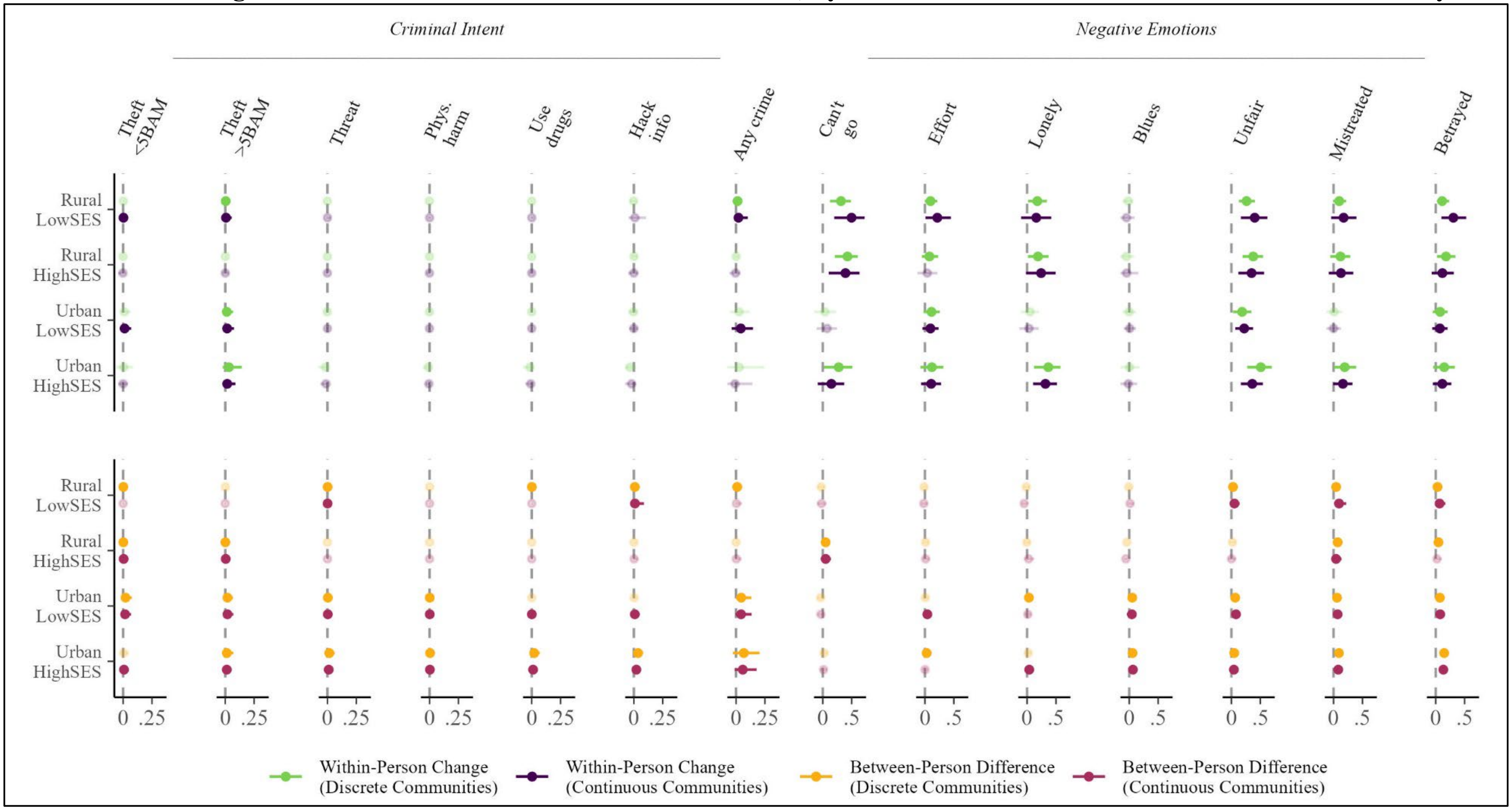
In conclusion, we encourage more research pursuing detailed documentation of messy description over tests of ambiguous theories that generate simple stories. Yes, our descriptive results are messy and, in a long manuscript, we have only been able to highlight basic patterns that perhaps muddy the waters in places more than they clarify. Yet, why would social scientists expect differently? We regularly regale students with the complexities of the social world and the challenges inherent in studying it scientifically. That this complexity often is ignored or glossed over in published literatures may bely more fundamental problems with normative practices in social scientific training, theorizing, researching, and reporting (cf. Blalock, 1989; Mears and Stafford, 2002; Eronen and Bringmann, 2021; Lundberg et al., 2021; Chin et al., 2023). Of course, by providing the data, code, and detailed results in an online supplement, we hope readers interested in particular aspects of the research can download the data, dig into the code, and reproduce specific estimates on their own, or reanalyze the data to pursue their own theoretical questions. Our hope is that, together, we might collectively approach more precise and convincing answers to foundational sociological and criminological questions that continue to nag our field.

APPENDIX 1. Marginal Effects of Stress on Outcome Probabilities, by Estimator, Scaling Method, & Community



Note: N=489 respondents participating at both survey waves. Estimates derived from multivariate (using `brms::mvbind()`) and multilevel between/within Bayesian logistic regression models simultaneously regressing all criminal intent outcomes (6*2=12 models) and all negative emotion outcomes (7*2=14 models) separately on a latent IRT and a standardized sum stress scale, and two separate models regressing "any criminal intent" on each stress scale. Both stress scales were separated into L2 cross-time average (Xbar_i) between-person and L1 within-person change (X_it - Xbar_i) "fixed effects" estimators. Models also included a factor variable for community and multiplicative interactions between community and both L1/L2 stress estimators. Models were estimated in brms with 4 chains and 4000 total post-warmup posterior draws per outcome and per community group. Marginal effect contrast distributions were estimated from the expectation of the posterior predictive distribution for each model as community-specific predicted probability difference distributions averaged over all 1-unit increases on the stress scale (within) or for a 1SD increase from mean (between; "0" vs "1") on initial IRT or standardized latent scale, averaged over the alternative (between or within) stress estimator levels. Median posterior density estimates with 95% intervals displayed. Bold point-intervals indicate at least 80% of posterior estimates for the average marginal effect contrast are greater than zero.

APPENDIX 2. Marginal Effects of Stress on Outcome Probabilities, by Estimator and Discrete or Continuous Community



Note: N=489 respondents participating at both survey waves. Estimates derived from multivariate (using `brms::mvbind()`) and multilevel between-within Bayesian logistic regression models simultaneously regressing all criminal intent outcomes (6*2=12 models) and all negative emotion outcomes (7*2=14 models) on a standardized sum stress scale separated into L2 cross-time average (Xbar_i) between-person and L1 within-person change (X_it - Xbar_i) "fixed effects" estimators. Two separate models also regressed "any criminal intent" on stress. "Discrete" community models included a factor variable for community and multiplicative interactions between community and both L1/L2 stress estimators. "Continuous" community models included three- way interactions between stress, a rural/urban binary indicator, and a continuous standardized community level SES variable to assess robustness of results across community measurement. Models were estimated in brms with 4 chains and 4000 total post-warmup posterior draws per outcome and per community group. Marginal effect contrast distributions were estimated from the expectation of the posterior predictive distribution for each model as community-specific predicted probability difference distributions averaged over all 1-unit increases on the stress scale (within) or for a 1SD increase from mean (between; "0" vs "1") on initial IRT or standardized latent scale, averaged over the alternative (between or within) stress estimator levels. In bottom panel, predicted contrasts were estimated for rural/urban communities with -1SD (low) and +1SD (high) continuous L2 SES levels. Median posterior density estimates with 95% intervals displayed. Bold point-intervals indicate at least 80% of posterior estimates for the average marginal effect contrast are greater than zero.

REFERENCES

Agnew, Robert. (1992). Foundation for a general strain theory of crime and delinquency. *Criminology 30*(1), 47-88.

Agnew, Robert. (2001). Building on the foundation of general strain theory: Specifying the types of strain most likely to lead to crime and delinquency. *Journal of Research in Crime and Delinquency 38*(4), 319-361.

Agnew, Robert. (2002). Experienced, vicarious, and anticipated strain: An exploratory study focusing on physical victimization and delinquency. *Justice Quarterly 19*(4), 603-632.

Agnew, Robert. (2006a). *Pressured into crime: An overview of general strain theory*. Los Angeles: Roxbury.

Agnew, Robert. (2006b). General strain theory: Current status and directions for further research. Pp. 101-123 in *Advances in Criminological Theory: Vol. 15. Taking Stock: The Status of Criminological Theory*, by Francis T. Cullen, John Paul Wright, and Kristie R. Blevins (Eds). Piscataway, NJ, US: Transaction.

Agnew, Robert. (2013). When criminal coping is likely: An extension of general strain theory. *Deviant Behavior 34*(8), 653-670.

Aiken, Mary P., Julia C. Davidson, Michel Walrave, Koen S. Ponnet, Kirsty Phillips, and Ruby R. Farr. (2024). Intention to hack? Applying the Theory of Planned Behaviour to youth criminal hacking. *Forensic Sciences 4*(1), 24-41.

Allison Paul D. (2009). *Fixed Effects Regression Models*. Thousand Oaks, CA: Sage.

Anderson, Elijah. (1999). *Code of the Street*. New York: Norton.

Aneshensel, Carol S. and William R. Avison. 2015. The stress process: An appreciation of Leonard I. Pearlin." *Society and Mental Health 5*(2), 67-85.

Baldwin, Simon, Craig Bennell, Brittany Blaskovits, Andrew Brown, Bryce Jenkins, Chris Lawrence, Heather McGale, Tori Semple, and Judith P. Andersen. (2022). A reasonable officer: Examining the relationships among stress, training, and performance in a highly realistic lethal force scenario. *Frontiers in psychology 12*, 759132.

Barnum, Timothy C., Daniel S. Nagin, and Greg Pogarsky. (2021). Sanction risk perceptions, coherence, and deterrence. *Criminology 59*(2), 195-223.

Baron, Stephen W. (2004). "General strain, street youth and crime: A test of Agnew's revised theory." *Criminology 42*(2), 457-484.

Bartolomucci, Alessandro, Paola Palanza, Paola Sacerdote, Alberto E. Panerai, Andrea Sgoifo, Robert Dantzer, and Stefano Parmigiani. (2005). Social factors and individual vulnerability to chronic stress exposure." *Neuroscience & Biobehavioral Reviews 29*(1), 67-81.

Bernard, Thomas J. (1990). Angry Aggression among the 'Truly Disadvantaged.' *Criminology 28*, 73-96.

Berk, Richard A. (2004). *Regression analysis: A constructive critique. Vol. 11*. Sage.

Bjerk, David. (2009). How much can we trust causal interpretations of fixed-effects estimators in the context of criminality? *Journal of Quantitative Criminology 25*, 391-417.

Blalock Jr, Hubert M. (1989). The real and unrealized contributions of quantitative sociology. *American Sociological Review 54*(3), 447-460.

Botchkovar, Ekaterina V., Charles R. Tittle, and Olena Antonaccio. (2009). General strain theory: Additional evidence using cross-cultural data." *Criminology 47*(1), 131-176.

Brauer, Jonathan R. and Jacob C. Day, (2023). Are you afraid of colliders? Accessed June 4, 2024. https://www.reluctantcriminologists.com/blog-posts/[5]/colliders.html

Brauer, Jonathan R., Jacob C. Day, and Brittany M. Hammond. (2021). Do employers "walk the talk" after all? An illustration of methods for assessing signals in underpowered designs. *Sociological Methods & Research 50*(4), 1801-1841.

Brauer, Jonathan R., Charles R. Tittle, and Olena Antonaccio. (2019). The costs of coercive control: Assessing behavioral and mental health correlates of erratic and oppressive coercion. *Justice Quarterly 36*(2), 255-286.

Brezina, Timothy. (2000). Delinquent problem-solving: An interpretive framework for criminological theory and research. *Journal of Research in Crime and Delinquency 37*(1), 3-30.

Brezina, Timothy. (2010). Anger, attitudes, and aggressive behavior: Exploring the affective and cognitive foundations of angry aggression. *Journal of Contemporary Criminal Justice 26*(2), 186-203.

Buchanan, Tony W., and Stephanie D. Preston. (2014). Stress leads to prosocial action in immediate need situations. *Frontiers in Behavioral Neuroscience 8*(Article 5), 1-6.

Bürkner, Paul-Christian. (2017). brms: An R Package for Bayesian Multilevel Models Using Stan. *Journal of Statistical Software 80*(1), 1-28. doi:10.18637/jss.v080.i01

Bürkner, Paul-Christian. (2024). Estimating multivariate models with brms. Published March 19, 2024. Accessed June 20, 2024. https://cran.r-project.org/web/packages/brms/vignettes/brms_multivariate.html

Bürkner, Paul-Christian, and Emmanuel Charpentier. (2020). Modelling monotonic effects of ordinal predictors in Bayesian regression models. *British Journal of Mathematical and Statistical Psychology 73*(3), 420-451.

Bürkner, Paul-Christian, and Matti Vuorre. (2019). Ordinal regression models in psychology: A tutorial. *Advances in Methods and Practices in Psychological Science 2*(1), 77-101.

Centers for Disease Control and Prevention (CDC). (2020). Risk and protective factors [for youth violence]. Last reviewed March 2, 2020; accessed May 10, 2024. https://www.cdc.gov/violenceprevention/youthviolence/riskprotectivefactors.html

Chin, Jason M., Justin T. Pickett, Simine Vazire, and Alex O. Holcombe. (2023). Questionable research practices and open science in quantitative criminology. *Journal of Quantitative Criminology 39*(1), 21-51.

Cooper, Jonathon A., Anthony Walsh, and Lee Ellis. (2010). Is criminology moving toward a paradigm shift? Evidence from a survey of the American Society of Criminology. *Journal of Criminal Justice Education 21*(3), 332-347.

Crisis House. (2022). The effects of stress and its ties to domestic violence. Updated Sep. 8, 2022. Accessed May 10, 2024. https://www.crisishouse.org/post/the-effects-of-stress-and-its-ties-to-domestic-violence

Cristóbal-Narváez, Paula, Josep Maria Haro, and Ai Koyanagi. (2020). Perceived stress and depression in 45 low-and middle-income countries. *Journal of Affective Disorders 274*, 799-805.

Curran, Patrick J., and Daniel J. Bauer. (2011). The disaggregation of within-person and between-person effects in longitudinal models of change." *Annual Review of Psychology 62*, 583-619.

Dooley, Brendan D., and Sean E. Goodison. (2020). Falsification by atrophy: The Kuhnian process of rejecting theory in US criminology. *The British Journal of Criminology 60*(1), 24-44.

Eronen, Markus I., and Laura F. Bringmann. (2021). The theory crisis in psychology: How to move forward. *Perspectives on Psychological Science*, *16*(4), 779-788.

Ethridge, Paige, Nida Ali, Sarah E. Racine, Jens C. Pruessner, and Anna Weinberg. (2020). Risk and resilience in an acute stress paradigm: Evidence from salivary cortisol and time-frequency analysis of the reward positivity. *Clinical Psychological Science 8*(5), 872-889.

Farrell, Albert D. and Steven E. Bruce. (1997). Impact of exposure to community violence on violent behavior and emotional distress among urban adolescents." *Journal of Clinical Child Psychology 26*(1), 2-14.

Fitzpatrick, Kevin M. (1993). "Exposure to violence and presence of depression among low-income, African-American youth." *Journal of Consulting and Clinical Psychology 61*(3), 528-31.

Felson, Richard B., D. Wayne Osgood, Julie Horney, and Craig Wiernik. (2012). Having a bad month: General versus specific effects of stress on crime. *Journal of Quantitative Criminology 28*, 347-363.

Fried, Eiko I., and Randolph M. Nesse. (2015). Depression is not a consistent syndrome: An investigation of unique symptom patterns in the STAR* D study. *Journal of Affective Disorders 172*, 96-102.

Gabbidon, Shaun L., and Danielle Boisvert. (2012). Public opinion on crime causation: An exploratory study of Philadelphia area residents. *Journal of Criminal Justice 40*(1), 50-59.

Gelman, A. (2007). Book Review: Berk, R. (2004). *Regression analysis: A constructive critique. Thousand Oaks, CA*: Sage. 259 pp. Criminal Justice Review, 32(3), 301-302.

Hamilton, J. Paul, Michael C. Chen, and Ian H. Gotlib. (2013). Neural Systems Approaches to Understanding Major Depressive Disorder: An Intrinsic Functional Organization Perspective. *Neurobiology of Disease 52*: 4-11.

Hammen, Constance. (2006). Stress generation in depression: Reflections on origins, research, and future directions. *Journal of Clinical Psychology 62*(9), 1065-1082.

Hammen, Constance L. (2015). Stress and depression: old questions, new approaches. *Current Opinion in Psychology 4*, 80-85.

Herman, James. (2013). Neural control of chronic stress adaptation. *Frontiers in Behavioral Neuroscience 7*, 61.

Herman, Shaina, Timothy C. Barnum, Paola Emilia Minà, Peter Wozniak, and Jean-Louis Van Gelder. (2024). Affect, emotions, and crime decision-making: emerging insights from immersive 360° video experiments. *Journal of Experimental Criminology*, 1-34.

Huntington-Klein, Nick. (2018). Causal inference animated plots. Accessed June 6, 2024. https://nickchk.com/causalgraphs.html#fixed-effects

Huntington-Klein, Nick. (2021). The effect: An introduction to research design and causality. Chapman and Hall/CRC. Accessed June 6, 2024. https://theeffectbook.net/index.html

Jones, Sarah. (2022). How stress, anxiety contribute to youth violence. Children's Hospital Los Angeles. Published Jan. 10, 2022. Accessed May 10, 2024. https://www.chla.org/blog/advice-experts/how-stress-anxiety-contribute-youth-violence

Juster, Robert-Paul, Bruce S. McEwen, and Sonia J. Lupien. (2010). Allostatic load biomarkers of chronic stress and impact on health and cognition. *Neuroscience & Biobehavioral Reviews 35*(1), 2-16.

Kaufman, Joanne M., Cesar J. Rebellon, Sherod Thaxton, and Robert Agnew. (2008). A general strain theory of racial differences in criminal offending." *Australian & New Zealand Journal of Criminology 41*(3), 421-437.

Kessler, Ronald C. (1997). The effects of stressful life events on depression. *Annual Review of Psychology 48*(1), 191-214.

Kim, Min-Sun, and John E. Hunter. (1993). Relationships among attitudes, behavioral intentions, and behavior: A meta-analysis of past research, part 2. *Communication research 20*(3), 331-364.

Kuriakose, Noble and Michael Robbins. (2016). Don't get duped: Fraud through duplication in public opinion surveys" *Statistical Journal of the IAOS 32*(3), 283-291.

Kurz, A. S. (2023a). Statistical Rethinking with brms, ggplot2, and the tidyverse: (version 0.4. 0). Published January 26, 2023. Accessed June 14, 2024. https://bookdown.org/content/4857/monsters-and-mixtures.html#ordered-categorical-predictors

Kurz, A. S. (2023b). Causal inference with ordinal regression. Published May 21, 2023. Accessed June 25, 2024. https://solomonkurz.netlify.app/blog/2023-05-21-causal-inference-with-ordinal-regression/

Link, Nathan W., Francis T. Cullen, Robert Agnew, and Bruce G. Link. (2016). Can general strain theory help us understand violent behaviors among people with mental illnesses? *Justice Quarterly 33*(4), 729-754.

Long, J. Scott, and Sarah A. Mustillo. (2021). Using predictions and marginal effects to compare groups in regression models for binary outcomes. *Sociological Methods & Research 50*(3), 1284-1320.

Lüdecke, Daniel, Mattan S. Ben-Shachar, Indrajeet Patil, Brenton M. Wiernik, Etienne Bacher, Réme Thériault, and Dominique Makowski. (2022). Easystats: Framework for easy statistical modeling, visualization, and reporting [R package]. *CRAN*. doi:10.32614/CRAN.package.easystats

Ludwig, Jens, Greg J. Duncan, Lisa A. Gennetian, Lawrence F. Katz, Ronald C. Kessler, Jeffrey R. Kling, and Lisa Sanbonmatsu. (2013). Long-term neighborhood effects on low-income families: Evidence from Moving to Opportunity." *American Economic Review 103*(3), 226-231.

Lundberg, Ian, Rebecca Johnson, and Brandon M. Stewart. (2021). What is your estimand? Defining the target quantity connects statistical evidence to theory. *American Sociological Review 86*(3), 532-565.

Maciejewski, Dominique, Eleonore van Sprang, Philip Spinhoven, and Brenda Penninx. (2021). Longitudinal associations between negative life events and depressive symptoms – A 9-year longitudinal study on between-person and within-person effects and the role of family history. *Journal of Personality and Social Psychology 121*(3), 707.

Maddock, Clementine, and Carmine M. Pariante. (2001). How does stress affect you? An overview of stress, immunity, depression and disease. *Epidemiology and Psychiatric Sciences 10*(3), 153-162.

Makowski, Dominque, Mattan S. Ben-Shachar, and Daniel Lüdecke. (2019). bayestestR: Describing effects and their uncertainty, existence and significance within the Bayesian framework. *Journal of Open Source Software 4*(40), 1541-8.

Matheson, Flora I., Rahim Moineddin, James R. Dunn, Maria Isabella Creatore, Piotr Gozdyra, and Richard H. Glazier. (2006). Urban neighborhoods, chronic stress, gender and depression." *Social Science & Medicine 63*(10), 2604-2616.

Mazerolle, Paul, and Alex Piquero. (1998). Linking exposure to strain with anger: An investigation of deviant adaptations. *Journal of Criminal Justice 26*(3), 195-211.

McEwen, Bruce S. (2004). Protection and damage from acute and chronic stress: Allostasis and allostatic overload and relevance to the pathophysiology of psychiatric disorders." *Annals of the New York Academy of Sciences 1032*(1), 1-7.

McEwen, Craig A. and Bruce S. McEwen. (2017). Social structure, adversity, toxic stress, and intergenerational poverty: An early childhood model." *Annual Review of Sociology 43*, 445-472.

McLeod, Jane D. (2012). The meanings of stress: Expanding the stress process model." *Society and Mental Health 2*(3), 172-186.

McNeish, Daniel. (2024). Practical implications of sum scores being psychometrics' greatest accomplishment. *Psychometrika*, 1-22. doi: 10.1007/s11336-024-09988-z

Mears, Daniel P., and Mark Christopher Stafford. (2002). Central analytical issues in the generation of cumulative sociological knowledge. *Sociological Focus 35*(1), 5-24.

Merton, Robert K. (1938). Social structure and anomie. *American Sociological Review 3*(5), 672-82.

Miller, Gregory E., Edith Chen, and Eric S. Zhou. (2007). "If it goes up, must it come down? Chronic stress and the hypothalamic-pituitary-adrenocortical axis in humans." *Psychological Bulletin 133*(1), 25-45.

Moullec, Grégory, Christophe Maïano, Alexandre JS Morin, Johana Monthuy-Blanc, Lisa Rosello, and Grégory Ninot. (2011). A very short visual analog form of the Center for Epidemiologic Studies Depression Scale (CES-D) for the idiographic measurement of depression. *Journal of Affective Disorders 128*(3), 220-234.

Mundlak Yair. (1978). On the pooling of time series and cross section data. *Econometrica 46*, 69–85.

Natelson, Benjamin H., John E. Ottenweller, John A. Cook, David Pitman, Richard McCarty, and Walter N. Tapp. (1988). Effect of stressor intensity on habituation of the adrenocortical stress response." *Physiology & Behavior 43*(1), 41-46.

Osgood, D. Wayne, Barbara J. McMorris, and Maria T. Potenza. (2002). Analyzing multiple-item measures of crime and deviance I: Item response theory scaling. *Journal of Quantitative Criminology 18*, 267-296.

Paternoster, Raymond, and Paul Mazerolle. (1994). General strain theory and delinquency: A replication and extension. *Journal of Research in Crime and Delinquency 31*(3), 235-263.

Pearl, Judea, and Dana Mackenzie. (2018). *The book of why: The new science of cause and effect*. Basic books.

Pearlin, Leonard I. (2010). The life course and the stress process: Some conceptual comparisons. *Journals of Gerontology Series B: Psychological Sciences and Social Sciences 65B*(2), 207-215.

Pearlin, Leonard I. and Alex Bierman. (2013). Current issues and future directions in research into the stress process." Pp.325-340 in *Handbook of the Sociology of Mental Health (Second Edition)*, by Carol S. Aneshensel, Jo C. Phelan, and Alex Bierman (Eds.). New York: Springer.

Pearlin, Leonard I., Elizabeth G. Menaghan, Morton A. Lieberman, and Joseph T. Mullan. (1981). The stress process. *Journal of Health and Social Behavior 22*(4), 337-356.

Porcelli, Anthony J., and Mauricio R. Delgado. (2017). Stress and decision making: Effects on valuation, learning, and risk-taking. *Current Opinion in Behavioral Sciences 14*, 33-39.

Proctor, K. Ryan, and Richard E. Niemeyer. (2019). *Mechanistic criminology*. Routledge.

Qin, Shaozheng, Erno J. Hermans, Hein JF van Marle, Jing Luo, and Guillén Fernández. (2009). Acute psychological stress reduces working memory-related activity in the dorsolateral prefrontal cortex. *Biological psychiatry* 66(1), 25-32.

Quintana, Rafael. (2021). Thinking within-persons: Using unit fixed-effects models to describe causal mechanisms. *Methods in Psychology 5*, 100076.

Radloff, Lenore Sawyer. (1977). The CES-D scale: A self-report depression scale for research in the general population. *Applied Psychological Measurement 1*(3), 385-401.

Revelle, William. (2024). The seductive beauty of latent variable models: Or why I don't believe in the Easter Bunny. Personality and Individual Differences 221, 112552.

Riesthuis, Paul. (2024). Simulation-based power analyses for the smallest effect size of interest: A confidence-interval approach for minimum-effect and equivalence testing. *Advances in Methods and Practices in Psychological Science 7*(2), 25152459241240722.

Robinette, Jennifer W., Susan T. Charles, David M. Almeida, and Tara L. Gruenewald. (2016). Neighborhood features and physiological risk: An examination of allostatic load. Health & Place 41, 110-118.

Rohrer, Julia M., and Kou Murayama. (2023). These are not the effects you are looking for: causality and the within-/between-persons distinction in longitudinal data analysis. *Advances in methods and practices in psychological science 6*(1). doi.org/10.1177/25152459221140842

Sampson, Robert J., Jeffrey D. Morenoff, and Thomas Gannon-Rowley. (2002). Assessing 'neighborhood effects': Social processes and new directions in research." Annual Review of Sociology 28(1), 443-478.

Sandi, Carmen, and József Haller. (2015). Stress and the social brain: Behavioural effects and neurobiological mechanisms." *Nature Reviews Neuroscience 16*(5), 290-304.

Schulz, Amy J., Graciela Mentz, Laurie Lachance, Jonetta Johnson, Causandra Gaines, and Barbara A. Israel. (2012). Associations between socioeconomic status and allostatic load: Effects of neighborhood poverty and tests of mediating pathways." *American Journal of Public Health 102*(9), 1706-1714.

Schwartz, Joseph A., Douglas A. Granger, Jessica L. Calvi, Christopher A. Jodis, and Benjamin Steiner. (2023). The implications of stress among correctional officers: a summary of the risks and promising intervention strategies. *International Journal of Offender Therapy and Comparative Criminology*. doi: 0306624X231213316.

Silver, Eric, Edward P. Mulvey, and Jeffrey W. Swanson. (2002). Neighborhood structural characteristics and mental disorder: Faris and Dunham revisited. *Social Science & Medicine 55*(8), 1457-1470.

Silver, Ian A., Holly Lonergan, and Joseph L. Nedelec. (2022). On the selection of variables in criminology: Adjusting for the descendants of unobserved confounders. *Journal of Criminal Justice*, *81*, 101924.

Sijtsma, Klaas, Jules L. Ellis, and Denny Borsboom. (2024). Recognize the value of the sum score, psychometrics' greatest accomplishment." *Psychometrika 89*(1), 84-117.

Skrzypiec, Grace. (2017). Adolescents' intentions to engage in criminal activity: A cross-disciplinary approach linking theories from social psychology and criminology. *Journal of Forensic Psychology Research and Practice 17*(5), 305-337.

Starcke, Katrin and Matthias Brand. (2016). Effects of stress on decisions under uncertainty: A meta-analysis." *Psychological Bulletin 142*(9), 909-933.

Sweeten, Gary. (2020). Standard errors in quantitative criminology: Taking stock and looking forward. *Journal of Quantitative Criminology 36*, 263-272.

Thoits, Peggy A. (1995). Stress, coping, and social support processes: Where are we? What next?" *Journal of Health and Social Behavior (Extra Issue)*, 53-79.

Thoits, Peggy A. (2010). Stress and health: Major findings and policy implications. *Journal of Health and Social Behavior 51*(S), S41-S53.

Tittle, Charles R., Lisa M. Broidy, and Marc G. Gertz. (2008). Strain, crime, and contingencies. *Justice Quarterly 25*(2), 283-312.

Van Gundy, Karen. (2002). Gender, the assertion of autonomy, and the stress process in young adulthood. *Social Psychology Quarterly 65*(4), 346-63.

Vuorre, Matti, and Niall Bolger. (2018). Within-subject mediation analysis for experimental data in cognitive psychology and neuroscience. *Behavior Research Methods 50*, 2125-2143.

Webb, Thomas L., and Paschal Sheeran. (2006). Does changing behavioral intentions engender behavior change? A meta-analysis of the experimental evidence. *Psychological bulletin 132*(2), 249.

Wheaton, Blair. (2009). The stress process as a successful paradigm. Pp. 231-252 in *Advances in the Conceptualization of the Stress Process: Essays in Honor of Leonard I. Pearlin*, by William R. Avison, Carol S. Aneshensel, Scott Schieman, and Blair Wheaton (Eds.). New York: Springer.

Wheaton, Blair, Marisa Young, Shirin Montazer, and Katie Stuart-Lahman. (2013). Social stress in the twenty-first century. Pp. 299-323 in *Handbook of the Sociology of Mental Health (Second Edition)*, by Carol S. Aneshensel, Jo C. Phelan, and Alex Bierman (Eds.). New York: Springer.

Willits, Dale. (2019). Violent propensity, strain, and violent intentions: A test of Agnew's revised conditioning hypothesis. *Deviant Behavior 40*(1), 122-137.

World Bank. (2025). Country Profile: Bangladesh (2017 PPP). Accessed Jan. 28, 2025 at https://pip.worldbank.org/country-profiles/BGD

Wright, Emily M. and Abigail A. Fagan. (2013). The cycle of violence in context: Exploring the moderating roles of neighborhood disadvantage and cultural norms." *Criminology 51*(2), 217-249.

Wright, Richard A. (2000). Recent changes in the most-cited scholars in criminology: A comparison of textbooks and journals. *Journal of Criminal Justice 28*(2), 117-128.

Wysocki, Anna C., Katherine M. Lawson, and Mijke Rhemtulla. (2022). Statistical control requires causal justification. *Advances in Methods and Practices in Psychological Science 5*(2). doi.org/10.1177/2515245922109582325152459221095823.

Zimmerman, Gregory M. and Steven F. Messner. (2011). Neighborhood context and nonlinear peer effects on adolescent violent crime. *Criminology 49*(3), 873-903.