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The Costs of Insecurity: Pay Volatility and Health Outcomes

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Every day, millions of individuals rely on fluctuating financial rewards in the form of customer tips, commissions, piece-rate, and performance-based pay. While these compensation systems are increasingly common, the volatility in pay that they create may harm employee health. Based on conservation of resource theory assumptions that money is a valued resource, I propose that volatility in pay represents *resource insecurity*, with costs to health. Across an experience sampling study of tipped workers (Study 1) and longitudinal studies of gig workers (Study 2) and those in sales, marketing, and finance (Study 3), findings demonstrate the harmful effects of pay volatility. Specifically, pay volatility had direct or indirect effects on physical symptoms, insomnia, sleep quality, and sleep quantity. Volatile pay was found to induce a scarcity mindset, where individuals ruminate and direct cognitive resources toward remedying the source of scarcity, with worse health outcomes as a result. Neither mindfulness nor savings rate moderated the effect. Exploratory analyses in Studies 2 and 3 revealed that one's dependence on volatile pay acted as a moderator that strengthened effects. Overall, performance-based pay creates pay volatility, which is linked to psychological threat and poor physical health for employees in a broad range of industries.

Keywords: pay volatility, conservation of resources theory, scarcity theory, occupational health

At its most fundamental level, work is about exchanging labor, time, and expertise for monetary reward. Organizations are increasingly moving away from stable salary and hourly compensation systems, instead favoring tips, piece-rate pay, commissions, and bonuses. These forms of "performance-based pay" shift risk away from organizations and onto employees (Aspen Institute, 2016), whose pay changes based on factors both within (performance quality, effort, skills) and outside (economic climate, busyness, customer generosity) their control. As a result, employees' pay fluctuates from one day, week, or month to the next—referred to as pay volatility (Conroy et al., 2021). Facing high pay volatility is common, as an estimated 4.8 million individuals (3% of the U.S. workforce) work in frequently tipped occupations (e.g., waiters, hair stylists, taxi drivers), 36% of U.S. workers (about 57 million individuals) participate in the so-called "gig economy" in some capacity (Gallup, 2020), and 9.5% work in sales jobs (Bureau of Labor Statistics, 2017), where commissions and performance bonuses are commonplace.

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Despite pay volatility becoming an increasingly common component of organizational life, there has been no research to date examining its effects on the health of employees. This is particularly problematic given that performance-based pay, which creates pay volatility, is a central component of high-performance work systems. The benefits of these approaches have long been touted in the compensation and strategic human resources literature (e.g., Combs et al., 2006; Han et al., 2019; Messersmith et al., 2011), but rarely do such studies acknowledge the implications that these compensation systems have for employee health (Ganster et al., 2011). This fundamental oversight creates an incomplete picture of costs and benefits. Whereas high-performance pay practices may enhance performance, the volatility they create might result in long-term harm that is currently ignored.

Prior work examining the connection between pay and health (e.g., Dahl & Pierce, 2019; Davis, 2016; Davis & Hoyt, 2020; Frick et al., 2013) has been largely atheoretical, focusing solely on the main effects of compensation systems on health and failing to consider *why* or *under what conditions* pay might affect health. Further, this research focuses on broad *systems* of compensation (e.g., pay-for-performance, piece-rate pay), whereas the present work focuses on one specific *characteristic* of pay—its volatility. This is an important distinction, as the effects of pay volatility can generalize across specific compensation systems and apply to any system that creates fluctuation in pay. Together, the greater theoretical precision in terms of antecedent, mechanisms, and moderators, combined with a focus on the underlying characteristics of pay that predict health, allows for more precise and actionable practical recommendations. It may be that performance-pay itself is not harmful, but the volatility that it creates is. As a result, strategies to reduce volatility (e.g., minimum wage for gig work platforms, spreading commissions and bonuses over a longer time period) could maintain the benefits of performance-based pay while ameliorating the harmful effects to health. I also test characteristics of the individual or situation that can buffer or weaken any detrimental effects—providing a path forward for individuals and organizations to minimize the harm from pay volatility.

To explain why and how pay volatility is linked to employee health and well-being, I draw on conservation of resources theory (COR; Hobfoll, 2001) to conceptualize pay as a valued resource, such that volatility in that resource represents insecurity and thus a threat. Based on COR predictions, I propose and test a model where the volatility in pay predicts health consequences such as physical symptoms, sleep difficulties, and heavy drinking. I test this model using a 2-week experience sampling study of tipped workers, examining relationships between pay and health at both the daily and person levels (Study 1). I then aim to replicate and extend these findings with dedicated gig workers (Study 2) and higher paid individuals working in finance, sales, and marketing (Study 3) to explore the mechanisms and buffers of the pay volatility relationship with health. To isolate the unique effects of pay volatility beyond one's level of pay, I control for household income level in all studies, and use within-person analyses to rule out the daily effects of making more or less than usual in Study 1.

The present research offers several theoretical, empirical, and practical contributions. Theoretically, I extend models of high-performance pay practices by examining a critically important yet largely ignored outcome—employee health. This represents a substantial oversight in previous research, and one with profound consequences for both individuals and organizations. To accomplish this, I draw on COR theory to conceptualize pay volatility as an indicator of resource insecurity, with costs to health. I advance COR theory and its understanding of resource threat by integrating it with emerging research on scarcity theory (Shah et al., 2012) to better understand the precise *mechanisms* through which resource insecurity may be affecting health. Doing so extends COR theory by identifying and rectifying a limitation in the theory while simultaneously answering calls to identify psychological processes underlying the pay volatility effect (Conroy et al., 2021).

Empirically, I address frequent criticisms of COR theory's vague and poorly defined resources (Ganster & Perrewé, 2011; Halbesleben et al., 2014; Hobfoll et al., 2018) by focusing on money as a tangible, easily observable, and valued resource. Further, this approach permits a critical test of COR theory by operationalizing both resource threat (pay volatility) and costs to health (physical symptoms, sleep problems, and heavy drinking) using more observable indicators than the typical perceptual or psychological measures. I also employ constructive replication across three studies, using different samples, measures, and timeframes to triangulate findings and assess the generalizability and consistency of the results (Köhler & Cortina, 2019; McGrath, 1981). Finally, I follow the latest recommendations in transparency and open science by preregistering two of the studies. Doing so provides further confidence in the findings and ensures that predictions were made a priori while eliminating researcher degrees of freedom (Simmons et al., 2011).

Practically, the popularity of compensation systems that create pay volatility suggests that organizations may be either unaware or unconvinced of their potential downsides. Either way, documenting the potential negative effects of pay volatility becomes critically important to preserving employee health and performance. The present studies seek to identify, isolate, and examine the effect of pay volatility as an underlying characteristic of many pay systems and one with potentially detrimental effects. Based on the proposed model, organizations could implement strategies to reduce volatility that would maintain the benefits of performance-based pay while eliminating some of the costs. These findings also have strong implications for public policy (Aguinis et al., 2021). For example, there has been significant debate around independent contractor work arrangements (e.g., Proposition 22; Conger, 2020), with companies like Uber, Deliveroo, and Instacart claiming that workers prefer the added flexibility of independent-contractor arrangements (Chen et al., 2019; Hall & Krueger, 2018). The present research points to a previously unconsidered cost of such flexible arrangements—the detrimental health effects that may result from volatile pay.

Theoretical Background and Hypotheses

Conservation of resources is a dominant theory of work stress and health, which argues that individuals are motivated to obtain, retain, foster, and protect resources, and stress occurs when these resources are threatened or lost (Hobfoll, 1989). Resources, according to COR, can be anything used to help achieve a goal (Halbesleben et al., 2014; Hobfoll, 2011) and are divided into four broad categories—objects (e.g., a house), conditions (e.g., marriage), personal (e.g., social support), and energy (e.g., time, money). COR argues that resource loss results in strain and diminished energy, whereas resource gain results in enhanced energy and activation (Quinn et al., 2012). Importantly, insecurity in resources also results in stress and detrimental health consequences (Hobfoll, 2001; Hobfoll et al., 2018). These basic assumptions have been supported in a wide variety of contexts, including work on emotional labor (Nguyen et al., 2016), incivility (Walker et al., 2017), and financial hardships (Ragins et al., 2014).

Money has long been considered a valuable energy resource according to COR theory (Hobfoll, 1989), with examples of resources including things such as adequate income, savings or emergency money, financial stability, and adequate credit (Hobfoll, 2001). One unique characteristic of pay from tips, gigs, or commissions and bonuses is that the amount one receives changes constantly, from day to day or month to month. Through a COR theory perspective, this high pay volatility represents *insecurity* in the valued resource of money, with negative consequences expected for health and well-being (Hobfoll, 2001; Hobfoll et al., 2018). Other forms of financial resource insecurity, for example, have been linked with increased stress and poorer health (De Cuyper et al., 2012; Odle-Dusseau et al., 2018). High pay volatility, in particular, has also been cited as a source of stress for service workers in popular press articles (e.g., Semuels & Burnley, 2019), as it elicits feelings of scarcity, makes budgeting harder, and reduces confidence that one has enough money to make ends meet. In short, I propose that high pay volatility is an indicator of resource insecurity, with detrimental effects for health and well-being according to COR theory.

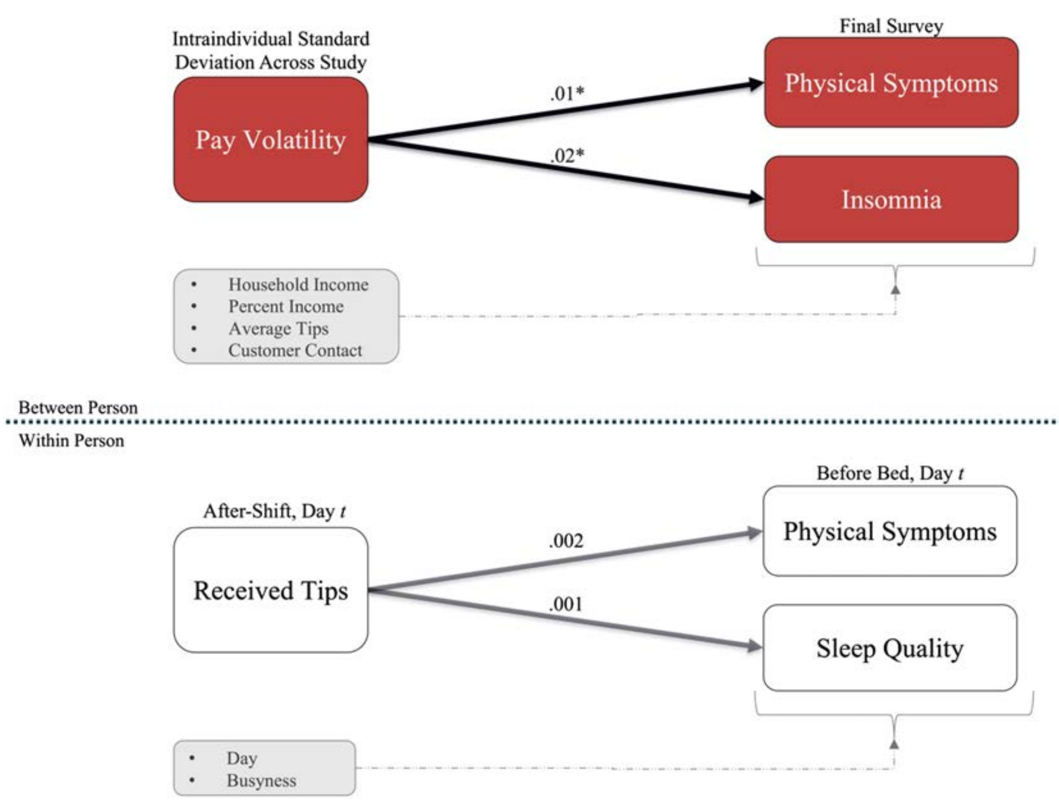
Physical health is a commonly studied outcome of financial insecurity (Shoss, 2017), with physical symptoms and sleep being two particularly important components of physical health. Both represent bodily indicators of stress that are associated with resource threat and have far-reaching implications for both individual and organizational functioning. Physical symptoms refer to somatic issues typically associated with job stress, including upset stomach, headache, and eye strain, and have been linked with job performance (Ford, 2011), absenteeism (Darr & Johns, 2008), and helping and withdrawal behaviors (Cho & Kim, 2021). Sleep is often closely linked with stress and rumination (Demsky et al., 2018; Syrek et al., 2017; Vahle-Hinz et al., 2014), and has well-documented effects on personal health (see Barnes & Drake, 2015 for a review), but has also been shown to predict a wide variety of organizational outcomes, including unethical behavior (Christian & Ellis, 2011), work engagement (Lanaj et al., 2014), and performance (Mullins et al., 2014).

Past meta-analytic and empirical studies portray a consistent pattern, where more financial resource insecurity is linked with more physical symptoms and worse sleep (Allen et al., 2016; Cheng & Chan, 2008; Jiang & Lavaysse, 2018; Odle-Dusseau et al., 2018; Virtanen et al., 2011). One general explanation for this effect suggested by COR theory is the "primacy of loss" (Principle 1; Hobfoll et al., 2018), which states that resource losses are stronger than resource gains. Individuals with high pay volatility will, by definition, experience more resource gains and losses in pay compared to those with lower volatility. Given that these losses will be weighted more heavily according to the primacy of loss principle, high pay volatility will induce more stress than more stable pay (Odle-Dusseau et al., 2018). Prior work has shown that income loss has a larger effect on well-being than equivalent income gains, further supporting this claim (Boyce et al., 2013). In other words, the resource losses experienced by those with high pay volatility will weigh more heavily than the resource gains. Such an explanation, however, lacks precision in terms of the psychosocial mechanisms underlying this effect.

Drawing from related work on financial insecurity, greater volatility in a valued resource is also likely to elicit more cognitive rumination (Jiang et al., 2020; Richter et al., 2020). Individuals facing insecurity need to think more about their finances (de Bruijn & Antonides, 2020), including their expected future income, budget, and cashflow, compared to those with a more stable income. This financial worry and rumination increase one's cognitive load, resulting in suboptimal performance and faulty judgment (Meuris & Leana, 2018). One's ability to get to sleep and stay asleep is likely diminished by such rumination, resulting in increased rates of insomnia (Berset et al., 2011; Demsky et al., 2018; Vahle-Hinz et al., 2014). As such, I argue that high pay volatility represents resource insecurity and will be related to more physical symptoms and insomnia. See Figure 1 for the hypothesized model.

To better isolate the unique effect of pay volatility, I control for several related variables in the analyses. It may be that health effects are driven by the amount of financial resources one has available and not volatility in pay. As such, I control for average tips received across the 2 weeks and household income (normed by household size; see also Conroy et al., 2021). Further, one's reliance on tips may also be acting as a confound, such that those who are more reliant on tips both experience more volatility and report worse health. I control for the percentage of the individual's income that comes from tips to capture this reliance. Finally, given that the sample includes individuals from a variety of jobs, I control for

Figure 1
Hypothesized Model and Results, Study 1



Note. See the online article for the color version of this figure.
$^{*} p < .05$.

customer contact to hold constant important occupational demands that could have a bearing on both volatility and health.

> *Hypothesis 1:* Higher pay volatility is positively related to physical symptoms (a) and insomnia (b), above and beyond household income, average tips, percent of income from tips, and customer contact.

An alternative explanation is that changes in health are driven not by higher volatility over time but rather by the daily effects of pay. For example, earning more than normal on a given day might be associated with feeling better that evening, whereas earning less than normal could be linked with feeling worse in terms of physical symptoms and insomnia. To address this possibility, I conduct a 2-week experience sampling study where I measure pay received each day along with evening health outcomes as well as a between-person measure of health over the 2 weeks. Doing so allows me to tease apart whether health effects are due to earning more or less on a particular day, or the volatility in earnings over the 2-week study period. I controlled for the study day as is customary in experience sampling research (Gabriel et al., 2019) and because tips are likely to change depending on the day of the week. I also controlled for *busyness* as it is likely positively related to both the amount of tips received and health outcomes after work.

Study 1 Method

Participants and Procedure

I conducted an experience sampling study of tipped workers, with three measurement occasions per day for 2 weeks. Tipped workers are frequently exposed to volatility in their pay, dependent on factors both within and outside their control (service quality, busyness, customer satisfaction), making them an ideal sample. To recruit this sample, I utilized Amazon's Mechanical Turk (MTurk) through CloudResearch, an online crowdsourcing website where individuals can post tasks to be completed by others in exchange for monetary payment. MTurk provides access to a more diverse and representative sample of participants (Buhrmester et al., 2011; Casler et al., 2013), with data quality comparable or better than traditional recruitment methods such as undergraduate or MBA student samples (Hauser & Schwarz, 2016; Ramsey et al., 2016). These data were part of a broader data collection effort, including data used in a previous publication (Kundro et al., 2022). The only overlapping variable between the two articles is the percent of income from tips, which is used as a control in the present article.

Consistent with best practices in the literature, I took several precautions to ensure the validity of these data. I followed best practices by blocking suspicious and duplicate IP addresses based on CloudResearch's internal database (Bernerth et al., 2021), limiting participation to those with a 95% approval rating or higher (Buhrmester et al., 2018), and using a prescreening survey to prevent deceptive responding (Chandler & Paolacci, 2017). Of the 1,556 initial prescreening responses collected in July and August of 2019 ("Health in the Service Industry," Pennsylvania State University institutional review board (IRB) approval no. 00012461), a total of 142 participants met all eligibility criteria: (a) received tips at work, (b) worked 35 or more hours per week, (c) working during the day or evening (to facilitate consistent daily measurement occasions), and (d) were fluent in English. These 142 eligible participants were invited to complete the baseline survey the following week, which collected both personal and work demographics. Individuals who completed this baseline were then invited to take part in the daily survey, which began 2 days later with surveys after waking, after one's shift, and before bed. Participants in the 2-week experience sampling study with three measurement occasions per day were compensated at or above the federal minimum wage (average hourly wage ranged from $7.30 to $12.00 per hour across surveys). Participants were then debriefed in one final survey that asked about their health over the 2 study weeks.

After eliminating nonwork days and participants with fewer than 2 days of observations, the final sample consisted of 85 individuals (60% between-person response rate) who completed 753 days of observations. After eliminating 20 observations for having missing values on any predictor or on all outcome variables, there were a total of 733 usable days of observations from 85 individuals for hypothesis testing (M = 8.62 days of observations per person, SD = 3.07). This final sample of 85 participants was 64% male and 36% female, averaged 34.3 years of age (SD = 9.38), with 50.6% never married, 41.2% married, and 8.2% divorced. For race, participants were allowed to select as many categories as applied such that the percentages do not add to 100%. In all, 67% selected White/Caucasian, 20% selected Black/African American, 9% selected Hispanic/Latino(a), 8% selected Asian, and 2% selected Native American. They worked in their current position for an average of 6.41 years (SD = 5.67) and 43.7 hr per week (SD = 8.44), with examples of job titles including delivery driver, server, event coordinator, personal stylist, and maid. Based on the daily portion of the study, participants reported receiving tips on 80.4% of workdays, with the average daily total being $36.18 ($SD$ = $41.07, range = $0–$250) for approximately 25% of their total income (SD = 23.01).

Measures

Pay Volatility

I assessed tips received in the after-shift survey through a single open-ended item asking, "How much money did you receive in tips today?" Single item measures are common in within-person research given the frequency of assessments (Ohly et al., 2010), and are acceptable when measuring "self-reported facts" such as duration or frequency of some event or narrowly defined psychological constructs (Gabriel et al., 2019). I then calculated the intraindividual standard deviation in received tips across the 2 weeks to measure pay volatility, consistent with prior work (Conroy et al., 2021).

Physical Symptoms (Final)

Physical symptoms were measured using 11 common somatic complaints (e.g., "headache," "upset stomach"; Spector & Jex, 1998) with responses ranging from 1 = *not at all* to 5 = *very much* (α = .84). I excluded two items related to sleep ("trouble sleeping" and "tiredness or fatigue") to avoid overlap with the insomnia outcome (see also Grandey et al., 2021).

Insomnia (Final)

Participants were asked how often they experienced insomnia symptoms over the last 2 weeks, such as, "having trouble falling asleep" (Jenkins et al., 1988), with responses ranging from 1 = *very rarely* to 5 = *very often* (α = .83).

Within-Person Model

To better isolate the unique effects of pay volatility beyond average and daily pay received, I replicated the between-person (Level 2) model at the within-person level (Level 1). Specifically, I measured *received tips* after one's shift, *physical symptoms* before bed using the same scale as above adapted for daily use ($R_c = .76$), and *sleep quality* after waking the next day with a single item from the Pittsburgh Sleep Quality Index (Buysse et al., 1989), "How would you rate your sleep quality overall?" with responses ranging from 1 = *I slept very poorly* to 5 = *I slept very well.*

Analyses

Given the repeated observation of days nested within people, I first calculated intraclass correlation coefficients (1) for the study variables. Results indicated substantial Level 2 variability in received tips (64%), physical symptoms (72%), and sleep quality (37%), confirming that these data violate the independence of error assumption of traditional ordinary least squares regression. Multilevel path analysis was used with latent person-mean centering to cleanly tease apart Levels 1 and 2 effects (Bolger & Laurenceau, 2013). At Level 2 (between person), the model tests whether volatility in pay over time predicts health 2 weeks later (Hypothesis 1). The Level 1 (within-person) component of the model rules out an alternative explanation by testing whether earning more or less than normal in tips *on a given day* affects employee health, eliminating any variance attributable to person-level factors (Gabriel et al., 2019). In testing the hypotheses, I followed past work and allowed intercepts and the slope of the received tips variable to vary randomly for each individual while fixing slopes for control variables for the sake of parsimony (e.g., Gabriel et al., 2018; Lanaj et al., 2018).

Transparency and Openness

The sampling plan, data exclusions, and measures are described above, and I also adhere to the *Journal of Applied Psychology* methodological checklist. All data, analysis code, output, and research materials including the full list of items are available at https://osf.io/g5fde/?view_only=9d79296c43b74e91b748703aabb2383c. Data were analyzed using Mplus Version 8 (Muthén & Muthén, 2017) through the Mplus Automation package (Hallquist & Wiley, 2018) in R Version 4.0.2 (R Development Core Team, 2020). The design and analyses were not preregistered.

Study 1 Results

See Table 1 for means, standard deviations, pooled Level 1 correlations, and Level 2 correlations of the study variables.

Hypothesis Testing

Hypothesis 1 predicted that volatility in pay is positively related to physical symptoms and insomnia at Level 2. Results indicated support for this prediction, as pay volatility was positively related to physical symptoms (estimate = .013, *SE* = .01, *p* = .05, 95% CI [.00, .03]) and insomnia (estimate = .02, *SE* = .01, *p* = .02, 95% CI [.002, .03]). At Level 1, daily received tips did not predict daily physical symptoms (estimate = .002, *SE* = .002, *p* = .21, 95% CI [−.001, .005]) or daily sleep quality (estimate = .001, *SE* = .002, *p* = .68, 95% CI [−.004, .006]), after controlling for day of the study and busyness. These results indicate that earning more or less on a particular day does not predict health (ruling out the alternative explanation provided above). Instead, it is the volatility in pay over time that is linked with health. See Table 2 for full results.[1]

Exploratory Analyses

Prior work has shown that individuals engage in efforts to "smooth out" their income, such that tips on one day might predict hours worked the following day (DeVaro, 2022). To rule out this alternative explanation and better isolate the observed effect, I tested whether tips (day *t*) predicted next-day work hours (day $t + 1$), but the effect was not significant (estimate = −.004, *SE* = .01, *p* = .45, 95% CI [−.01, .01]). Another alternative explanation is that the daily causal sequence is reversed, such that employee health on one day might dictate their earnings the following day. Those who are experiencing symptoms or slept poorly may perform worse or may not be as upbeat and friendly at work (Grandey et al., 2013), all of which could result in fewer tips. I tested this possibility, with results indicating that tips were not predicted by previous day physical symptoms (estimate = .06, *SE* = 4.32, *p* = .99, 95% CI [−8.41, 8.54]) or sleep quality (estimate = 1.24, *SE* = 1.16, *p* = .28, 95% CI [−1.03, 3.52]).

Study 1 Discussion

Higher pay volatility predicts person-level health in the form of increased physical symptoms and insomnia in the present study. Those contending with more volatility in their daily tips also report worse health, holding constant factors like their household income, average tips, their reliance on tips, and the amount of customer contact they have. Importantly, this finding also extends prior work on pay volatility, which has shown the detrimental results that volatility has on employee voluntary turnover (Conroy et al., 2021). Interestingly, there do not appear to be clear benefits to physical symptoms or sleep when earning more in tips than normal at the daily level. In short, daily tips do not predict health, but the volatility inherent in those tips does.

Despite these findings, however, several questions remain regarding the relationship between pay volatility and health. First, while I draw on notions of rumination and cognitive load to explain the link between pay volatility and health, they were not measured in Study 1. As a result, the precise mechanism underlying the pay volatility effect remains untested, and confounding variables could also explain this relationship. It may be that industries with more volatility in pay (e.g., bartenders, servers) also have more physically

[1] This pattern of findings was also robust to most changes in the model, as results held when negative affect and sleep duration were added as Level 1 controls, when age and tenure were added as Level 2 controls, and when positive and negative affectivity were added as Level 2 controls. The effect of pay volatility on symptoms (estimate = .01, *SE* = 01, *p* = .25, 95% CI [−.01, .02]) and insomnia (estimate = .01, *SE* = .01, *p* = .17, 95% CI [−.004, .02]) did drop to nonsignificance when all control variables were excluded from the model. The inclusion of these covariates is critical to isolating the unique effect of pay volatility above and beyond average level of pay and industry-level differences. As such, I continue to report the model that includes control variables in the test of the hypotheses.

Table 1
Means, Standard Deviations, and Correlations Among Study 1 Variables

Variable	*M*	*SD*	1	2	3	4	5	6	7	8	9	10
Level 1												
1. Received tips (after-shift)	36.18	41.07	—									
2. Busyness (after-shift)	3.09	0.94	.36**	—								
3. Physical symptoms (before bed)	1.65	0.73	.03	−.02	—							
4. Sleep quality (after-wake, $t + 1$)	3.49	1.12	.02	−.03	.03	—						
Level 2												
5. Pay volatility (over 2 weeks)	15.54	19.14					—					
6. Household income (baseline)	1.95	1.45					.15	—				
7. Percent tips (baseline)	24.89	23.01					.01	−.01	—			
8. Average tips (baseline)	35.35	34.14					.55**	.22*	.31**	—		
9. Customer contact (baseline)	3.73	1.10					.08	.11	.12	.14	—	
10. Physical symptoms (final)	1.83	0.66					.20†	−.12	.16	−.05	.06	—
11. Insomnia (final)	2.86	1.07					.15	−.16	−.05	−.08	−.23*	.58**

Note. All means and standard deviations are reported prior to centering, Level 1 correlations computed after person-mean centering. Household income was normed by household size. For observed scale ranges and correlations with demographic variables, please see output available on OSF (https://osf.io/g5fde/?view_only=9d79296c43b74e91b748703aabb2383c). Level 1 $N = 733$; Level 2 $N = 85$.
† $p < .10$. * $p < .05$. ** $p < .01$.

demanding jobs with frequent shift work that leads to more symptoms, or work later in the evening and night, which could impact sleep, compared to industries with less volatility in pay (e.g., hair stylists, taxi drivers). If true, this would suggest that the occupational demands, and not pay volatility per se, would be driving the detrimental consequences on health. I extend these findings in Studies 2 and 3 by examining a specific form of rumination likely to be evoked by high pay volatility—scarcity mindset.

Second, the specific *boundary conditions* under which this relationship exists remain unknown. Individuals who are more mindful, for example, have greater regulatory resources at their disposal and may be able to minimize the stressful effects of volatility. Individuals with more slack in their budgets (i.e., higher savings rate) could also be less affected by pay volatility, indicating another potential boundary condition. Understanding who is most at risk, or which conditions are likely to elicit the greatest costs from pay volatility, are critical steps that enhance the practical implications of the present findings. Third, I strengthen the design to address concerns about reverse causality, where those experiencing worse health outcomes might also experience higher pay volatility as a result of fluctuations in performance, for example.

Study 2

To address the limitations described above and to increase confidence in the present findings, I conducted a preregistered longitudinal study to constructively replicate (Köhler & Cortina, 2019) and extend the theoretical model, with several specific aims. First, I direct the focus of inquiry to the between-person effect of pay volatility to test both a mechanism (scarcity mindset) and a buffer (trait mindfulness). Second, I focus on dedicated MTurk workers as a way of addressing concerns over the participant's occupational

Table 2
Unstandardized Coefficients From Multilevel Path Analysis, Study 1

Predictor	Physical symptoms				Insomnia			
	Estimate	*SE*	*z*	95% CI	Estimate	*SE*	*z*	95% CI
Level 2								
Intercept	1.84***	.07	26.67	[1.70, 1.97]	2.88***	.11	25.58	[2.65, 3.10]
Pay volatility	.01*	.01	1.96	[.00, .03]	.02*	.01	2.27	[.002, .03]
Household income	−.04	.05	−.78	[−.14, .06]	−.08	.08	−.95	[−.24, .08]
Percent tips	.01	.004	1.76	[−.001, .01]	.001	.01	.21	[−.01., .01]
Average tips	−.01*	.003	−2.05	[−.01, .00]	−.01	.004	−1.60	[−.01, .001]
Customer contact	.03	.06	.51	[−.09, .15]	−.21	.11	−1.91	[−.42, .01]
Residual variance	.38***	.05	7.55	[.28, .47]	.99***	.12	8.07	[.75, 1.23]
Pseudo R^2	.14				.12			
Level 1								
Day	−.02**	.01	−3.23	[−.02, −.01]	.01	.01	.43	[−.02, .03]
Received tips	.002	.002	1.26	[−.001, .01]	.001	.002	.42	[−.004, .01]
Busyness	−.02	.03	−.74	[−.07, .03]	−.04	.06	−.62	[−.14, .08]
Residual variance	.12***	.02	4.92	[.07, .17]	.77***	.07	11.26	[.63, .90]
Pseudo R^2	.02				.003			

Note. Household income was normed by household size. Level 1 $N = 733$; Level 2 $N = 85$. Pseudo R^2 calculated using the Bryk and Raudenbush (1992) formula and a model with fixed slopes (LaHuis et al., 2014). *SE* = standard error; CI = confidence interval.
* $p < .05$. ** $p < .01$. *** $p < .001$.

demands acting as a confounding variable in Study 1, and to assess generalizability beyond the customer service domain. These workers experience volatility in pay due to changing pay rates and bonuses that can have drastic effects on hourly rates (Aspen Institute, 2016; Farrell & Greig, 2016). Third, I conduct a more rigorous empirical test by controlling for baseline levels of all three health outcomes in order to assess *change* in health over the study period (see also Hillebrandt & Barclay, 2020; Meier et al., 2013), which also alleviates some concerns about reverse causality (Lin et al., 2016). Below, I expand on scarcity mindset as a mechanism linking pay volatility to health and mindfulness as a buffer.

Scarcity Mindset Mechanism

Findings from Study 1 suggest that higher pay volatility is linked with more physical symptoms and insomnia, but it is unclear exactly *why* this is the case. COR theory offers little explanation beyond the notion that resource insecurity is harmful. The hypothesis development of Study 1 invokes rumination and cognitive load to explain the connection between pay volatility and health, but these mechanisms were not directly measured in the study. To resolve this question and advance understanding of precisely why high pay volatility is harmful, I draw on scarcity theory (Mani et al., 2013). Scarcity theory proposes that dealing with resource scarcity (money, time, stable employment) induces a "scarcity mindset," a psychological state where individuals devote increased attention and cognitive resources to address the immediate source of scarcity. As a result, individuals experiencing a scarcity mindset will have fewer resources at their disposal, reducing self-control, and harming decision-making quality (Shah et al., 2012). The theory proposes two complimentary mechanisms: increased attentional focus on the source of the scarcity (i.e., rumination) and cognitive load (de Bruijn & Antonides, 2021; Mani et al., 2020).

First, individuals will direct their attention toward remedying the scarcity they are experiencing. As described by scarcity theorists, "People focus on problems where scarcity is most salient" (Shah et al., 2012, p. 682). Relatedly, thoughts of finances arise more often and are harder to suppress for those with fewer financial resources (Shah et al., 2018). As such, scarcity is expected to result in intense attentional focus and rumination about the source of this scarcity. Second, and relatedly, this attentional focus and rumination results in an increased cognitive load and fewer resources available for other issues that arise (Mani et al., 2013; Shah et al., 2012). Individuals facing scarcity are forced to think more about their financial situation, their spending, cashflow, and budget compared to those who do not experience scarcity (de Bruijn & Antonides, 2021). As a result, executive control is diminished and counterproductive behaviors occur such as attentional neglect, impulsive spending, and poor planning (Mani et al., 2020). Indeed, participants experiencing scarcity in both a lab experiment (Shah et al., 2012) and field study (Mani et al., 2020) showed increased cognitive load and reduced attentional focus.

Applying scarcity theory to the current context, I first argue that high pay volatility among workers will elicit a scarcity mindset. Highly volatile pay is insecure by its very nature, as individuals contend with frequent boom and bust periods. To contend with this insecurity, individuals are forced to devote cognitive resources to carefully budgeting, planning, and accounting for pay volatility compared to those with more stable income (Mullainathan & Shafir, 2013). In short, individuals must manually "smooth" their income through budgeting and saving techniques that are not required of those with a stable salary or hourly paycheck (Meuris & Leana, 2015). Indeed, proponents of scarcity theory suggest that, "financial instability is costly, financially and psychologically, and can result in cognitive load, worry, and fatigue, ultimately leading to deeper poverty traps" (Mani et al., 2020, p. 366).

Consistent with this, lower income individuals were less likely to exhibit a scarcity mindset when public benefits were spread over biweekly (vs. monthly) installments (Mani et al., 2020), as more frequent payments reduced income volatility over the study period. Past work has also shown that uncertainty in income has stronger cognitive effects than low income levels (Lichand & Mani, 2020), further underscoring the connection between pay volatility and a scarcity mindset. Given this, I expect that higher pay volatility will induce a scarcity mindset as individuals are forced to devote cognitive resources to carefully budgeting, planning, and accounting for this volatility compared to those with more stable income levels. I also control for household income here, as a more conservative test of the hypothesis by showing the effect of pay volatility above and beyond the average level of pay.

> *Hypothesis 2:* Higher pay volatility is positively related to scarcity mindset, controlling for household income.

According to scarcity theory, those in a scarcity mindset will both ruminate about the source of this scarcity and be less able to exercise self-control—ultimately resulting in a reduced likelihood of engaging in long-term investments in their health and well-being (de Bruijn & Antonides, 2021; Liang et al., 2020). Rumination is a key factor associated with sleep disturbances, for example (Lundh & Broman, 2000), and can result in disturbances to the hypothalamic–pituitary–adrenal axis (Belogolovsky et al., 2012; Melamed et al., 2006). The rumination associated with experiencing a scarcity mindset, then, is likely to result in worse health. Relatedly, a scarcity mindset makes exerting self-control and appropriately weighing long-term costs more difficult. For example, those contending with scarcity in the form of job or financial insecurity were less likely to follow Centers for Disease Control health guidelines related to the COVID-19 pandemic (e.g., maintain distance, wash hands frequently; Probst et al., 2020), indicating an inability to exercise self-control and weigh the long-term costs of one's actions.

In the spirit of constructive replication and extension, I examine two of the same health indicators as in Study 1, physical symptoms and insomnia. Given the centrality of self-control and inhibition, I also examine heavy drinking as a critically important and costly health behavior (Frone, 2019) that requires self-control (Muraven et al., 2002). Broadly speaking, I expect that those with a scarcity mindset will ruminate more and be less likely to engage in health behaviors that typically require self-control and a long-term perspective (e.g., eating right, exercising, practicing good sleep hygiene, limiting alcohol consumption; de Ridder et al., 2012), and health will suffer as a result (Conner et al., 2017; Gennetian & Shafir, 2015; Spears, 2011; Wichers et al., 2012).

Regarding physical symptoms specifically, those with a lower socioeconomic status (education, income, financial strain) are less likely to participate in leisure-based physical activity (Cerin & Leslie, 2008; Cleland et al., 2012; Humphreys & Ruseski, 2011; Macy et al., 2013; Spinney & Millward, 2010) and eat worse (Drewnowski & Specter, 2004; Lallukka et al., 2007; Macy et al., 2013; Ricciuto & Tarasuk, 2007; Turrell et al., 2003). Research also shows that scarcity in time or money predicts reduced physical activity, consuming fewer fruits and vegetables, eating out more, and consuming more discretionary calories (Venn & Strazdins, 2017). This sedentary lifestyle and poor diet will likely result in more physical symptoms like aches, pains, and digestive issues (Calderwood et al., 2020; Rueggeberg et al., 2012).

The persistent thoughts and ruminations regarding finances are also likely to make sleep more difficult (Demsky et al., 2018; Koen & van Bezouw, 2021), as individuals worry about making ends meet (Belogolovsky et al., 2012). Sleep hygiene behaviors, such as avoiding screens before bed, maintaining a consistent sleep/wake schedule, and minimizing caffeine consumption and daytime naps, are important for good sleep (Chung et al., 2018; Irish et al., 2015), but these behaviors require self-control to enact (Kroese et al., 2016). As such, individuals experiencing a scarcity mindset will have difficulty following such best practices. Consistent with this logic, public benefit recipients sleep less at the end of the month, when finances are stretched before new benefits are received (Gennetian & Shafir, 2015). Scarcity mindset is also associated with a willingness to take risks (Liang et al., 2020), such as engaging in heavy drinking. Past work shows that regulating one's alcohol consumption requires self-control (Muraven et al., 2002, 2005), which is in short supply for those in a scarcity mindset (Spears, 2011). Drawing on similar logic, past research has shown that drug use is higher when welfare checks are paid monthly (higher volatility), compared to smaller and more frequent payments (Richardson et al., 2021).

Importantly, these health effects may not manifest themselves immediately, but instead may require a number of days of poor self-control and a lack of exercise, poor eating, or bad sleep hygiene before impacting health outcomes. As such, I measure health outcomes over the last week. Overall, pay volatility induces a scarcity mindset, which makes self-control and behavioral inhibition difficult, with costs to health. As with Hypothesis 2, I control for household income to isolate the unique effect of *volatile* pay over level of pay. To capture change in health over time, I also control for each health outcome's score at Time 1 on its score at Time 3.

> *Hypothesis 3:* Scarcity mindset mediates the positive relationship between pay volatility and changes in physical symptoms (a), insomnia (b), and heavy drinking (c), controlling for household income.

Trait Mindfulness Buffer

Understanding the conditions under which pay volatility relates to health also provides useful theoretical insights and practical recommendations (Spencer et al., 2005). Mindfulness is an increasingly hot topic in the organizational sciences (Good et al., 2016) and refers to "a receptive attention to and awareness of present events and experiences" (Brown et al., 2007, p. 212). This awareness is nonjudgmental in order to reduce rumination and focus on the present moment (Kiken & Shook, 2011). Mindfulness is frequently touted as an effective intervention for dealing with stress (Beehr, 2019), yet recent work has highlighted that mindfulness may not always be beneficial (Lyddy et al., 2021). Given this, I conduct a critical test of a potential boundary condition of mindfulness—is it still helpful when contending with *objective* resource insecurity in the form of pay volatility?

Specific to the current context, those higher in trait mindfulness are thought to have increased concentrative capacity and regulatory ability (Good et al., 2016), and are less likely to ruminate (Borders et al., 2010; Long & Christian, 2015). Given that these are the precise mechanisms thought to underline the pay volatility effect, it stands to reason that more mindful individuals should be better equipped to handle the insecurity of volatile pay without falling into a scarcity mindset. Further, mindfulness reduced negativity bias (Kiken & Shook, 2011), which is a key component of COR theory's prediction around the relative strength of resource losses compared to gains (Hobfoll et al., 2018). More mindful individuals should be able to handle the ups and downs of pay volatility without feelings of scarcity to the same extent as less mindful individuals. As such, mindfulness should buffer the relationships between pay volatility and scarcity mindset, and as a result moderate the indirect effect of pay volatility on health outcomes. See Figure 2 for the hypothesized model.

> *Hypothesis 4:* Trait mindfulness moderates the positive effect of pay volatility on scarcity mindset, such that the relationship is weaker when trait mindfulness is higher, compared to when trait mindfulness is lower.

> *Hypothesis 5:* Trait mindfulness moderates the positive indirect effect of pay volatility on physical symptoms (a), insomnia (b), and heavy drinking (c), such that the indirect effects are weaker when trait mindfulness is higher, compared to when trait mindfulness is lower.

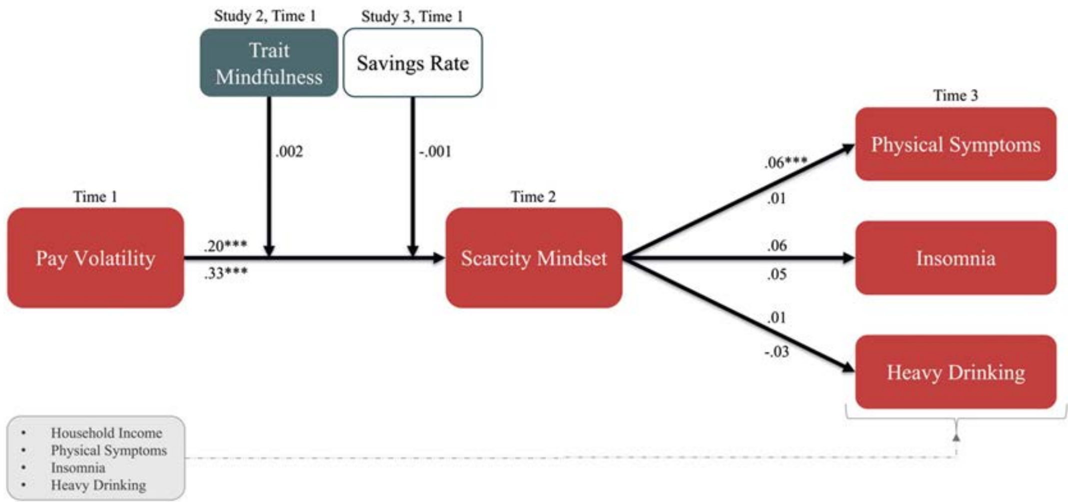
Study 2 Method

Participants and Procedure

To sample individuals with volatility in pay while holding the occupational demands constant, MTurk workers were recruited as part of a broader data collection effort. This is the first publication from this broader data set. While MTurk is sometimes critiqued as a source of data in the organizational sciences, MTurk workers represent an ideal sample for the present study given that they must contend with pay volatility due to the piece-rate nature of their work and MTurk requestors who pay varying rates. As one participant from the study succinctly put it, "when there is work, everything is nice and happy and I'm able to make enough money, when the work is gone it becomes very stressful." To enhance generalizability to other jobs with volatility in pay I sampled "dedicated" MTurk workers who relied on the platform as a major source of income (vs. a minor side income). As such, eligibility was limited to those working 20 hr or more per week on MTurk, with 1,000 prior tasks completed. Additionally, participants had to be 18 years or older, currently in the United States, fluent in English, have a 95% MTurk approval rating or higher, and could not have participated in Study 1.

Participants were invited to take part in a three-wave study of health in the gig economy ("Pay Variability and Employee Health," Emlyon Business School IRB approval no. 01-13/04/2021) in late July and early August of 2021. Given that pay volatility is necessarily a longitudinal phenomenon (see also Scott et al., 2012), I sent out surveys once per week and gave participants 3 days to complete each survey. The choice of survey timing (weekly) was based on the financial cycle of participants. MTurk workers are paid piece-rate for each task completed, meaning they experience daily changes in pay and typically withdraw their earnings once or several times per week (86% fit this description in Study 2). As such, a weekly survey was most

Figure 2
Hypothesized Model and Results, Studies 2 and 3



Note. Coefficients above the line are from Study 2, coefficients below the line are from Study 3. See the online article for the color version of this figure.
*** $p < .001$.

appropriate for capturing pay volatility and closely corresponded with the financial cycle of earning and spending of MTurk participants.

In total, 461 individuals submitted surveys at Time 1, with 33 being eliminated for failing to meet eligibility criteria, resulting in 428 eligible responses. A total of 397 individuals completed the Time 2 survey, and 379 completed the Time 3 survey. Four Time 3 responses were eliminated due to missing all dependent variables or duplicate responses, and no participants were removed for failing two or more attention checks. As such, the final longitudinal sample size was N = 375 participants (88% retention rate).[2] Participants were 53.6% male, 45.9% female, and 0.53% other, and averaged 42.9 years old (SD = 12.07). In terms of race, multiple selections could be made such that percentages add to more than 100%. In all, 84% selected White/Caucasian, 8.5% selected Black/African American, 6.9% selected Asian, 4% selected Hispanic/Latino(a), 1.3% selected Native American, and 0.8% selected Hawaiian/Pacific Islander. A majority (52%) were married or cohabiting with a partner, and 32.8% had children living with them. Participants worked on MTurk for 5.97 years (SD = 3.26) on average, spending 28.9 hr per week (SD = 8.57) on the platform, and with 41.2% of their individual income coming from MTurk (SD = 34.99).

Measures

Pay Volatility (Time 1)

Prior pay volatility research has derived the construct from the intraindividual standard deviation in pay, such that a self-report scale does not exist. As such, pay volatility was measured with three items created for the present study. Participants were asked, "Over the last week …" "… the amount of money I've received from MTurk has been inconsistent," "… my pay has remained steady" (reversed), and "… my pay has frequently changed" (α = .94). Participants could respond on a 1 = *strongly disagree* to 5 = *strongly agree* Likert scale. Similar to tipped work, pay on MTurk is a function of factors both within the participant's control (number of tasks completed) and outside it (amount requestors choose to pay). As one participant wrote, "Some requesters pay very well, some pay fairly, some pay extremely low, and some want free data." Just as tipped workers are dependent on customer generosity, MTurk workers are dependent on the pay rates offered by requestors.

Trait Mindfulness (Time 1)

Trait mindfulness was measured using the abbreviated six-item version (Black et al., 2012; Van Dam et al., 2010) of the Mindfulness Attention Awareness Scale (Brown & Ryan, 2003). Participants were asked to rate how often the following statements applied to them, such as "I find myself preoccupied with the future or the past" (α = .90). Participants could respond on a 1 = *almost never* to 6 = *almost always* Likert scale.

Scarcity Mindset (Time 2)

Scarcity mindset was measured with four items from Carvalho et al. (2016). The items asked participants, "In the last week, how often …" "… were you troubled about coping with ordinary bills?" "… did you worry about having enough money to make ends meet?" "… did you think about future expenses, some of which may be unexpected?" and "… were you preoccupied with thoughts about your personal finances?" Participants could respond on a 1 = *never* to 5 = *very often* Likert scale (α = .92).

Physical Symptoms (Time 3)

Physical symptoms over the last week were measured with the same 11-item scale as in Study 1, also excluding the two sleep-related items (α = .84).

[2] Those that completed all three surveys did not differ significantly from those that completed only the Time 1 or Time 2 survey, on any of the study variables (measured at Time 1).

Insomnia (Time 3)

Insomnia over the last week was measured with the same three-item scale as in Study 1 ($\alpha = .82$).

Heavy Drinking (Time 3)

To indicate a lack of self-control over alcohol consumption, I used three items such as "drinking to intoxication" (Frone, 2015; Grandey et al., 2019) on a 1 = *not at all* to 6 = *6–7 days per week* scale ($\alpha = .86$).

Controls

The scales used to control for Time 1 *physical symptoms* ($\alpha = .84$), *insomnia* ($\alpha = .80$), and *heavy drinking* ($\alpha = .88$) were the same as those used at Time 3, described above. Importantly, I deviated from the AsPredicted preregistered model by also controlling for the effect of *household income* on both the mediator and outcomes (normed for household size), using a single item asking participants their total household income, in \$20,000 increments (e.g., 1 = *less than \$20,000* to 7 = *more than \$120,000*). Substantive results do not change when household income is excluded as a control variable.

Analysis

Prior to hypothesis testing, a confirmatory factor analysis indicated that the hypothesized six-factor model fit the data well ($\chi^2 = 871.89$, $df = 390$, comparative fit index [CFI] = .93, Tucker-Lewis index [TLI] = .92, root-mean-square error of approximation [RMSEA] = .06, standardized root-mean-squared residual [SRMR] = .06) and better than models that combined pay volatility and scarcity mindset ($\chi^2 = 2098.21$, $df = 395$, CFI = .75, TLI = .72, RMSEA = .11, SRMR = .14) or the three health outcomes ($\chi^2 = 1657.36$, $df = 399$, CFI = .82, TLI = .80, RMSEA = .09, SRMR = .09). Details can be found in the output on OSF (https://osf.io/g5fde/?view_only=9d79296c43b74e91b748703aabb2383c). All predictor variables and controls were grand-mean centered, and the interaction term was computed with grand-mean centered variables (Aiken et al., 1991). The model was consistent with the first-stage moderated mediation model from Edwards and Lambert (2007), with the indirect effect tested with 10,000 bootstrapped samples.

Transparency and Openness

The sampling plan, data exclusions, and measures are described above, and I also adhere to the *Journal of Applied Psychology* methodological checklist. All data, analysis code, output, and research materials including the full list of items are available at https://osf.io/g5fde/?view_only=d79296c43b74e91b748703aabb2383c. Data were analyzed using *lavaan* (Rosseel, 2012) in R Version 4.0.2 (R Development Core Team, 2020). The design, hypotheses, and analyses were preregistered prior to data collection (https://aspredicted.org/5cw7x.pdf).

Study 2 Results

See Table 3 for correlations and descriptives for the study variables. Worth noting is the significant correlation between pay volatility and both physical symptoms ($r = .18$, $p < .001$) and insomnia ($r = .22$, $p < .001$), replicating the Level 2 findings from Study 1.

Hypothesis Testing

I first examined the direct effect of pay volatility on the three health outcomes, with results indicates that pay volatility did not predict physical symptoms ($b = .002$, $SE = .01$, $p = .87$, 95% CI [−.02, .03]), insomnia ($b = .004$, $SE = .03$, $p = .90$, 95% CI [−.06, .06]), or heavy drinking ($b = .004$, $SE = .02$, $p = .80$, 95% CI [−.03, .03]) above and beyond scarcity mindset and the other controls. Hypothesis 2 predicted that pay volatility is positively related to scarcity mindset, and results supported this prediction ($b = .20$, $SE = .05$, $p < .001$, 95% CI [.11, .29]). Hypothesis 3 predicted that scarcity mindset mediates the positive relationship between pay volatility and changes in physical symptoms (a), insomnia (b), and heavy drinking (c). The indirect effect of pay volatility on physical symptoms was significant ($b = .01$, $SE = .004$, $p = .007$, 95% CI [.005, .022]), but the indirect effects on insomnia ($b = .01$, $SE = .008$, $p = .13$, 95% CI [−.001, .03]) and heavy drinking ($b = .002$, $SE = .004$, $p = .53$, 95% CI [−.005, .01]) were not. As such, Hypothesis 3a was supported, but not Hypothesis 3b or c. Hypothesis 4 concerned mindfulness as a moderator of the pay volatility to scarcity mindset relationship; however, this was not supported ($b = .002$, $SE = .04$, $p = .96$, 95% CI [−.08, .09]). As such, Hypotheses 5a–c regarding the moderated indirect effects were also not supported (see Table 4, for full results).[3]

Exploratory Analyses

As described in the preregistration, several additional variables were collected to serve as alternative moderators or more sensitive indicators of employee health. Specifically, despite mindfulness being a positive attribute in dealing with stress, it did not buffer the effect of pay volatility on scarcity mindset. Given this nonsignificant effect, I examined one's *dependence* on volatile pay as a more objective resource and potential moderator. Volatility should be more strongly linked with a scarcity mindset when volatile pay makes up a larger percent of one's total income, making one more dependent on this income source. I examine percent of income from variable pay as a moderator, with a single item asking, "What percent of your individual income comes from MTurk?"

Additionally, two of the health indicators used, insomnia and heavy drinking, capture more extreme health behaviors that may not be experienced by most participants. As such, more sensitive measures of sleep and alcohol consumption frequency were also collected. Sleep quality and quantity were both measured with single items (Buysse et al., 1989), as is common in the sleep literature; sleep quality: "How would you rate your sleep quality over the last week?"; sleep quantity: "Over the last week, how many hours a night have you slept, on average? Round to the nearest half hour (e.g., 7.5 hr)." Alcohol frequency was measured with a single item asking, "Over the last week, how often have you consumed at least one alcoholic drink?" with responses ranging from 1 = *not at all* to 5 = *6–7 days per week*.

The hypothesized model was then rerun with dependence on volatile pay replacing mindfulness, sleep quality and quantity

[3] Importantly, this pattern of findings did not change when 59 potential outliers (based on 1.5 times the interquartile range) were excluded. Further, in a model controlling for demographic factors (age, gender, race), household income, and negative affect, the indirect effect of pay volatility on physical symptoms remained significant ($b = .03$, $SE = .01$, $p = .004$, 95% CI [.01, .05]), and the indirect effect on insomnia became significant ($b = .06$, $SE = .02$, $p = .002$, 95% CI [.03, .10]).

Table 3
Means, Standard Deviations, and Correlations Among Study 2 Variables

Variable	*M*	*SD*	1	2	3	4	5	6	7	8	9	10
1. Pay volatility (T1)	3.37	1.14	—									
2. Mindfulness (T1)	4.72	1.02	−.10*	—								
3. Pay Vol. × Mindfulness	−0.12	1.14	.06	.04	—							
4. Household income (T1)	1.90	1.18	−.06	−.08	.03	—						
5. Physical symptoms (T1)	1.50	0.56	.20**	−.42**	−.05	−.08	—					
6. Insomnia (T1)	2.41	1.12	.24**	−.45**	−.04	−.09	.66**	—				
7. Heavy drinking (T1)	1.45	0.81	−.01	−.33**	.05	.10*	.25**	.18**	—			
8. Scarcity mindset (T2)	2.57	1.11	.25**	−.37**	.00	−.15**	.48**	.50**	.08	—		
9. Physical symptoms (T3)	1.45	0.55	.18**	−.35**	−.05	−.03	.82**	.60**	.16**	.48**	—	
10. Insomnia (T3)	2.34	1.13	.22**	−.39**	.00	−.06	.60**	.87**	.13*	.47**	.61**	—
11. Heavy drinking (T3)	1.39	0.73	.00	−.31**	.06	.13*	.17**	.17**	.84**	.08	.20**	.14**

Note. $N = 375$. Pay vol. = pay volatility; T1 = Time 1; T2 = Time 2; T3 = Time 3. All means, standard deviations, and correlations are reported prior to centering with the exception of the interaction term. Household income was normed by household size. For observed scale ranges and correlations with demographic variables, please see output available on OSF (at https://osf.io/g5fde/?view_only=d79296c43b74e91b748703aabb2383c).
* $p < .05$. ** $p < .01$.

replacing insomnia, and alcohol frequency replacing heavy drinking. All other aspects of the model, including controls, centering, and bootstrapping, remained identical to the hypothesized model. Results from this model showed that pay volatility similarly predicted scarcity mindset ($b = .23$, $SE = .05$, $p < .001$, 95% CI [.14, .32]), and dependence on volatile pay moderated the effect ($b = .003$, $SE = .001$, $p = .04$, 95% CI [.00, .01]) such that pay volatility was more strongly related to scarcity mindset when one is more dependent on variable pay ($b = .34$, $SE = .06$, $p < .001$) than less dependent ($b = .13$, $SE = .06$, $p = .03$; see Figure 3).

Additionally, the indirect effects of pay volatility on physical symptoms ($b = .02$, $SE = .01$, $p = .004$, 95% CI [.01, .03]), sleep quality ($b = −.03$, $SE = .01$, $p = .01$, 95% CI [−.06, −.01]), and sleep quantity ($b = −.04$, $SE = .02$, $p = .03$, 95% CI [−.09, −.01]) through scarcity mindset were significant, whereas the indirect effect on alcohol consumption was not ($b = −.01$, $SE = .01$, $p = .56$, 95% CI [−.02, .01]). The index of moderated mediation was marginally significant for physical symptoms ($b = .00$, $SE = .00$, $p = .07$, 95% CI [.00, .00]) and sleep quality ($b = .00$, $SE = .00$, $p = .097$, 95% CI [−.001, .00]), but not sleep quantity ($b = .00$, $SE = .00$, $p = .11$, 95% CI [−.001, .00]) or alcohol consumption

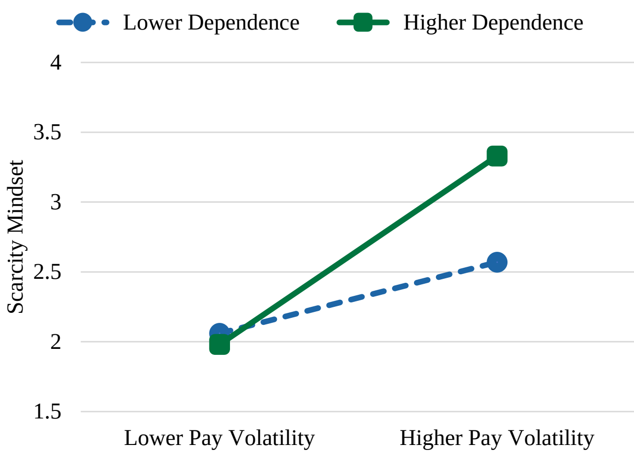
Table 4
Unstandardized Coefficients From Path Analysis Model Predicting Health Outcomes, Study 2

	Scarcity mindset (T2)			
Predictor	Est.	*SE*	*z*	95% CI
Intercept	2.57***	.05	50.28	[2.47, 2.67]
Household income (T1)	−.16***	.04	−3.53	[−.24, −.07]
Pay volatility (T1)	.20***	.05	4.28	[.11, .29]
Mindfulness (T1)	−.39***	.05	−8.30	[−.48, −.30]
Pay Vol. × Mindfulness	.002	.04	.05	[−.08, .09]
R^2	.21	—	—	—

	Physical symptoms (T3)				Insomnia (T3)				Heavy drinking (T3)			
Predictor	Est.	*SE*	*z*	95% CI	Est.	*SE*	*z*	95% CI	Est.	*SE*	*z*	95% CI
Intercept	1.30***	.04	30.52	[1.22, 1.38]	2.19***	.09	24.65	[2.02, 2.37]	1.36***	.05	27.13	[1.26, 1.46]
Household income (T1)	.02*	.01	2.05	[.002, .05]	.02	.02	.92	[−.02, .06]	.03	.02	1.42	[−.01, .06]
Physical symptoms (T1)	.76***	.05	14.12	[.65, .86]	—	—		—	—	—		—
Insomnia (T1)	—	—		—	.85***	.03	28.67	[.79, .90]	—	—		—
Heavy drinking (T1)	—	—		—	—	—		—	.77***	.05	14.30	[.66, .87]
Pay volatility (T1)	.002	.01	.16	[−.02, .03]	.004	.03	.13	[−.06, .06]	.004	.02	.25	[−.03, .03]
Scarcity mindset (T2)	.06***	.02	3.77	[.03, .09]	.06	.03	1.68	[−.01, .13]	.01	.02	.65	[−.02, .05]
R^2	.68	—	—	—	.75	—	—	—	.71	—	—	—
Indirect effects												
Pay vol.→Scar. mind.→	.01**	.004	2.71	[.01, .02]	.01	.01	1.52	[−.001, .03]	.002	.004	.62	[−.01, .01]
IMM	.00	.003	.05	[−.01, .01]	.00	.003	.04	[−.01, .01]	.00	.001	.03	[−.002, .002]

Note. Pay vol. = pay volatility; scar. mind. = scarcity mindset; IMM = index of moderated mediation; T1 = Time 1; T2 = Time 2; T3 = Time 3. Household income was normed by household size. $N = 375$. Est. = estimate; *SE* = standard error; CI = confidence interval.
* $p < .05$. ** $p < .01$. *** $p < .001$.

Figure 3
Interaction of Pay Volatility and Dependence on Scarcity Mindset, Study 2



Note. See the online article for the color version of this figure.

($b = .00$, $SE = .00$, $p = .61$, 95% CI [.00, .00]). These results indicate that one's *dependence* on variable pay is a key factor influencing scarcity mindset and ultimately health, and that pay volatility has an impact on more sensitive measures of health such as sleep quality and quantity. The effect of pay volatility on alcohol use remained nonsignificant regardless of how it was operationalized.

Study 3

While Studies 1 and 2 offer several distinct advantages, they are also limited in important ways. First, both studies focus on lower income samples (e.g., tipped workers, gig workers), making it difficult to determine if the pay volatility effect is limited to only lower income individuals, or if it applies more broadly. The negative effects of pay volatility may not occur for higher earning samples that have sufficient savings and cash flow to weather volatility in income. Second, both studies focus on relatively short timeframes (2 weeks) given the daily nature of the earnings (tips, piece-rate pay). It remains to be seen, then, if volatility in pay spread over longer timeframes (e.g., biweekly, monthly) has a similar impact on health. Third, results did not support mindfulness as a boundary condition, leaving it unclear how the detrimental effects of pay volatility might be buffered.

To address these shortcomings, I conducted a third study of individuals working full time in sales, finance, and marketing positions. Volatility in this sample is likely to differ substantially from workers who are paid in tips or piece-rate. First, individuals in sales and finance are likely to have a higher base salary, such that they are less dependent on volatile forms of pay to make ends meet compared to prior samples. As such, the strength of effects may be weaker in this sample. Second, variable components of pay in sales and finance occur on a less frequent basis, often through monthly commission checks or annual performance bonuses. This stands in contrast to Studies 1 and 2, where volatility occurred daily through customer tips or changing piece-rate work. Together, these conditions combine to create a conservative test of the pay volatility effect. If volatility predicts a scarcity mindset even in this higher paid sample with more stable jobs, it demonstrates the pernicious nature of this effect. If pay volatility does not have any significant effects, it points to some potential boundary conditions in the form of pay level or temporal dynamics of volatility.

In addition to retesting Hypotheses 2 and 3a–c, I also consider participants' savings rate as a first-stage moderator to better understand a more objective boundary conditions of the pay volatility effect. One's savings rate represents financial resources that can cushion and smooth out volatility in income, dampening the effect of pay volatility on scarcity mindset. As an added advantage, savings rate accounts for *both* the income received but also the financial obligations owed (e.g., mortgage/rent, childcare expenses, car payments). As scarcity theorists have pointed out, "some of those whom we classified as well off might well have been experiencing scarcity, for example, some were surely burdened by mortgage payments, credit card debt, college loans, or large families" (Mullainathan & Shafir, 2013, p. 72). In short, savings rate can capture the amount of "slack" in one's finances, which can absorb shocks due to high pay volatility. I expect that savings rate should buffer the relationships between pay volatility and scarcity mindset, moderating the indirect effect of pay volatility on health outcomes. See Figure 2 for the hypothesized model.

> *Hypothesis 6:* Savings rate moderates the positive effect of pay volatility on scarcity mindset, such that the relationship is weaker when savings rate is higher, compared to when savings rate is lower.

> *Hypothesis 7:* Savings rate moderates the positive indirect effect of pay volatility on physical symptoms (a), insomnia (b), and heavy drinking (c), such that the indirect effects are weaker when savings rate is higher, compared to when savings rate is lower.

Study 3 Method

Participants and Procedure

To sample individuals with a wider range of income levels, individuals working full time (31+ hr per week) in the finance, marketing, and sales occupations in the United States were recruited through Prolific as part of a broader data collection effort. This is the first publication from this broader data set. Commissions and bonuses are common in these industries, meaning that I maintain focus on pay volatility but broaden the sample to one with a higher base level of pay and who experiences volatility over a longer timeframe. Prolific was chosen given its high-quality research participants (Palan & Schitter, 2018) and the ability to limit the sample to specific industries. I ensured participants met eligibility criteria by also asking which industry they worked in on the survey itself and excluding those who did not meet eligibility criteria. Participants were invited to take part in a three-wave study of health at work under the same IRB approval as Study 2 in late February through April 2022. To align surveys with the financial cycle of participants, surveys were sent out once per month. This longer timespan was needed to ensure that individuals could actually experience volatility in their earnings, given that 84% were paid biweekly or monthly.

In total, 466 eligible participants completed the Time 1 survey, with three participants eliminated for a failed attention check and seven indicating they did not wish to participate in the subsequent survey waves. Of the 456 participants invited to the Time 2 survey, 315 submitted completed surveys (69% response rate), none failed both attention checks, and all were invited to the Time 3 survey. In total, 252 participants completed the Time 3 survey (80% response rate), and none were eliminated for failed attention checks. As such, the longitudinal complete sample was $N = 252$. Participants were 54% male, 46% female, and 0% other and averaged 35.6 years old ($SD = 10.56$). In terms of race, multiple selections could be made such that percentages add to more than 100%. In all, 80% selected White/Caucasian, 8.7% selected Black/African American, 9.5% selected Asian, and 5.2% selected Hispanic/Latino(a). Participants worked in their current job for 4.5 years ($SD = 4.17$), on average, typically working 42.5 hr per week ($SD = 5.52$), and with 13.6% of their individual income coming from commissions or bonuses ($SD =$ 20%). Participants also reported a higher average household income ($M = 4.87$, $SD = 1.76$) compared to Studies 1 ($M = 3.34$, $SD = 1.62$) and 2 ($M = 3.29$, $SD = 1.74$), consistent with the goal of testing the pay volatility effect in a higher earning sample.

Measures

The scales used to measure pay volatility ($\alpha = .89$), scarcity mindset ($\alpha = .90$), physical symptoms ($\alpha = .85$), insomnia ($\alpha = .75$), and heavy drinking ($\alpha = .87$) were identical to Study 2, except for the time frame being "over the last month" instead of "over the last week."

Savings Rate (Time 1)

To measure savings rate, I asked participants, "Approximately what percent of your net (after-tax) monthly income do you save, on average? Do not include mortgage payments/home equity in your answer."

Controls

Consistent with Study 2, I controlled for the relationship of Time 1 measurement of each outcome variable on itself to predict change in the outcome variables over time. The scales used for *physical symptoms* ($\alpha = .84$), *insomnia* ($\alpha = .74$), and *heavy drinking* ($\alpha = .90$) were the same as above. Similar to Study 2, I also deviated from the AsPredicted preregistered model by controlling for the effect of *household income* (normed by household size) on both the mediator and outcomes, using a single item asking participants their total household income, in \$20,000 increments (e.g., 1 = *less than \$20,000* to 7 = *more than \$120,000*). Substantive results do not change when household income is excluded as a control variable.

Analysis

Prior to hypothesis testing, a confirmatory factor analysis indicated that the hypothesized five-factor model fit the data well ($\chi^2 = 425.75$, $df = 242$, CFI = .93, TLI = .92, RMSEA = .06, SRMR = .06) and better than models that combined pay volatility and scarcity mindset ($\chi^2 = 1019.8$, $df = 246$, CFI = .72, TLI = .69, RMSEA = .11, SRMR = .12) or the three health outcomes ($\chi^2 = 894.6$, $df = 249$, CFI = .77, TLI = .74, RMSEA = .10, SRMR = .09). Details can be found in the output on OSF (https://osf.io/g5fde/?view_only=d79296c43b74e91b748703aabb2383c). Analyses were identical to Study 2 in terms of centering, computing the interaction term, and testing indirect effects.

Transparency and Openness

The sampling plan, data exclusions, and measures are described above, and I also adhere to the *Journal of Applied Psychology* methodological checklist. All data, analysis code, output, and research materials are available at https://osf.io/g5fde/?view_only=d79296c43b74e91b748703aabb2383c. Data were analyzed using *lavaan* (Rosseel, 2012) in R Version 4.0.2 (R Development Core Team, 2020). The design, hypotheses, and analyses were preregistered prior to data collection (https://aspredicted.org/y25dr.pdf).

Study 3 Results

See Table 5 for correlations and descriptives for the study variables.

Hypothesis Testing

To conduct an initial test of the model, I first examined the effect of pay volatility at Time 1 on *levels* of health at Time 3, excluding the Time 1 health controls but including household income (normed) as a control. Pay volatility significantly predicted scarcity mindset at Time 2 ($b = .33$, $SE = .06$, $p < .001$, 95% CI [.21, .45]), and the indirect effect on physical symptoms ($b = .06$, $SE = .02$, $p = .001$, 95% CI [.03, .10]) and insomnia ($b = .11$, $SE = .03$, $p < .001$, 95% CI [.06, .18]) at Time 3 through scarcity mindset were significant, whereas the indirect effect through heavy drinking was not ($b = .003$, $SE = .02$, $p = .85$, 95% CI [−.03, .03]). However, consistent with Study 2 and the preregistration, I formally tested the hypotheses controlling for Time 1 health, to assess the impact of pay volatility on *changes* in health over time. In line with Study 2, the direct effect of pay volatility on the three health outcomes in this model were not significant (physical symptoms: $b = .01$, $SE = .03$, $p = .71$, 95% CI [−.05, .07]; insomnia: $b = -.05$, $SE = .05$, $p = .29$, 95% CI [−.15, .05]; heavy drinking: $b = -.04$, $SE = .03$, $p = .18$, 95% CI [−.09, .02]) above and beyond scarcity mindset and the other controls. Also consistent with Study 2, pay volatility significantly predicted scarcity mindset ($b = .33$, $SE = .06$, $p < .001$, 95% CI [.21, .45]), supporting Hypothesis 2. However, the indirect effects of pay volatility on physical symptoms ($b = .01$, $SE = .01$, $p = .52$, 95% CI [−.01, .02]), insomnia ($b = .02$, $SE = .02$, $p = .29$, 95% CI [−.01, .05]), and heavy drinking ($b = -.01$, $SE = .01$, $p = .34$, 95% CI [−.03, .01]) through scarcity mindset were no longer significant after controlling for health at Time 1, failing to support Hypotheses 3a–c. Regarding Hypothesis 6, savings rate did not moderate the effect of pay volatility on scarcity mindset ($b = -.001$, $SE = .004$, $p = .87$, 95% CI [−.01, .01]). As such, Hypotheses 7a–c regarding the moderated indirect effects were also not supported (see Table 6, for full results).[4]

Exploratory Analyses

Measurement

To better compare the results with those of Study 1 and test an alternative measure of pay volatility, I also asked participants at Time 1 to report their monthly pay over the last 6 months. I calculated the intraindividual standard deviation in these monthly earnings in the same way as Study 1, eliminating 19 outliers (those

[4] Substantive results remain the same when personal income used in place of household income.

Table 5

Means, Standard Deviations, and Correlations Among Study 3 Variables

Variable	*M*	*SD*	1	2	3	4	5	6	7	8	9	10
1. Pay volatility (T1)	1.85	0.91	—									
2. Savings rate (T1)	19.79	16.31	−.09	—								
3. Pay Vol. × Savings Rate	−1.38	14.00	−.23**	−.14*	—							
4. Household income (T1)	2.35	1.37	−.01	.22**	.00	—						
5. Physical symptoms (T1)	1.65	0.57	.10	−.14*	.08	−.11	—					
6. Insomnia (T1)	2.65	1.00	.18**	−.05	.07	−.12	.54**	—				
7. Heavy drinking (T1)	1.63	0.88	.11	.10	−.06	.16**	.05	.12	—			
8. Scarcity mindset (T2)	2.66	1.08	.30**	−.31**	−.04	−.17**	.40**	.40**	.06	—		
9. Physical symptoms (T3)	1.66	0.57	.11	−.04	.06	−.11	.80**	.50**	.04	.34**	—	
10. Insomnia (T3)	2.70	1.06	.11	.03	.07	−.08	.51**	.79**	.10	.34**	.57**	—
11. Heavy drinking (T3)	1.58	0.80	.05	.10	.00	.15*	.04	.09	.86**	−.00	.04	.07

Note. Pay vol. = pay volatility; T1 = Time 1; T2 = Time 2; T3 = Time 3. All means, standard deviations, and correlations are reported prior to centering with the exception of the interaction term. Household income was normed by household size. For observed scale ranges and correlations with demographic variables, please see output available on OSF (https://osf.io/g5fde/?view_only=d79296c43b74e91b748703aabb2383c). $N = 252$.

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

with scores above the 3rd quartile + 3 times the interquartile range) and log transforming to address positive skew. This more "objective" measure of pay volatility was significantly correlated with the self-report measure ($r = .36$, $p < .001$) demonstrating convergent validity, and the results using this objective measure were consistent with those reported above. Pay volatility calculated as intraindividual standard deviation in monthly earnings also predicted scarcity mindset ($b = .08$, $SE = .02$, $p < .001$), scarcity mindset did not predict physical symptoms ($b = .004$, $SE = .02$, $p = .84$), insomnia ($b = .02$, $SE = .05$, $p = .66$), or heavy drinking ($b = −.03$, $SE = .03$, $p = .29$), and the indirect effects were not significant (see Study 3 output file in OSF, for full details).

Survey Timings

The results indicate that scarcity mindset does not predict changes in health 1 month later. A majority of research on scarcity theory focuses on the impacts of scarcity in the short term (e.g., Huijsmans et al., 2019; Shah et al., 2012), making the temporal dynamics of scarcity mindset less known. To gain a better understanding of how scarcity mindset functions over time, I reran the hypothesized model (including household income and Time 1 health controls) but with scarcity mindset and health measured concurrently (at Time 2) using the same $N = 252$ participants as the hypothesized model. Results indicated that pay volatility significantly predicted scarcity mindset

Table 6

Unstandardized Coefficients From Path Analysis Model Predicting Health Outcomes, Study 3

Predictor	Scarcity mindset (T2)			
	Est.	*SE*	*z*	95% CI
Intercept	2.65***	.06	42.08	[2.53, 2.78]
Household income (T1)	−.09	.05	− 1.90	[−.17, .001]
Pay volatility (T1)	.33***	.06	5.23	[.21, .45]
Savings rate (T1)	−.02***	.004	− 4.34	[−.03, −.01]
Pay Vol. × Savings Rate	−.001	.004	−.16	[−.01, .01]
R^2	.19	—	—	—

Predictor	Physical symptoms (T3)				Insomnia (T3)				Heavy drinking (T3)			
	Est.	*SE*	*z*	95% CI	Est.	*SE*	*z*	95% CI	Est.	*SE*	*z*	95% CI
Intercept	1.62***	.07	24.9	[1.49, 1.75]	2.57***	.12	21.9	[2.34, 2.81]	1.65***	.08	19.9	[1.50, 1.82]
Household income (T1)	−.01	.01	−.44	[−.03, .02]	.01	.03	.51	[−.04, .06]	.00	.02	.03	[−.04, .04]
Physical symptoms (T1)	.77***	.06	12.60	[.66, .90]	—	—		—	—	—		—
Insomnia (T1)	—	—		—	.80***	.04	19.68	[.72, .88]	—	—		—
Heavy drinking (T1)	—	—		—	—	—		—	.79***	.04	20.22	[.71, .87]
Pay volatility (T1)	.01	.03	.37	[−.05, .07]	−.05	.05	−1.06	[−.15, .05]	−0.04	.03	−1.34	[−.09, .02]
Scarcity mindset (T2)	.01	.02	.65	[−.03, .06]	.05	.04	1.10	[−.04, .13]	−.03	.03	−.99	[−.09, .03]
R^2	.63	—	—	—	.61	—	—	—	.74	—	—	—
Indirect effects												
Pay vol.→Scar. mind.→	.01	.01	.64	[−.01, .02]	.02	.02	1.07	[−.01, .05]	−.01	.01	−.96	[−.03, .01]
IMM	.00	.00	−.09	[.00, .00]	.00	.00	−.12	[−.001, .00]	.00	.00	.11	[.00, .00]

Note. Pay vol. = pay volatility; Scar. mind. = scarcity mindset; IMM = index of moderated mediation; T1 = time 1; T2 = Time 2; T3 = Time 3. Household income was normed by household size. $N = 252$. Est. = estimate; *SE* = standard error; CI = confidence interval.

*** $p < .001$.

at Time 2 (b = .34, SE = .06, p < .001, 95% CI [.20, .46]), and the indirect effect on changes in Time 2 physical symptoms (b = .03, SE = .01, p = .01, 95% CI [.01, .05]) and insomnia (b = .03, SE = .01, p = .01, 95% CI [.01, .07]) through scarcity mindset were significant, whereas the indirect effect on heavy drinking was not (b = .01, SE = .01, p = .65, 95% CI [−.02, .03]).

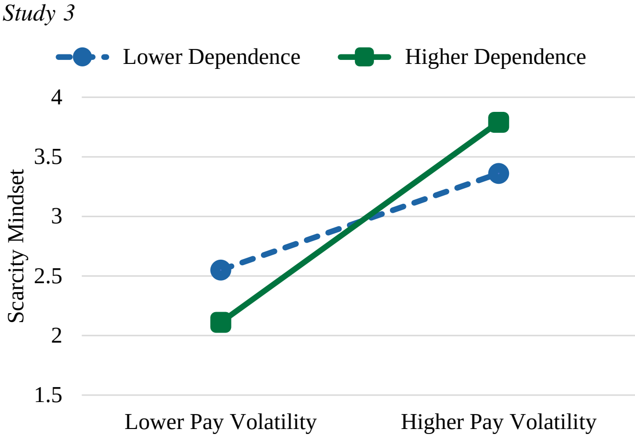
Alternative Model

Another possible explanation for the lack of significant indirect effects is differences in job characteristics across the samples. Specifically, individuals in finance and sales are likely to have a higher base salary, making them less dependent on volatile pay compared to tipped or MTurk workers and potentially weakening any effects. To test this potential moderation, I collected the same measure of dependence on volatile pay as in Study 2. Dependence was captured by asking participants, "What percent of your individual income comes from sources other than your salary or hourly wage (e.g., commission, bonuses, etc.)?" To fully replicate the alternative model from Study 2, I also collected the same, more sensitive measures of health (sleep quality, sleep quantity, alcohol consumption frequency).

Results replicated those of Study 2, as pay volatility predicted scarcity mindset (b = .34, SE = .07, p < .001, 95% CI [.20, .49]), and dependence on volatile pay moderated this effect (b = .01, SE = .002, p = .01, 95% CI [.002, .01]). Simple slopes analysis revealed that the relationship between pay volatility and scarcity mindset was stronger for those who are more dependent on variable pay (b = .46, SE = .08, p < .001) than those who are less dependent (b = .22, SE = .08, p = .01; see Figure 4). Additionally, the indirect effects of pay volatility on sleep quality (b = −.06, SE = .02, p = .003, 95% CI [−.11, −.03]) and sleep quantity (b = −.03, SE = .02, p = .045, 95% CI [−.07, −.01]) were significant, whereas the indirect effects on physical symptoms (b = .002, SE = .01, p = .70, 95% CI [−.01, .02]) and alcohol consumption were not (b = −.004, SE = .01, p = .79, 95% CI [−.04, .02]). The index of moderated mediation was significant for sleep quality (b = −.001, SE = .00, p = .04, 95% CI [−.002, .00]), but not for physical symptoms (b = .00, SE = .00, p = .70, 95% CI [.00, .00]), sleep quantity (b = −.001, SE = .00, p = .10, 95% CI [−.001, .00]), or alcohol consumption (b = .00, SE = .00, p = .80, 95% CI [−.001, .00]).

Figure 4

Interaction of Pay Volatility and Dependence on Scarcity Mindset, Study 3



Note. See the online article for the color version of this figure.

These results largely replicate what was found in Study 2, demonstrating that one's *dependence* on variable pay matters more than objective resources like savings rate—even among a higher earning sample. The indirect effect on physical symptoms was not significant here, though, suggesting some differences due to the sample or timeframe of Study 3.

General Discussion

The present studies sought to better understand the impact of pay volatility on employee health. While not all hypotheses were supported, a consistent pattern emerged where pay volatility was directly or indirectly related to health across three studies with diverging samples. With lower income tipped (Study 1) and gig workers (Study 2), pay volatility predicted physical symptoms. Across all three studies, including higher earning individuals in finance, marketing, and sales (Study 3), pay volatility predicted sleep health (insomnia in Study 1, sleep quality and quantity but not insomnia in Studies 2 and 3). Both Studies 2 and 3 provided evidence for scarcity mindset as an explanatory mechanism, such that constantly fluctuating resources induce feelings of scarcity, with cognitive and emotional costs that manifest in poorer health. These conclusions are strengthened by controlling for Time 1 health in Studies 2 and 3, meaning that pay volatility predicts *changes* in health across these studies. Exploratory analyses also demonstrated that pay volatility had a stronger effect when individuals were more dependent on volatile pay in both Studies 2 and 3. Having a larger percentage of one's income come from tips, piece-rate, or commissions and bonuses heightens the risk involved, increasing the likelihood that volatility will result in a scarcity mindset.

Not all hypotheses were supported, as neither mindfulness nor savings rate buffered the link between pay volatility and health. This finding points to a critical limitation of mindfulness, which may not be able to counter the detrimental effects of objective resource insecurity. Likewise, individual financial strategies like a higher savings rate also seem ineffective at preventing scarcity mindset in the face of pay volatility, highlighting the strength of this effect. Study 3 was also the only study where the indirect effect of pay volatility on physical symptoms was not significant. It may be that scarcity mindset in this higher earning sample manifests itself more in psychological rumination and worry, which impacts sleep but does not rise to the level of affecting physical symptoms. Alternatively, effects on physical symptoms may be shorter lived, such that the longer timeframe used in this study (2 months vs. 2 weeks) obscured significant effects. Consistent with this possibility, when scarcity mindset and physical symptoms were both measured at Time 2, a significant indirect effect of pay volatility on physical symptoms through scarcity mindset was observed. Nevertheless, confidence in the present findings is bolstered through the use of longitudinal designs to strengthen causal inference (Liu et al., 2016; Ployhart et al., 2009), constructive replication (Köhler & Cortina, 2019), and preregistration.

Theoretical Implications

The present work extends compensation research in important ways, through looking beyond the effects of pay-for-performance on performance or motivation and instead considering how such practices relate to the health of employees. COR theory appears to be a useful framework for these inquiries, as it accurately identified pay volatility, a form of resource insecurity, as a particularly detrimental facet of these compensation systems. These findings extend recent work showing the costs of performance-based pay in white-collar jobs on mental health (Dahl & Pierce, 2019), by showing *what* specific features of performance-based pay are costly (volatility), *why* these costs occur (eliciting a scarcity mindset), and *when* they are most likely (high dependence on volatile pay). In short, pay volatility is an important contributor to employee health and well-being and deserves continued attention moving forward.

The present findings also highlight the detrimental effects of high volatility in general. Volatility and resource insecurity have become an increasingly common facet of organizational life (Benach et al., 2014; Shoss, 2017). It seems critical, then, to better incorporate volatility into theories of occupational health and performance. Assessing how other forms of volatility (e.g., volatility in work hours) impact employee health and performance and exploring ways to minimize its harmful consequences are also critical. Finally, the present studies demonstrate that integrating scarcity theory with COR theory is a promising avenue for better understanding the effects of resource insecurity broadly. Findings from Studies 2 and 3 largely supported the predictions of scarcity theory, which simultaneously advances COR theory by helping to understand precisely *why* resource insecurity is stressful. Specifically, contending with scarcity demands attention and cognitive resources, leaving individuals exhausted and less able to focus on other areas of their lives. The nonsignificant effect on physical symptoms in Study 3 also underscores the importance of explicitly considering time when examining pay volatility and scarcity mindset. Prior work has largely used experimental designs with short-term manipulations of scarcity mindset (e.g., Huijsmans et al., 2019; Shah et al., 2012), making it impossible to assess the temporal components of scarcity mindset and demonstrating the value of the current field test to the growing literature.

Practical Implications

Taken together, these findings are troubling, especially given the large number of individuals who contend with high pay volatility. While more work is needed to better establish causality, present findings suggest that minimizing volatility in pay may help enhance employee health, in addition to previously established relationships with voluntary turnover (Conroy et al., 2021). Given the collective costs of high turnover and poor health, organizations that utilize performance-based pay for its flexibility and risk reduction may not be adequately accounting for its costs (see also Meuris & Leana, 2015). These results suggest that organizations should explore possibilities within their own compensation systems to minimize volatility where possible. For example, rideshare drivers in New York City have successfully bargained for a wage floor, which can prevent dips in earnings from changing passenger volumes (Holley, 2018). Shifting from tipped work to a fair hourly wage is another approach that is gaining traction (National Public Radio, 2016) and may also offer other benefits like less sexual harassment from customers (Kundro et al., 2022). Organizations could also pursue ways of spreading bonuses and commission pay over a longer timeframe to smooth out some of this volatility. If volatile pay is a necessity, organizations could also try to reduce employees' dependence on it to alleviate some of the negative effects.

These findings also have substantial policy implications, given recent debates over the independent contractor status of may gig workers (e.g., Proposition 22 in California; Conger, 2020). According to the present findings, the instability of this flexible work arrangement can have serious costs for individual and societal health and should be adequately accounted for. Unemployment programs may also be more beneficial if they are designed to better supplement volatile earnings and hours (Gennetian & Shafir, 2015). In short, organizations and lawmakers need to pay attention not just to the *level* of pay individuals receive but also *how that pay is distributed*, as volatile pay appears to have wide-ranging consequences.

Limitations and Future Directions

Despite its strengths, the results and conclusions of the present studies should be interpreted in light of several limitations. First, it should be noted that causality cannot be established given the lack of experimental designs. While the present field surveys help demonstrate a connection between pay volatility and health in several contexts, even when baseline health is controlled, future work is needed to test the causal effect of pay volatility in the lab. Doing so would provide a stronger impetus for organizations to redesign their compensation systems to minimize volatility. Such an approach would also require examining more immediate health outcomes, such as physiological reactivity (e.g., skin conductance, heartrate variability), in place of broader measures like physical symptoms and sleep.

Second, all three studies rely on self-reported data, raising the possibility of common method bias. This concern is minimized to an extent in Study 1, as received tips represent a self-reported fact, which occurs outside of a participant's perception, and pay volatility was calculated using variability in daily tips. Additionally, all three studies utilized temporal separation between variables in the model, with Studies 2 and 3 controlling for baseline measures of the dependent variables, which reduces concerns about common method bias (Podsakoff et al., 2012). Third, all three studies use online participant pools, raising concerns about the quality of participants recruited online. I did, however, follow recommendations and best practices when collecting the data (e.g., Aguinis et al., 2020). Further, sampling dedicated MTurk workers fits theoretically with the current interest in pay volatility, given that they are forced to contend with piece-rate wages and varying bonuses, eliciting high levels of pay volatility.

Future work should explore and expand on boundary conditions of the pay volatility effect. Dependence on volatile pay was the only significant moderator, and even so, the pattern indicated that pay volatility predicts scarcity mindset regardless of dependence but that the effect is stronger for those who are more dependent. Identifying additional boundary conditions and buffers would help provide organizations and individuals with more practical solutions. For example, can interventions designed to reduce volatility (e.g., spreading commission payments evenly over a year) minimize the harms of pay volatility? Are recovery experiences like detachment, mastery, or physical activity able to replenish resources and minimize the harmful consequences of pay volatility?

Future work could also explore the impact of pay volatility on a broader range of outcomes, including employee performance and family functioning. Volatility in pay may, for example, spillover to affect a partner or child's sense of stability and security, with cascading effects. Interestingly, pay volatility did not predict heavy drinking or alcohol consumption in any study, raising questions about what sets this health outcome apart. Prior work has suggested that alcohol consumption may act as a more distant outcome, such that individuals experiencing sleep difficulty self-medicate with alcohol use (Belogolovsky et al., 2012). Other forms of volatility would also be worth exploring, such as volatility in the number of hours worked or in the workload of employees. It could be interesting to directly compare these different sources of volatility to better delineate whether volatility is inherently detrimental or only when it is volatility in a critically important resource like pay. Finally, there are likely other mechanisms through which performance-based pay can impact employee health that should be examined in greater detail. For example, insecure or uncertain pay may result in individuals overworking to hedge against this insecurity (Corgnet et al., 2020), increasing the risk of exhaustion and burnout (Dahl & Pierce, 2019). Volatility and any associated inequity in pay may also result in unfavorable upward comparisons and negative emotions, particularly if pay transparency is high (Bamberger & Belogolovsky, 2017). Future work should try to tease apart these mechanisms to understand how performance-based pay impacts health, and under which conditions.

Conclusion

While some differences exist in the results across these three studies, the overall pattern of effects is consistent across different samples, methods, and measures. In short, volatility in pay is associated with greater psychological threat and worse health for employees. These effects on health are most consistent for sleep health (quality and quantity), although more work is needed to understand the true impact of volatility. Taken together, these findings suggest that performance-based pay structures seem to have costs to health and that organizations should address such volatility to foster a healthy and productive workforce.

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