Effects of Perceived Scarcity on Mental Health, Time and Risk Preferences, and Decision-Making During and After COVID-19 Lockdown: A Quasi-Natural Experimental Study

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Abstract

Background: The COVID-19 lockdowns led to significant resource constraints, potentially impacting mental health and decision-making behaviors. Understanding the psychological and behavioral consequences could inform designing interventions to mitigate the negative impacts of episodic scarcity during crises like pandemics.

Objective: To investigate the effects of perceived scarcity on mental health (stress and fear), cognitive functioning, time and risk preferences (present bias and risk aversion), and trade-offs between groceries, health, and temptation goods during and after the COVID-19 lockdown in Shanghai.

Methods: A quasi-natural experiment was conducted in Shanghai during and after the COVID-19 lockdown. Online surveys were administered in May 2022 (during lockdown) and September 2022 (post-lockdown). Propensity Score Matching (PSM) was used to balance demographic factors between the groups (During: n=332; After: n=339). Data were analyzed using regression analyses, controlling for potential confounders.

Results: Perceived scarcity was significantly higher during the lockdown (mean=7.97) than after (mean=4.35; P<.001). Higher perceived scarcity was associated with increased stress levels both during (?=0.62, P<.001) and after the lockdown (?=0.65, P<.001). While cognitive functioning remained stable, possibly due to a ceiling effect from high education levels, monetary risk aversion increased under prolonged scarcity during lockdown (interaction ?=4.68, P<.001). During lockdown, participants allocated more budget to groceries (?=0.67, P=.01) and less to health items (?=-0.61, P=.02).

Conclusions: The study highlights that perceived scarcity during lockdown intensified stress and altered decision-making behaviors, including increased monetary risk aversion and shifts in spending priorities. Theoretically, this study advances the understanding of perceived scarcity by exploring its domain-specific effects on mental health and decision-making. Practically, these findings emphasize the need for public health strategies that mitigate the psychological impact of scarcity during crises, ensure access to essential goods, and support adaptive decision-making behaviors.

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Keywords: Perceived Scarcity; COVID-19 Lockdown; Mental Health; Wellbeing; Cognitive Function; Present Bias; Risk Aversion; Natural Experiment; Public Health Interventions; Consumer Behavior

Introduction

Lockdown policies have been among the most effective public health interventions during the COVID-19 pandemic, saving millions of lives worldwide [1,2]. However, lockdown measures,

including social distancing, self-isolation and prolonged home quarantine, along with disruptions to supply chains and shortages of essential products and services, have significantly altered many aspects of people's daily lives[3,4]. Research has shown that such measures have exacerbated mental health problems, leading to increased stress, depression, and negative affect [5–8], affected job, financial and food security [9,10], and caused panic buying [11,12] and adverse health decisions and behaviors [13–15]. While many studies have employed longitudinal and natural experiments to investigate the impact of lockdowns [16–18], few have focused on the psychological and behavioral consequences arising from the radical resource constraints individuals face during these periods.

A location where a stringent lockdown was implemented in response to a widespread COVID-19 outbreak was Shanghai, China's largest city by population (over 24 million) and one of the largest cities in the world. The lockdown lasted from March to May 2022 and residents were largely quarantined at home, facing significant shortages of products and services. After the city reopened on June 1, 2022, the supply and delivery of products and services returned to normal. This abrupt change in resource availability created a unique opportunity to examine how resource scarcity during lockdown affected various aspects of residents' lives in one of the largest urban populations in the world. The timing of this study is important since it captured a real-world episode of intense scarcity[19,20]. Understanding how these episodic constraints affect mental health and health-related decisions and behaviors can provide valuable empirical evidence on the impacts of pandemic lockdowns.

The concept of perceived scarcity, or psychological scarcity, is rooted in poverty literature and is well-established in the psychology and economics literature [21–23]. It refers to the subjective feelings that arise from the gap between one's needs and the resources available to fulfil them [24,25]. Feelings of scarcity can preoccupy one's thoughts, making everyday decisions, such as whether to visit a doctor or buy groceries, more difficult and stressful [26]. While traditionally studied in the context of poverty, recent research suggests that perceived scarcity can affect individuals across socioeconomic statuses, particularly during crises that disrupt normal resource access [27]. Previous studies have linked perceived scarcity to increased stress and negative affect [21,28,29]. Research also suggests that scarcity can directly impair cognitive functions, including decision making, reasoning, problem-solving, and attention, by reducing cognitive bandwidth and limiting the mental resources necessary to process information and make decisions [24,30]. However, these effects have not been consistently confirmed in other empirical studies [27–29]. Both the negative emotional states and the cognitive load induced by scarcity are seen as mechanisms that cause scarcity-reinforcing decisions and behaviors, leading to a cycle where poor decisions exacerbate conditions of health and well-being [17]. During the COVID-19 pandemic, stress and fear became widespread as individuals faced uncertainty and isolation, along with increasing cognitive load[34–37]. However, it remains unclear how these feelings and cognitive functioning may have been exacerbated by perceived scarcity.

Perceived scarcity can also impact decision-making in various domains by inducing biases and trade-off thinking. Time and risk preferences are fundamental components of human decision-making, with present bias and risk aversion representing systematic deviations from rational behavior [38,39]. Present bias refers to the tendency to prioritize immediate rewards over future gains, leading to short-sighted decisions that come at the expense of long-term goals [40,41]. Risk aversion, on the other hand, describes the preference for avoiding risks, making individuals less inclined to engage in actions with uncertain outcomes [42]. Both biases and risk aversion influence not only financial decisions but also health-related behaviors, such as smoking [43,44] and obesity [45], which are considered irrational. Research on perceived scarcity shows mixed outcomes, with some studies

indicating increased risk-taking [32] and time-discounting [46,47], while others find no significant effects [47]. During the pandemic, the impact of scarcity on biases in time and risk preferences remains underexplored. In terms of trade-off thinking, feelings of scarcity induced by financial worries seem to shift attention toward pressing needs, such as food and groceries, at the expense of forward-looking decisions like saving for health and education [48,49]. Additionally, scarcity may lead to the overconsumption of temptation goods, including junk food, sugary drinks, and cigarettes [50]. Nonetheless, these findings are inconsistent, suggesting that the effects of perceived scarcity may vary based on context and population characteristics. It remains unclear whether scarcity caused by supply shortages would force individuals making trade-offs between pressing needs and their health.

This paper aims to fill these gaps by leveraging the natural experiment provided by the COVID-19 lockdown in Shanghai, drawing on the economic theory of perceived scarcity. As outlined, the city of Shanghai, as one of China's most populous and economically significant cities, with a highly educated population and advanced infrastructure, provides an ideal context for this study. Examining the effects of perceived scarcity in such an environment allows to explore whether the psychological and behavioral impacts observed in low-income settings extend to higher-income, urban populations as well. By comparing psychological and behavioral outcomes during and after the lockdown, this paper investigates how perceived scarcity affects stress, fear, cognitive functioning, time and risk preferences, and spending priorities among groceries, health items, and temptation goods. Furthermore, to estimate the potential cumulative effects of lockdown, the paper also examines whether the length of exposure to lockdown—specifically, the duration of home quarantine and the length of time without shopping—exacerbated mental health problems and influenced decision-making. This study contributes to the literature by extending the concept of perceived scarcity in a high-income, urban population during a crisis, advancing the understanding of its impact on their mental health and decision-making behaviors. The findings can inform policymakers and public health practitioners in designing interventions to mitigate the negative impacts of scarcity during crises and emergencies, ensuring that strategies are tailored to address both supply shortages and psychological needs.

Methods

Study Design

This study adopted the target trial framework [19] for the design, analysis and reporting of the natural experimental study. The COVID-19 lockdown policy in Shanghai served as the intervention, with the treatment group comprising participants affected during the lockdown, and the control group comprising participants who had returned to normal life by September 2022, three months after the city's reopening. Shanghai was chosen due to its unique and stringent lockdown measures during the COVID-19 pandemic, which lasted from March to May 2022. Shanghai's lockdown provided a rare opportunity to study the psychological and behavioral impacts of prolonged confinement and resource scarcity in an urban setting. According to prior conceptualizations of natural experiment [19,20] and the Medical Research Council (MRC) guidelines [51,52], this study qualifies as a between-group natural experiment, as it utilizes the natural occurrence of the lockdown to assign exposure to participants in a manner akin to randomization, which is pivotal for establishing causal relationships in situations where controlled random assignment is not feasible or ethical [53]. The study was approved by the ethics committee of the first author’s institution.

Sample and Data Collection

Two online surveys with identical items were distributed to collect data from participants living in Shanghai during two periods: May 2022 (during lockdown) and September 2022 (after lockdown).

Data collection was conducted using Wenjuanxing, a widely used online survey platform in China [54]. The survey was disseminated via the platform's participant pool. Additionally, the researchers leveraged their social networks and online community groups, such as WeChat and local forums, to reach individuals living in Shanghai. Several measures were taken to ensure high-quality responses. First, respondents were limited to individuals living in Shanghai. Second, participants in the "During" group were asked to confirm they were in quarantine and specify the starting date, while participants in the "After" group confirmed they were not in quarantine and provided the end date of their quarantine. Finally, multiple quality control means, include attention checks, minimum answering time control for each section, and system and human screening, were used to filter out inattentive respondents.

A statistical power analysis, adjusted for multiple comparisons ($\alpha \approx 0.0045$) to account for all 11 primary outcome measures and targeting a power of 0.80, determined that at least 288 participants per group were required to detect significant differences with medium effect sizes across all primary outcomes. A total of 747 participants completed the survey—367 during the lockdown and 380 after the lockdown. Data collection completion was determined based on practical considerations, including resource availability and distribution duration. The criteria of data exclusion and the number excluded include: 1) not in quarantine for During group or still in quarantine for After group (n=23); 2) IP address not in Shanghai (n=27); 3) outliers (n=20) who may have been distracted or encountered technical difficulties, and took excessively long to complete the survey (Z-score> mean+3σ, representing the top 0.15% of completion times). After applying these criteria, 70 participants were excluded (n = 36 from the "During" group; n = 34 from the "After" group), resulting in a final sample of 677 participants.

Propensity Score Matching

To address potential confounding variables and ensure comparability between the "During" and "After" groups, propensity score matching (PSM) was implemented. Each participant in the "After" group was matched to a participant in the "During" group with a similar propensity score based on demographic variables including gender, age, education, monthly income, and monthly expenditure. The PSM results indicated a well-balanced match, with bias for matched control variables ranging between -5.7% to 5.0% (see Multimedia Appendix 2 Table S1). After matching, six observations were off-support and excluded. This left a total of 671 observations (332 "During" and 339 "After") on-support, which were used for the main analysis.

Measurements

The measurements for both During and After groups include perceived scarcity, stress, fear of COVID-19, cognitive functioning, time and risk preferences, purchase decisions and demographic information. Multimedia Appendix 1 gives an overview of the constructs and their measurement items.

For the measurement of perceived scarcity, the study used a 4-item perceived scarcity scale, adapted from Yuen et al. [11] and Byun and Sternquist [55], to assess participants' subjective perception of product availability during lockdown. Perceived scarcity might be impacted by the length of quarantine and the time since the last shopping trip. To investigate the interactive effects, the study asked participants to specify the start date of their home quarantine and the last date they shopped. For the After group, participants provided the date their quarantine ended and the date they went shopping. The study measured participants' perceived stress over the past month using the well-known 10-item Perceived Stress Scale (PSS) from Cohen et al. [56]. To measure their fear of COVID-19, the study employed the 7-item Fear of COVID-19 Scale from Ahorsu et al. [57]. For the

measurement of cognitive function, participants were asked to complete a 12-trial Raven's Progressive Matrices [58], which require them to match a set of graphic patterns. This test is widely used for measuring fluid intelligence, a core feature of individuals' cognitive capacity to think logically and solve problems in novel situations [59].

The study measured both monetary-framed and health-framed time preferences using two sets of choice scenarios based on Laibson's quasi-hyperbolic discounting model [41]. In both monetary (job payment) and health (physical examination subsidy) contexts, participants chose between smaller immediate rewards and larger delayed rewards, indicating their level of impatience or present bias [44]. Additional health-related tasks involved choosing between immediate medical attention versus continuing to work for compensation, and immediate medical attention versus traveling to a distant hospital. Present bias was identified by the point at which participants switched from preferring later payoffs to earlier ones. The study then measured risk preferences using the Eckel & Grossman lottery task (2002) [60] in both monetary-framed and one health-framed contexts. In the monetary task, participants selected among six lotteries, each with a 50/50 chance of winning a lower or higher amount of money. In the health task, they chose between vaccine options offering different durations of protection with associated risks. Risk aversion was estimated based on choices between riskier and safer options. Additionally, Tversky and Kahneman's [61] disease problem was used to assess risk aversion. This study used the non-incentivized elicitation methods for time and risk preferences. The reason was that participants during the lockdown found themselves within a 'naturally occurring' state of both financial and health distress. This context improved the likelihood of respondents perceiving the intertemporal and risk trade-offs as more realistic and vivid even in the absence of actual incentive compatible consequences for their responses.

For the measurement of trade-offs, participants were asked to allocate a hypothetical budget of ¥300 over three categories: daily groceries, medicine and health-related goods, and temptation goods. Each category represents different facets of decision-making, informed by existing literature on trade-off thinking in decision-making [48,50,62]. The budget allocation task was designed to mimic the experience of online shopping, aiming to make the decision-making process feel as realistic as possible for participants, thereby potentially eliciting choices that are representative of their real-world trade-offs and priorities. The items selected in each category were popular and well-known in the local market. The proportion of the budget allocated to each category provides a measure of the importance or priority given to that category, which allows researchers to measure individuals' decision priority under conditions of scarcity. At the end of the survey, the study collected demographic information, including gender, age, education, monthly income and monthly expenditure.

Data Analysis

Data were analyzed using Stata 17. Ordinary Least Squares (OLS) regressions were used for continuous variables, logistic regressions for binary outcomes, and ordinal logistic regressions for ordinal variables. All regressions applied propensity score-matching weights to adjust for baseline differences between the groups. Demographic variables (gender, age, education, income, expenditure) were included as covariates to control for potential confounding factors. Robust standard errors were used to account for heteroskedasticity and ensure reliable inference.

Results

Demographic Characteristics

Table 1 presents the demographic characteristics of participants included in the analysis. The total

sample size comprises 671 participants, with 332 in the “During” group and 339 in the “After” group. Females comprise 56.6% of the “During” group and 53.1% of the “After” group. Males make up 43.4% and 46.9% of these groups, respectively. Most participants are aged 18-40, with 86.4% in the “During” group and 89.1% in the “After” group falling within this range. The majority of participants have an undergraduate degree—61.7% in the “During” group and 77.6% in the “After” group. Graduate degrees or higher are more common in the “During” group (31.3%) than in the “After” group (14.5%). The largest income bracket is ¥10,001 and above, representing 54.5% of the “During” group and 56.9% of the “After” group. Most participants spend between ¥3,001 and ¥7,000 monthly, with 51.2% in the “During” group and 56.7% in the “After” group. These demographics suggest a relatively consistent distribution across both groups.

Table 1 Demographic characteristics of participants included in the analysis

	During (n = 332)	After (n = 339)	Total (N = 671)
Gender n (%)			
Female	188 (56.6%)	180 (53.1%)	368 (54.8%)
Male	144 (43.4%)	159 (46.9%)	303 (45.2%)
Age n (%)			
18-30 years old	176 (53.0%)	199 (58.7%)	375 (55.9%)
31-40 years old	111 (33.4%)	103 (30.4%)	214 (31.9%)
41-50 years old	42 (12.7%)	32 (9.4%)	74 (11.0%)
51 years old and above	3 (0.9%)	5 (1.5%)	8 (1.2%)
Education n (%)			
Middle school and below	7 (2.1%)	10 (2.9%)	17 (2.5%)
High school	16 (4.8%)	17 (5.0%)	33 (4.9%)
Undergraduate	205 (61.7%)	263 (77.6%)	468 (69.7%)
Graduate and above	104 (31.3%)	49 (14.5%)	153 (22.8%)
Monthly Income n (%)			
¥2000 and below	9 (2.7%)	12 (3.5%)	21 (3.1%)
¥2001-¥4000	13 (3.9%)	9 (2.7%)	22 (3.3%)
¥4001-¥6000	26 (7.8%)	15 (4.4%)	41 (6.1%)
¥6001-¥8000	39 (11.7%)	34 (10.0%)	73 (10.9%)
¥8001-¥10000	64 (19.3%)	76 (22.4%)	140 (20.9%)
¥10001 and above	181 (54.5%)	193 (56.9%)	374 (55.7%)
Monthly Expenditure n (%)			
¥1000 and below	7 (2.1%)	6 (1.8%)	13 (1.9%)
¥1001-¥3000	66 (19.9%)	63 (18.6%)	129 (19.2%)
¥3001-¥5000	107 (32.2%)	108 (31.9%)	215 (32.0%)
¥5001-¥7000	63 (19.0%)	84 (24.8%)	147 (21.9%)
¥7001-¥9000	34 (10.2%)	48 (14.2%)	82 (12.2%)
¥9001 and above	55 (16.6%)	30 (8.8%)	85 (12.7%)

The Impact of COVID-19 Lockdown

Table 2 presents the summary statistics comparing various psychological and behavioral measures between participants during the lockdown and those after the lockdown. Figure 1 illustrates the estimated treatment effects from regression analyses, adjusting for demographic variables and using propensity score matching to control for baseline differences between the During and After groups (see Multimedia Appendix 2 Table S2 for full results).

Participants experiencing the lockdown reported significantly higher levels of perceived scarcity (Mean = 7.97, SD = 2.10) compared to those surveyed after the lockdown (Mean = 4.35, SD = 2.27; $P < .001$). This increase was further validated by regression analyses (see Figure 1), which showed a substantial rise in perceived scarcity during the lockdown ($\beta = 1.28$, $P < .001$). Concurrently, stress levels were markedly elevated during the lockdown (Mean = 2.76, SD = 0.70) versus post-lockdown (Mean = 2.55, SD = 0.68) and the increase was significant ($\beta = 0.31$, $P < .001$). Fear of COVID-19 was slightly higher after the lockdown (Mean = 4.39, SD = 2.11) compared to during the lockdown (Mean = 4.05, SD = 2.06; $P = .04$). However, when controlling for other variables, this difference was not statistically significant in regression analyses ($\beta = -0.08$, $P = .29$), suggesting that

the initial difference may be influenced by confounding factors. No significant differences were observed in cognitive functioning between the two groups in terms of their accuracy on the Raven's Matrices task (Mean_During = 87%, SD = 18.85 vs. Mean_After = 87.7%, SD = 16.34; *P* = .53).

Table 2. Summary statistics for during and after lockdown groups

	During		After			
	n	mean (SD)	n	mean (SD)	t/z	*P*
Scarcity						
Perceived scarcity	332	7.97(2.10)	339	4.35(2.27)	-21.44	<.001
Days since quarantine	326	31.47(10.10)	259	93.27(24.78)	40.95	<.001
Days without shopping	247	6.08(8.52)	124	16.56(25.81)	5.79	<.001
Mental health						
Stress	332	2.76(0.70)	339	2.55(0.68)	-3.94	<.001
Fear of Covid-19	332	4.05(2.06)	339	4.39(2.11)	2.09	.04
Cognitive function						
Raven' Matrices	332	87.00(18.85)	339	87.86(16.34)	0.63	.53
Preference						
Proportion of present bias (monetary)	219	0.54(0.50)	226	0.49(0.50)	-1.10	.27
Proportion of present bias (health)	219	0.47(0.50)	226	0.42(0.50)	-0.97	.33
Risk aversion (monetary)	332	3.30(1.70)	339	3.11(1.62)	-1.43	.15
Risk aversion (health)	332	2.19(1.45)	339	2.54(1.47)	3.58	<.001
Purchase decision						
Proportion of grocery	332	0.68(0.18)	339	0.64(0.19)	-2.94	<.001
Proportion of health	332	0.18(0.13)	339	0.19(0.13)	1.52	.13
Proportion of temptation	332	0.14(0.15)	339	0.17(0.17)	2.21	.03

Notes:

[a]*P* values were calculated using two-sided t-tests for continuous variables, a two-sample proportion test for Present Bias with a binary indicator of whether individuals exhibited bias, and the Wilcoxon rank-sum (Mann–Whitney) test for ordinal variables assessing Risk Aversion.

[b]To align with the timing of the lockdown, the analysis of "Days since quarantine" included only those who had quarantined ("During" group, n=326) or had not quarantined ("After" group, n=259) within 120 days. Similarly, the analysis of "Days without shopping" was limited to individuals who had not shopped in the last 90 days for both During (n=247) and After (n=124) groups.

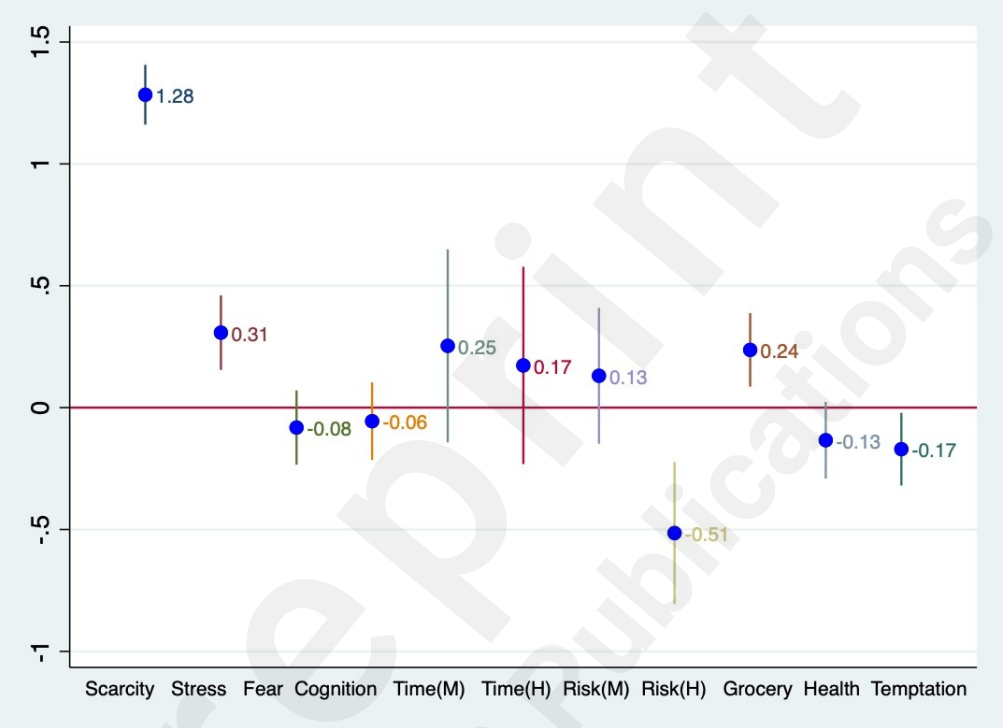
[c]The sample for Present bias was limited to participants (("During" group, n=219; "After" group, n=226) who consistently chose either the earlier or later payment in both monetary and health time-discounting tasks, switching no more than once between options.

In monetary-framed choices, the proportion of participants exhibiting present bias was 54.3% in the During group and 49.1% in the After group, with an insignificant difference (z = -1.10, *P* = 0.27; 95% CI: -14.5% to 4.1%). Similarly, in health-framed choices, the proportion was 47.0% in the During group and 42.5% in the After group, and the difference is also not statistically significant (z = -0.97, *P* = 0.33; 95% CI: -13.8% to 4.7%). While monetary risk aversion showed a non-significant difference (z = -1.43, *P* = .15), health-related risk aversion was significantly greater during the lockdown than after (z = 3.58, *P* < .001).

Participants during the lockdown allocated a significantly higher proportion of their hypothetical budget to groceries (Mean = 68.3%, SD = 0.18) compared to those after the lockdown (Mean = 64.2%, SD = 0.19; *P* < .001). This trend was reinforced by regression

results (β = 0.24, *P* < .001). Conversely, spending on temptation goods was lower during the lockdown (Mean = 13.9%, SD = 0.15) than after (Mean = 16.5%, SD = 0.17; *P* = .03), with regression analyses indicating a significant reduction (β = -0.17, *P* = .03). There was no significant difference in the proportion allocated to health-related goods between the two groups (Mean_During = 17.8%, SD = 0.13 vs. Mean_After = 19.3%, SD = 0.13; *P* = .13).

Figure 1. Lockdown treatment effects by group



Notes:

[a]Effects are presented as standardized coefficients with 95% confidence intervals. Each estimate was obtained from OLS regression except for present bias (logistic regression) and risk aversion (ordinal regression).

[b]All regressions applied propensity score-matching weights to adjust for baseline differences between the groups and controlled demographic variables, including gender, age, education, monthly income and monthly expenditure, to adjust for potential confounding. All variables were normalized to z-scores to facilitate comparison. Robust standard errors were employed across all regressions to ensure the accuracy of the estimates.

Effects of Perceived Scarcity and Lockdown Duration

The cumulative effects of the lockdown were examined by analyzing how perceived scarcity and its interactions with lockdown status, and lockdown duration affected various outcomes. To align with the timing of the lockdown, the analysis included participants who had quarantined within 120 days and those who had not shopped in the last 90 days. All variables were normalized to z-scores to facilitate comparison.

Table 3 presents the results of regression analyses for the During and After groups. Perceived scarcity was significantly associated with increased stress in both During (β = 0.62, p < .001) and After (β = 0.65, p < .001) groups. Neither length of quarantine (days in quarantine for the During group and days after quarantine for After group) nor days

since last shop had significant direct effects on stress. Their interactions with perceived scarcity were also non-significant for both groups. These findings indicate that perceived scarcity remained a robust predictor of stress, independent of quarantine duration. Among participants surveyed during lockdown, perceived scarcity did not significantly affect fear of COVID-19 (β = 0.04, p = .88), but its interaction with days in quarantine was significantly negative (β = -1.25, p < .001), suggesting that the relationship between scarcity and fear diminished as quarantine duration increased. In the after-lockdown group, perceived scarcity significantly increased fear of COVID-19 (β = 0.38, p < .001). During lockdown, perceived scarcity was associated with a slight enhancement in cognitive performance (β = 0.80, p = .04), but as lockdown days extended cognitive functioning decreased marginally (β = -4.13, p = .06). After lockdown, perceived scarcity had no significant effect on cognitive functioning (β = -0.03, P = .78), while longer days post-lockdown was associated with improved cognitive performance (β = 2.22, p = .03).

Table 3. Effects of perceived scarcity and lockdown duration on stress, fear and cognitive function

	Stress level			Fear of COVID-19			Cognitive functioning		
	b	se	p	b	se	p	b	se	p
Panel A: During lockdown									
Perceived scarcity	0.62	0.22	<.001	0.04	0.28	.88	0.80	0.39	.04
Days in quarantine	-0.89	1.18	.45	1.63	1.53	.29	-4.13	2.15	.06
Perceived scarcity # Days in quarantine	-0.47	0.55	.39	-1.25	0.37	<.001	0.64	0.37	.08
Days since last shopping	-0.08	0.69	.91	0.94	0.49	.06	1.05	0.57	.07
Perceived scarcity # Days since last shopping	-0.71	0.51	.17	-0.24	0.31	.44	-0.40	0.33	.23
Panel B: After lockdown									
Perceived scarcity	0.65	0.10	<.001	0.38	0.12	<.001	-0.03	0.12	.78
Days after quarantine	1.27	0.82	.12	-1.34	1.01	.19	2.22		.03
Perceived scarcity # Days after quarantine	0.48	0.53	.37	0.21	0.57	.72	0.97	0.56	.09
Days since last shopping	-0.41	0.40	.31	-0.22	0.66	.74	-0.80	0.83	.33
Perceived scarcity # Days since last shopping	-0.04	0.29	.89	0.00	0.45	.99	-0.57	0.56	.31

Notes:

[a]Each estimate was obtained from OLS regression.

[b]To align with the timing of the lockdown, the analysis of “Days since quarantine” included only those who had quarantined (“During” group, n=326) or had not quarantined (“After” group, n=259) within 120 days. Similarly, the analysis of “Days without shopping” was limited to individuals who had not shopped in the last 90 days for both During (n=247) and After (n=124) groups.

[c]All regressions applied propensity score-matching weights to adjust for baseline differences between the groups and controlled demographic variables, including gender, age, education, monthly income and monthly expenditure, to adjust for potential confounding. Robust standard errors were employed across all regressions to ensure the accuracy of the estimates.

For both groups, present bias in monetary context showed limited significant relationships with perceived scarcity and lockdown duration, indicating that scarcity may not substantially alter time preferences in decision-making within these domains (Table 4). Present bias in health context showed mixed results. For the During group, no significant effect was found. For the After group, days after quarantine significantly reduced health-related present bias (β = -9.38, p = 0.01), and their interaction with

scarcity is also significant (β = -6.24, p = 0.01). Interaction between perceived scarcity and days since last shopping also significantly reduced health-related present bias (β = -3.02, p = 0.03). In general, neither perceived scarcity nor lockdown duration significantly influence risk aversion across monetary and health contexts. However, the interaction with days in quarantine is significantly positive (β = 4.68, p < .001), indicating that scarcity's impact on increasing monetary risk aversion with longer quarantine durations.

Table 4. Effects of perceived scarcity and lockdown duration on time and risk preferences

	Present bias (monetary)			Present bias (health)			Risk aversion (monetary)			Risk aversion (health)		
	b	se	p	b	se	p	b	se	p	b	se	p
Panel A: During lockdown												
Perceived scarcity	1.05	0.84	.21	0.17	0.87	.85	0.32	0.65	.62	-0.03	0.52	.96
Days in quarantine	-4.46	4.48	.32	0.15	4.70	.97	-5.06	3.99	.20	-1.50	3.30	.65
Perceived scarcity # Days in quarantine	0.34	1.34	.80	1.28	1.34	.34	4.68	1.44	<.001	-0.23	1.90	.90
Days since last shopping	0.30	1.88	.87	-0.17	1.85	.93	-3.13	1.84	.09	-1.50	2.04	.46
Perceived scarcity # Days since last shopping	1.05	1.41	.46	0.77	1.39	.58	2.68	1.51	.08	-0.34	1.65	.84
Panel B: After lockdown												
Perceived scarcity	-0.42	0.32	.19	-0.15	0.32	.64	-0.00	0.24	.99	-0.13	0.26	.61
Days after quarantine	-6.00	3.40	.08	-9.38	3.73	.01	-0.19	1.99	.92	-3.44	1.93	.07
Perceived scarcity # Days after quarantine	-3.80	2.07	.07	-6.24	2.28	.01	-1.20	1.23	.33	-2.67	1.11	.02
Days since last shopping	-2.67	2.07	.20	-4.04	2.17	.06	-1.96	1.21	.10	-0.89	1.16	.44
Perceived scarcity # Days since last shopping	-2.70	1.37	.05	-3.02	1.42	.03	-1.55	0.83	.06	-1.08	0.81	.18

Notes:

[a]Logistic regressions were performed for present bias and ordinal regressions were performed for risk aversion.

[b]The sample for Present bias was limited to participants ((“During” group, n=219; “After” group, n=226) who consistently chose either the earlier or later payment in both monetary and health time-discounting tasks, switching no more than once between options.

[c]All regressions applied propensity score-matching weights to adjust for baseline differences between the groups and controlled demographic variables, including gender, age, education, monthly income and monthly expenditure, to adjust for potential confounding. Robust standard errors were employed across all regressions to ensure the accuracy of the estimates.

Table 5 presents the regression results for budget allocations to groceries, health items, and temptation goods, assessing trade-off thinking in decision-making. During lockdown, perceived scarcity significantly increased the proportion of the budget allocated to groceries (β = 0.67, p = 0.01) and reduced the proportion to health items (β = -0.61, p = 0.02). Even though longer quarantine duration led to decreased grocery spending (β = -4.43, p <.001) and increased health spending (β = 3.98, p =.01), its interaction with scarcity significantly increased groceries spending (β = 1.52, p =.01) and decreased health spending (β = -1.41, p <.001). In contrast, after lockdown, perceived scarcity and

days after lockdown seem reduced spending on groceries (β = -0,35, p <.001) and increased spending on temptation goods (β = 0.29, p = 0.01), while it did not significantly affect expenditures on health items (β = 0.29, p = 0.12). But it is important to note that the overall effect sizes were small.

Table 5. Effects of perceived scarcity and lockdown duration on grocery, health and temptation goods

	Proportion of groceries			Proportion of health items			Proportion of temptation goods		
	b	se	p	b	se	p	b	se	p
Panel A: During lockdown									
Perceived scarcity	0.67	0.27	.01	-0.61	0.26	.02	-0.29	0.29	.32
Days in quarantine	-4.43	1.41	<.001	3.98	1.46	.01	1.96	1.57	.21
Perceived scarcity # Days in quarantine	1.52	0.54	.01	-1.41	0.42	<.001	-0.64	0.51	.21
Days since last shopping	-1.01	0.79	.20	0.54	0.73	.46	0.75	0.72	.30
Perceived scarcity # Days since last shopping	0.77	0.59	.19	-0.64	0.57	.26	-0.38	0.53	.47
Panel B: After lockdown									
Perceived scarcity	-0.35	0.12	<.001	0.15	0.13	.24	0.29	0.12	.01
Days after quarantine	-1.82	1.01	.07	0.06	1.09	.96	2.10	1.06	.05
Perceived scarcity # Days after quarantine	-1.07	0.57	.06	0.36	0.65	.58	0.97	0.60	.11
Days since last shopping	0.05	0.55	.93	-0.02	0.44	.97	-0.04	0.69	.95
Perceived scarcity # Days since last shopping	-0.32	0.39	.41	0.16	0.30	.59	0.24	0.47	.61

Notes:

[a]Each estimate was obtained from OLS regression.

[b]All regressions applied propensity score-matching weights to adjust for baseline differences between the groups and controlled demographic variables, including gender, age, education, monthly income and monthly expenditure, to adjust for potential confounding. Robust standard errors were employed across all regressions to ensure the accuracy of the estimates.

Discussion

This paper examined the psychological and behavioral impacts of perceived scarcity during and after the COVID-19 lockdown in Shanghai. By analyzing variables such as stress, fear of COVID-19, cognitive functioning, present bias, risk aversion, and budget allocation, the study aimed to understand how perceived scarcity arising from resource constraints influences mental health and decision-making processes during a pandemic. The findings provide empirical evidence on the nuanced effects of scarcity in a real-world crisis, advancing understanding of its impact on various psychological and behavioral outcomes.

Findings and comparison with prior work

Perceived scarcity and stress were significantly higher during the lockdown compared to after, aligning with existing literature that lockdown measures exacerbate mental health problems [6–8]. The increase in stress levels was positively associated with perceived scarcity across both during and after lockdown groups. This finding aligns with prior

research that poverty and resource constraints elevate stress[21,63] and extends the understanding of scarcity's psychological impact beyond low-income populations to include individuals in higher-income urban settings during crises. It underscores that sudden resource constraints can affect stress levels, regardless of socioeconomic status. Fear of COVID-19 was slightly higher after the lockdown, although this difference was not statistically significant when controlling for other variables. During lockdown, the interaction between perceived scarcity and days in quarantine was significantly negative. This may indicate that as the duration of home quarantine extends and individuals are less exposed to the pandemic environment, their perception of fear diminishes.

Cognitive functioning, measured using Raven's Progressive Matrix, showed no significant difference between groups. One possible explanation is that the high educational levels of most participants, along with consistently strong cognitive task performance, may have resulted in a ceiling effect. Regression results showed that during lockdown, longer quarantine durations were associated with decreased cognitive function, whereas after lockdown, longer post-lockdown periods were associated with improved cognitive performance. These cumulative effects are consistent with findings from longitudinal studies that examine how scarcity impacts cognitive function over time [30,64].

The stability of time preferences reported in both monetary- and health-framed choices is consistent with study [65] but contradicts study [66] conducted during COVID-19. Regarding the effects of perceived scarcity and lockdown duration, present bias was generally unchanged, except in health-framed choices post-lockdown, where individuals displayed a reduced present bias and became more future-oriented. However, the small sample sizes ($n = 91$ for the During group; $n = 64$ for the After group) in the analyses limit the confidence in these conclusions. Further research is necessary to confirm and clarify these trends. Risk preference in monetary-framed choices remained stable, aligning with previous studies[65,67,68]. In contrast, within health-framed choices, the During group exhibited greater risk aversion compared to the After group. This may be because the risk preference questions focused on vaccination, which was more urgent and relevant health concerns during the lockdown period. Furthermore, perceived scarcity, when interacting with days in quarantine, increased monetary risk aversion in the During group, while its interaction with days after quarantine decreased health-related risk aversion in the After group. Together, these findings indicate that perceived scarcity and the timing of lockdown influence individuals' time and risk preferences differently across monetary and health-related contexts, highlighting the importance of context in understanding preferences and biases.

Lastly, when faced with trade-offs in purchasing decisions during the lockdown, participants prioritized spending on groceries over health items, reflecting immediate survival needs taking precedence under resource constraints [10,14, 15]. This shift in spending priorities toward essential goods is also in line with findings from studies on purchase behaviors during COVID-19, such as online grocery shopping [12], and panic buying [11]. After lockdown, scarcity was associated with increased spending on temptation goods, indicating a shift toward non-essential purchases when restrictions

eased. These changes highlight the dynamic nature of consumer behavior in response to external stressors and the role of scarcity in influencing trade-off decisions.

Policy implications

The above findings inform policymakers on the importance of addressing both material and psychological needs during crises. To mitigate perceived scarcity and its consequences in future crises, there are three aspects of implications for the design of public health interventions, including resource allocation, mental health mitigation, and public communications. However, it is worth emphasizing that epidemic control policies must be balanced against the broader well-being of people in resource-limited settings and designed with parallel support systems when such policies threaten peoples' access to basic services [14,69].

For resource allocation strategies, policymakers should focus on creating resilient supply chains to mitigate perceived scarcity in future crises. Governments can implement measures such as food distribution programs and support for online delivery services to facilitate access. For instance, establishing community distribution centers or partnering with grocery stores to deliver essentials to vulnerable populations can ensure that basic needs are met. Implementing real-time monitoring systems to track inventory levels and demand patterns can also help in proactive resource distribution.

For public health practice targeting on mental health, findings suggest that mental health interventions may be necessary both during and after quarantine measures are lifted. Interventions aimed at enhancing coping strategies may be effective in reducing stress, anxiety and fear during extended lockdowns[70]. This could involve providing virtual mental health services, such as online counseling or stress management workshops, to help individuals develop resilience[71]. Additionally, community support programs, like peer support groups or virtual social events, can foster a sense of connectedness and reduce feelings of isolation. To mitigate mental health challenges both during and after quarantine, governments should invest in digital mental health tools and offer support resources accessible to the public. Government can also partner with app developers to create mental health applications specifically designed for crisis situations, incorporating features such as daily wellness check-ins, stress management techniques, and mindfulness exercises[72].

For public health communications, transparent updates on supply levels and distribution timelines can significantly reduce perceived scarcity and stress [73,74]. Public health campaigns should acknowledge inherent biases in individual decision-making and tailor messages accordingly. This could involve creating personalized messages that highlight potential health losses during times when risk aversion in health contexts is heightened, such as during lockdowns. Post-lockdown, public health campaigns can promote balanced spending, encouraging individuals to maintain healthy consumption patterns. These messages would also resonate with individuals' increased future orientation after lockdowns by emphasizing the long-term benefits of investing in health. Public health campaigns can also utilize social media influencers and involve influential community figures to promote positive messaging[75].

Limitations and future research

Like for all research projects, this study comes with a few limitations that need to be acknowledged. Firstly, the cross-sectional design, comparing two independent groups, limits causal interference or change tracking within individuals. Future studies could utilize a longitudinal design, tracking the same participants across different stages of a crisis, which would offer insights into how perceived scarcity impacts individuals over time. Furthermore, the reliance on self-reported data introduces potential biases, such as recall bias or social desirability bias. Future research could incorporate objective data, such as actual purchasing behaviors through transaction records or physiological stress indicators like cortisol levels. Additionally, the use of incentivized tasks for measuring time and risk preferences could provide more accurate assessments of decision-making behaviors. Another limitation is the limited sample size for specific analyses, particularly those related to present bias, which may affect result reliability. Future studies should aim for larger samples to confirm these findings and enhance statistical power. Broadening participants from different regions and cultural backgrounds can also help generalize the findings and explore cultural influences on the effects of scarcity. This research highlights the need to further examine how perceived scarcity shapes mental health and decision-making in the long term, especially as crises like pandemics and climate-related events may become more frequent. Future research could investigate the potential for lasting behavioral changes induced by scarcity, such as persistent shifts in spending priorities and purchase behaviors. Studies could also further examine the roles of cognitive function, time, and risk preferences as mediators in scarcity's impact on health and well-being, enabling targeted interventions that support individuals in making more resilient and sustainable decisions during and after resource-scarce periods.

Conclusions

This paper provides a nuanced understanding of the psychological and behavioral impacts of perceived scarcity during a pandemic, focusing on an urban population during and after the COVID-19 lockdown in Shanghai. The findings reveal that scarcity significantly influences stress levels, cognitive function, financial risk aversion, and budget allocation, while fear and present bias show more moderate effects. From a theoretical perspective, the study extends the concept of perceived scarcity to encompass situational constraints experienced by higher-income populations during crises and advances current literature by demonstrating that the psychological and behavioral effects of perceived scarcity are multifaceted and context dependent. Therefore, this study advances theoretical understanding by highlighting the domain-specific effects of perceived scarcity and the resilience observed in cognitive functioning among highly educated populations. From a policy perspective, findings provide evidence for policymakers to design interventions that address both the material and psychological needs of populations during times of scarcity. By implementing targeted strategies, such as leveraging technology for resource management, providing mental health support, and tailoring communication to individual biases, governments can mitigate the negative impacts of scarcity and enhance resilience in future crises.

Acknowledgements

Conflicts of Interest

None declared.

Abbreviations

COCID-19: Coronavirus Disease 2019
MRC: Medical Research Council
OLS: Ordinary Least Squares
PSM: Propensity Score Matching
PSS: Perceived Stress Scale

Multimedia Appendix 1

Multimedia Appendix 2

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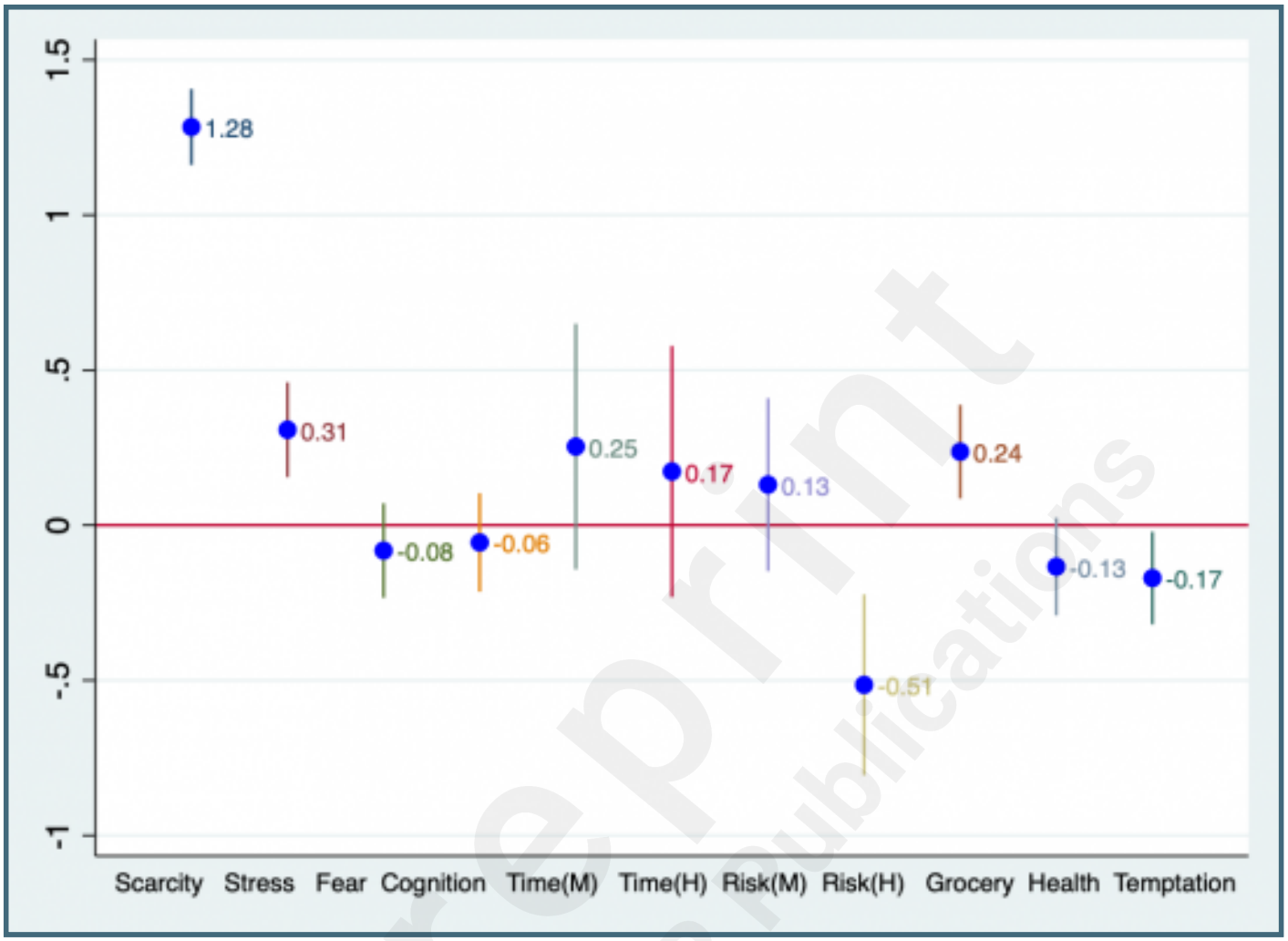
Supplementary Files

Figures

Lockdown treatment effects by group.



Multimedia Appendixes

Online survey questions.
URL: http://asset.jmir.pub/assets/f8b1ff1254d279e9d226d8d970c33458.docx

Supplementary Tables.
URL: http://asset.jmir.pub/assets/52c9d0a176aaca6ee74a9e19a9bea901.docx