Does Your Gain Define My Loss?: Socially-Defined Counterfactual Loss and Prevention-Focused Decision-Making (Supplementary Materials)

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Data Loading and Cleaning

Load Libraries and Define Functions

All code used to load libraries and define functions can be found in the .Rmd file used to generate this PDF.

Import and Clean Data

All code used to import and clean data can be found in the .Rmd file used to generate this PDF. Please note: To reproduce the reported results and ensure all code runs properly, the raw dataset should be exported from Qualtrics with the *numeric values* (**not** *choice text*) option selected.

Participants

Exclusions

Excluding participants who did not complete our IV and/or DV

As per our pre-defined exclusion criteria, 19 participants were excluded for not submitting a Bitcoin allocation percentage (our dependent measure) or completing the Regulatory Focus Questionnaire ("RFQ"), which was used to calculate chronic prevention pride scores (one of our two independent measures).

Deciding whether to exclude participants with fraudulent IP addresses

Soon after running this study, it became clear that data quality issues had recently surfaced on M-Turk due to foreign workers masking their location through Virtual Private Servers (see, for example, Dennis, Goodson, and Pearson 2018; Kennedy et al. 2018). As a result, although not specified in our preregistration, we decided to consider excluding participants for data quality issues resulting from fraudulent IP addresses based on an investigation of the reliability of these responses.

We examined our dataset for fraudulent responses based on users' IP addresses using R (Version 3.6.1; R Core Team 2018) and the R-package *rIP* (Version 1.2.0; Kennedy and Waggoner 2018). This package returns the dataset with a "block" column including a coded score indicating if the IP address is likely from a server farm and warrants exclusion. In doing so, we discovered 147 participants who met this criterion and received an *rIP* "block" score of 1. (We selected the less stringent of the two "block" scores within the *rIP* package to minimize exclusions, but the following findings are consistent regardless of which "block" score was used.) We then probed these purportedly fraudulent responses to determine if their quality differed substantially from the rest of our sample.

First, we examined internal reliability. In previous research, Higgins and colleagues (2001) found that the reliability of the prevention scale was 0.80, and among participants who did *not* receive a block score of 1, the Cronbach's alpha of the prevention items was in line with this estimate ($\alpha = 0.86$). However, among the responses who received a block score of 1 (thus indicating fraudulence), the Cronbach's alpha of the prevention items was 0.55. In particular, this reduced reliability appeared to be driven by reverse-coded items, as among this group, the function produced a warning message prompting us to confirm that the reverse-coded items were coded correctly (which we confirmed). To be clear, participants flagged as fraudulent did not respond to reverse-coded items as if they were reverse-coded, whereas other participants did. Following a method by Feldt et al. (1987) to determine the equality of two Cronbach's alphas in which the statistic W is distributed as F, we also used the R-package *cocron* (Version 1.0.1; Diedenhofen 2016) to perform a statistical comparison of these two reliabilities. We found that the chronic prevention pride scores among participants flagged as fraudulent were significantly less reliable than non-flagged participants' scores, $W(333, 146) = 3.11, p < .001$.

Additionally, we examined the variance of responses to prevention-specific items from the RFQ. The variance across prevention items in the RFQ was also significantly greater among participants in the potentially fraudulent group (0.95) than among the non-flagged participant group (0.61), $t(284.01) = -5.37, p < .001$.

As a result, we excluded all participants with a "block" score of 1. (We selected the less stringent of the two "block" scores within the package to minimize exclusions, but the following findings are consistent regardless of which "block" score was used.) We also excluded all participants whose IP addresses revealed they were not located in the United States, which was required for all participants.

Deciding whether to exclude participants who had not previously invested in Bitcoin

Among the remaining participants, we noted in our preregistration that if less than 10% of our sample comprises participants who report previously investing in Bitcoin, then we would exclude all participants who previously invested in Bitcoin (as this group might be expected to respond differently to our experimental manipulation); if 10% or more of our data is made of participants who previously invested in Bitcoin, then we will also conduct our analyses both including and excluding those participants, and will report any differences that emerge.

12.62% previously invested in Bitcoin (more than 10%), so we *did not* proceed with exclusion.

Deciding whether to exclude those who learned about the study from other participants

Similarly, we noted in our preregistration that if less than 10% of our sample is composed of participants who report being told details about the beta-test or the DigiVest platform from another participant, then we will exclude these participants.

Only 1.99% of our sample reported learning about the study from other participants (less than 10%), so we *did* proceed with exclusion. As described in our preregistration, we also reran our primary analyses without this exclusion to confirm that our findings were consistent (see final section of this Supplementary Materials document).

Redefining dataset to reflect exclusions (per pre-registration; to be edited if either excluded group is >10%)

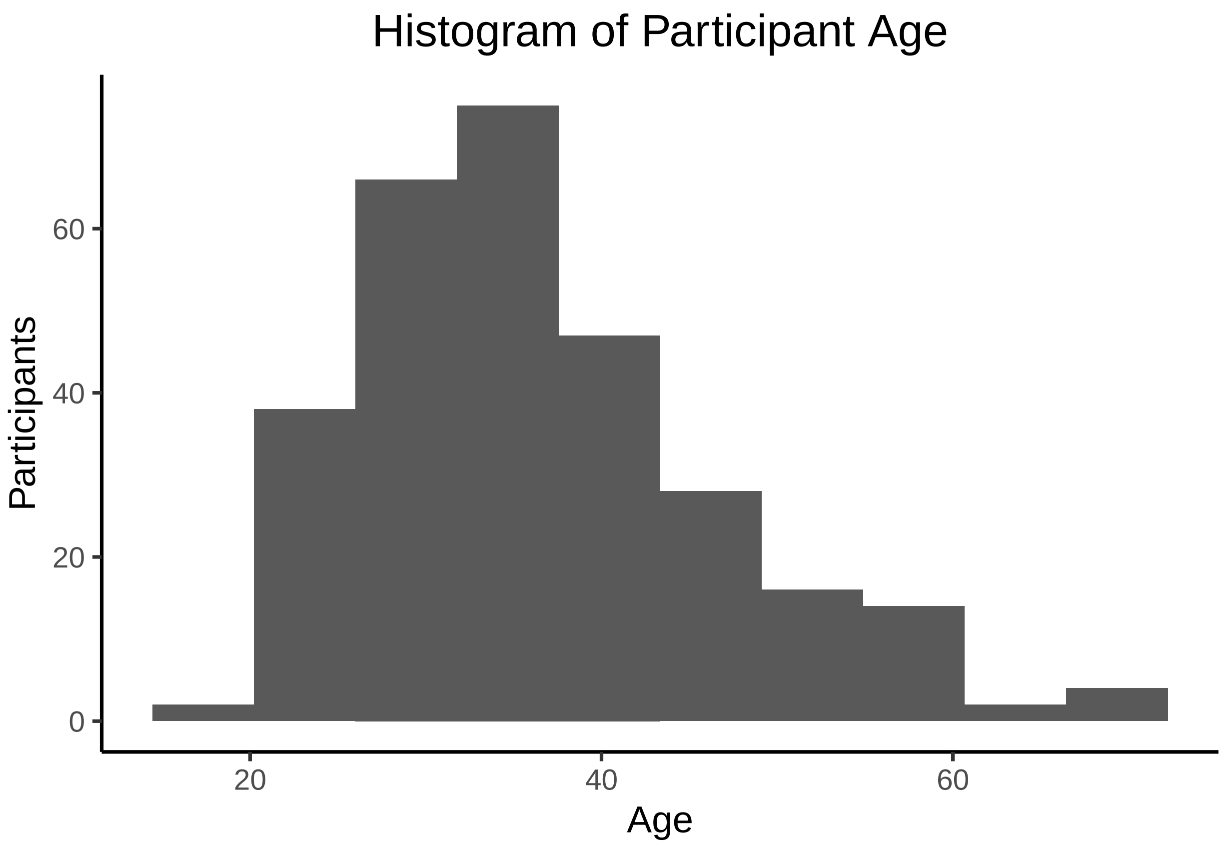
These exclusions left us with a final sample size of 295.

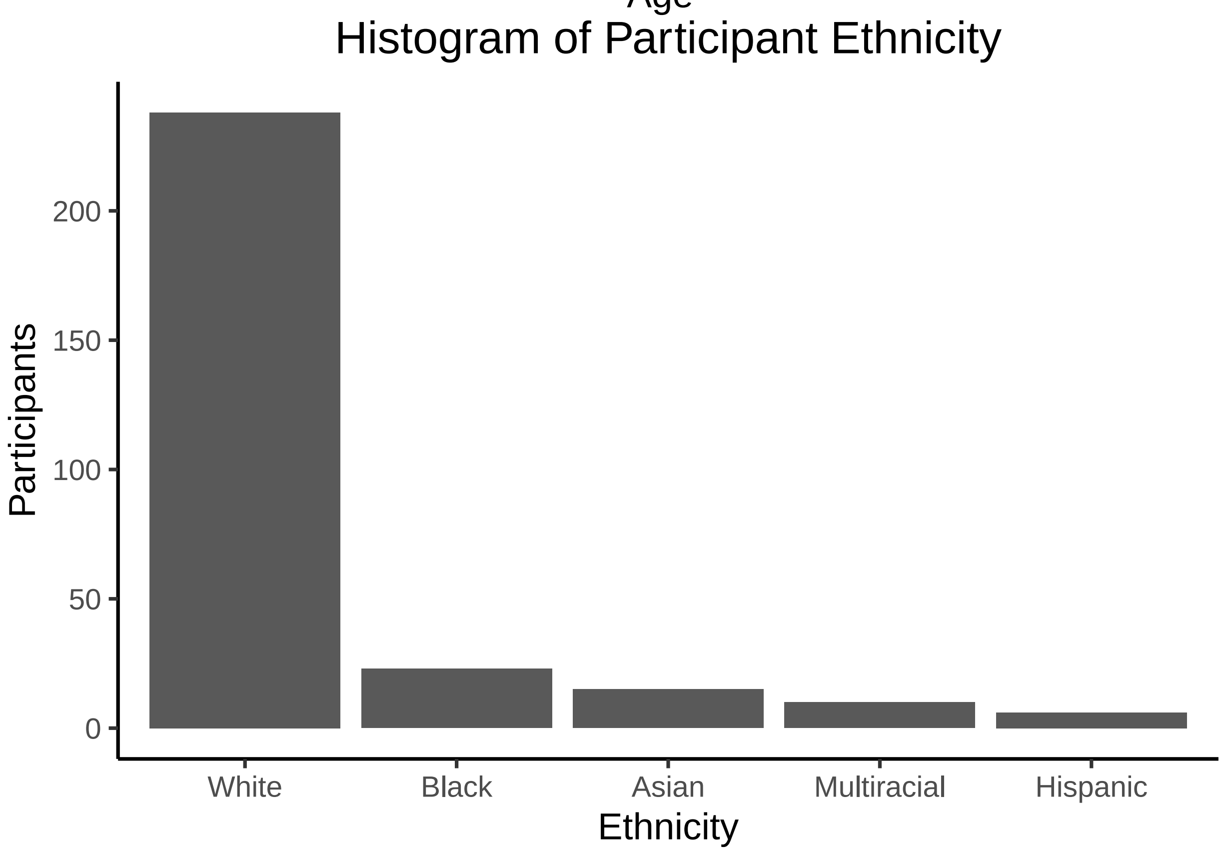
Final Sample

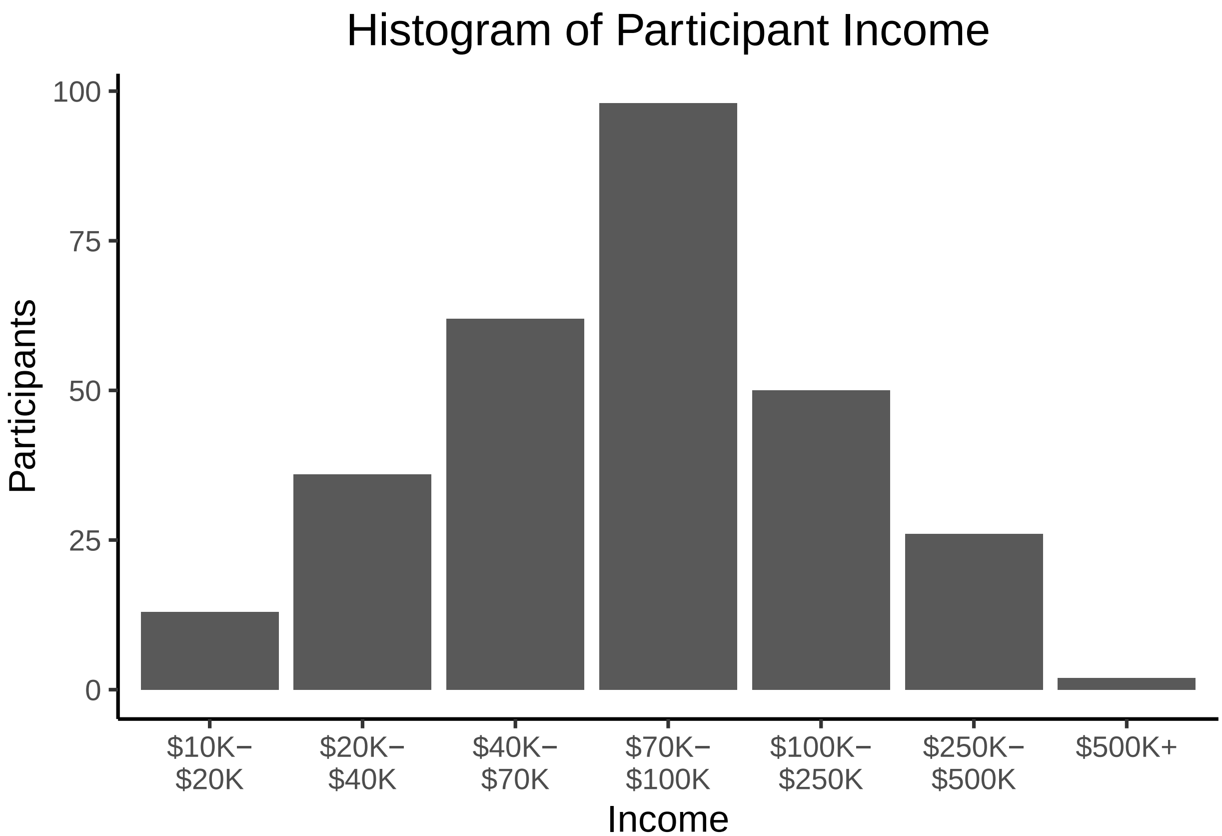
Our final dataset includes observations from these 295 M-Turk participants. The sample had a mean age of 36.43 years ($SD = 10.14$, ranging from 19 to 71) and were 50.17% male and 49.15% female. 98.31% of participants ($n = 290$) reported English as their native language. The ethnic breakdown in order of size was white ($n = 238$, 80.68%), black ($n = 23$, 7.80%), Asian ($n = 15$, 5.08%), and Hispanic ($n = 6$, 2.03%). The income breakdown in order of size was $70K - $100K ($n = 98$, 33.22%), $40K - $70K ($n = 62$, 21.02%), $100K - $250K ($n = 50$, 16.95%), $20K - $40K ($n = 36$, 12.20%), $250K - $500K ($n = 26$, 8.81%), $10K - $20K ($n = 13$, 4.41%), and $500K+ ($n = 2$, 0.68%). The highest level of education participants reported attaining in order of size was a graduate degree ($n = 105$, 35.59%), an associate's degree ($n = 66$, 22.37%), some college ($n = 50$, 16.95%), a bachelor's degree ($n = 44$, 14.92%), a doctorate ($n = 21$, 7.12%), and a high school diploma ($n = 4$, 1.36%). Histogram plots for each of these demographic measures are included below.

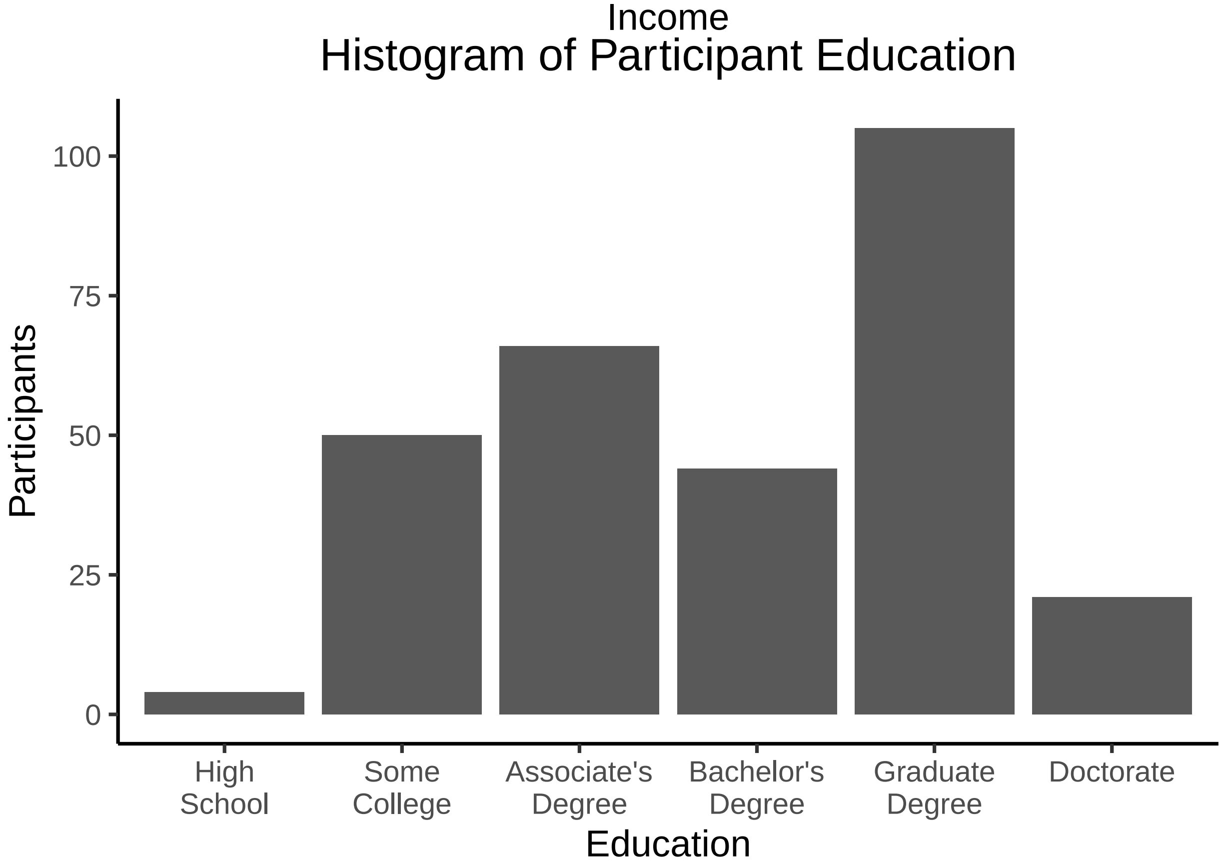
Descriptive Plots

Participants

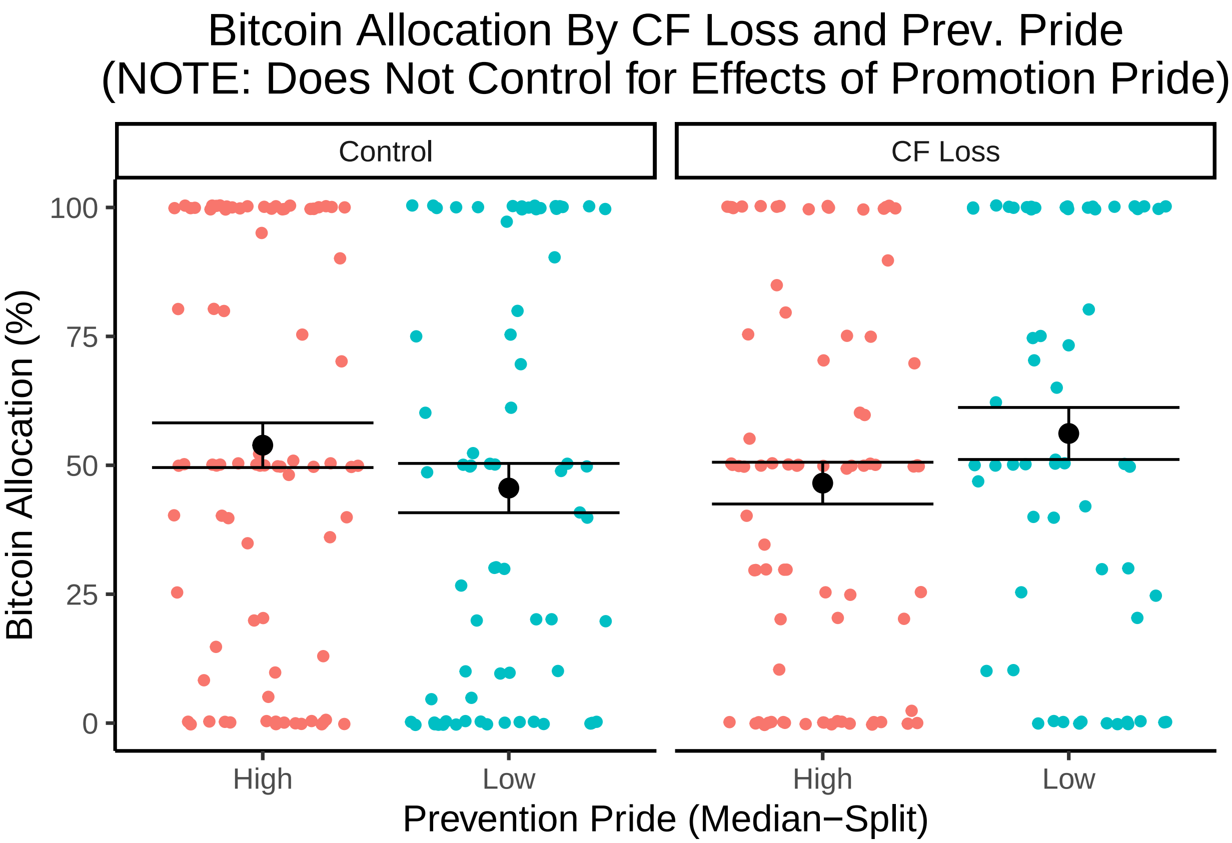





Histogram of Participant Income
Participants
100
75
50
25
0
$10K–
$20K
$20K–
$40K
$40K–
$70K
$70K–
$100K
$100K–
$250K
$250K–
$500K
$500K+
Income


Histogram of Participant Education
Participants
100
75
50
25
0
High
School
Some
College
Associate's
Degree
Bachelor's
Degree
Graduate
Degree
Doctorate
Education

Bitcoin Allocation by Prevention Pride and Condition



Primary Linear Analyses

Hypothesized Model

As described in the article, we were primarily interested in examining if participants' chronic prevention pride interacted with counterfactual loss to predict allocation of one's funds toward a risky investment in Bitcoin. To test our hypothesis, we entered these predictors into a linear regression analysis, the results of which are presented in Table 1. To supplement these results, a visualization of the model's predictions is presented in the following figure. Additionally, we built an application to dynamically generate model predictions using R (Version 3.6.1; R Core Team 2018) and the R-package *shiny* (Version 1.4.0; Chang et al. 2018). The application is located online at https://emilynakka.shinyapps.io/RFCFLoss/ (Nakkawita, Mathmann, and Higgins 2019).

Table 1: Summary of Linear Regression Analysis

Predictor	Estimate	SE	t	p
Intercept	49.50	3.14	15.76	< .001
Prevention Pride	5.10	3.44	1.48	0.140
Counterfactual Loss	2.10	4.57	0.46	0.646
Prevention Pride x Counterfactual Loss	-13.41	5.22	-2.57	0.011
Promotion Pride	1.34	4.39	0.30	0.761
Promotion Pride x Counterfactual Loss	5.61	6.72	0.83	0.405

Note. This analysis included a dummy-coded variable for the counterfactual loss manipulation: 0 = control, 1 = counterfactual loss. Additionally, prevention and promotion pride were mean-centered within this model. Estimated effect sizes reported here are unstandardized regression coefficients.

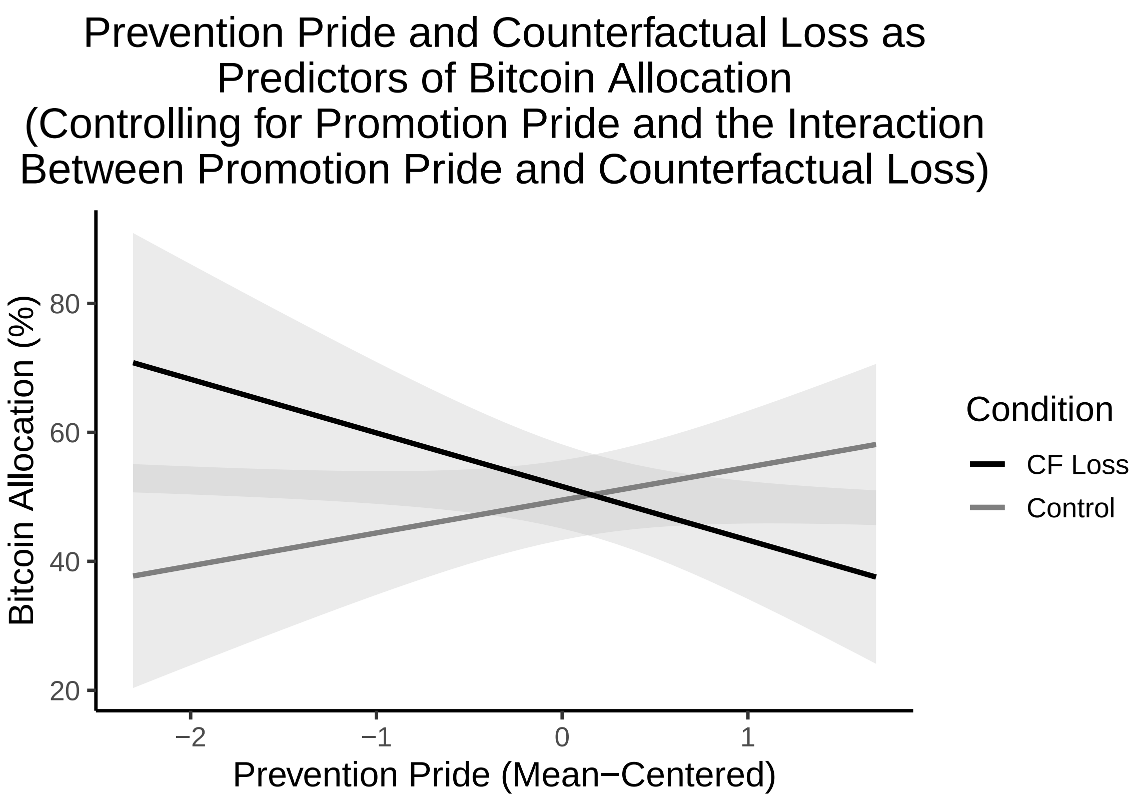


Figure 1: Predicted Bitcoin allocation by prevention pride and counterfactual loss experience, controlling for promotion pride and the interaction between promotion pride and counterfactual loss.

The results revealed no main effects of any single predictor. However, as predicted, the analysis yielded a significant two-way interaction between prevention pride and counterfactual loss condition ($B = -13.41, t(289) = -2.57, p < .05$).

Hypothesized Model Without Promotion Pride and With Demographic Covariates

As described in the article, the interaction between prevention pride and counterfactual loss remained significant when *not* including promotion pride in the model, as well as when controlling for a range of

Table 2: Summary of Linear Regression Analysis Not Controlling for Promotion Pride or the Interaction Between Promotion Pride and Counterfactual Loss

Predictor	Estimate	SE	t	p
Intercept	49.52	3.14	15.78	$< .001$
Prevention Pride	5.34	3.35	1.59	0.113
Counterfactual Loss	2.35	4.56	0.52	0.607
Prevention Pride x Counterfactual Loss	-12.61	5.11	-2.47	0.014

Note. This analysis included a dummy-coded variable for the counterfactual loss manipulation: 0 = control, 1 = counterfactual loss. Additionally, prevention pride was mean-centered within this model. Estimated effect sizes reported here are unstandardized regression coefficients.

Table 3: Summary of Linear Regression Analysis Not Controlling for the Interaction Between Promotion Pride and Counterfactual Loss

Predictor	Estimate	SE	t	p
Intercept	49.46	3.14	15.76	$< .001$
Prevention Pride	4.68	3.40	1.37	0.170
Counterfactual Loss	2.27	4.56	0.50	0.619
Promotion Pride	3.74	3.32	1.12	0.262
Prevention Pride x Counterfactual Loss	-12.51	5.10	-2.45	0.015

Note. This analysis included a dummy-coded variable for the counterfactual loss manipulation: 0 = control, 1 = counterfactual loss. Additionally, prevention and promotion pride were mean-centered within this model. Estimated effect sizes reported here are unstandardized regression coefficients.

demographic variables. Tables 2-8 contain the results of these analyses.

Exploratory Mediation Analyses (Hayes PROCESS Model 8): Counterfactual Thought and Hypothetical Emotion Mediators

As described in the article, in order to more clearly understand our hypothesized effect, we included a number of single-item measures examining the counterfactual thoughts that participants generated in the process of making their Bitcoin allocations. The results of all exploratory mediation analyses can be found in Tables 9-12.

Table 4: Summary of Linear Regression Analysis Controlling for Gender

Predictor	Estimate	SE	t	p
Intercept	5.71	27.37	0.21	0.835
Prevention Pride	5.21	3.44	1.52	0.131
Counterfactual Loss	1.26	4.59	0.27	0.784
Gender: Female	45.96	27.69	1.66	0.098
Gender: Male	43.11	27.61	1.56	0.120
Promotion Pride	0.43	4.43	0.10	0.923
Prevention Pride x Counterfactual Loss	-13.68	5.21	-2.62	0.009
Promotion Pride x Counterfactual Loss	6.64	6.76	0.98	0.327

Note. This analysis included a dummy-coded variable for the counterfactual loss manipulation: 0 = control, 1 = counterfactual loss. Additionally, prevention and promotion pride were mean-centered within this model. Estimated effect sizes reported here are unstandardized regression coefficients.

Table 5: Summary of Linear Regression Analysis Controlling for Age

Predictor	Estimate	SE	t	p
Intercept	47.00	8.59	5.47	< .001
Prevention Pride	5.09	3.45	1.47	0.141
Counterfactual Loss	1.71	4.62	0.37	0.712
Age	0.08	0.23	0.35	0.723
Promotion Pride	1.29	4.40	0.29	0.770
Prevention Pride x Counterfactual Loss	-13.03	5.26	-2.48	0.014
Promotion Pride x Counterfactual Loss	5.86	6.80	0.86	0.390

Note. This analysis included a dummy-coded variable for the counterfactual loss manipulation: 0 = control, 1 = counterfactual loss. Additionally, prevention and promotion pride were mean-centered within this model. Estimated effect sizes reported here are unstandardized regression coefficients.

Table 6: Summary of Linear Regression Analysis Controlling for Ethnicity

Predictor	Estimate	SE	t	p
Intercept	69.83	38.83	1.80	0.073
Prevention Pride	5.56	3.50	1.59	0.113
Counterfactual Loss	2.75	4.59	0.60	0.549
Ethnicity: Asian	-10.70	39.93	-0.27	0.789
Ethnicity: Black	-11.99	39.47	-0.30	0.762
Ethnicity: Hispanic	-7.12	41.74	-0.17	0.865
Ethnicity: Multiracial	-45.96	40.59	-1.13	0.258
Ethnicity: Other	31.92	54.70	0.58	0.560
Ethnicity: Pacific Islander	-31.35	55.21	-0.57	0.571
Ethnicity: White	-21.71	38.72	-0.56	0.575
Promotion Pride	-0.10	4.46	-0.02	0.983
Prevention Pride x Counterfactual Loss	-12.97	5.25	-2.47	0.014
Promotion Pride x Counterfactual Loss	6.22	6.79	0.92	0.361

Note. This analysis included a dummy-coded variable for the counterfactual loss manipulation: 0 = control, 1 = counterfactual loss. Additionally, prevention and promotion pride were mean-centered within this model. Estimated effect sizes reported here are unstandardized regression coefficients.

Table 7: Summary of Linear Regression Analysis Controlling for Income

Predictor	Estimate	SE	t	p
Intercept	24.34	10.98	2.22	0.027
Prevention Pride	4.79	3.47	1.38	0.169
Counterfactual Loss	2.53	4.62	0.55	0.585
Income: $20K-$40K	31.95	12.45	2.57	0.011
Income: $40K-$70K	19.91	11.79	1.69	0.092
Income: $70K-$100K	26.44	11.41	2.32	0.021
Income: $100K-$250K	33.14	12.06	2.75	0.006
Income: $250K-$500K	20.81	13.15	1.58	0.115
Income: $500K+	-6.72	29.23	-0.23	0.818
Promotion Pride	0.86	4.60	0.19	0.852
Prevention Pride x Counterfactual Loss	-13.32	5.26	-2.53	0.012
Promotion Pride x Counterfactual Loss	4.62	6.82	0.68	0.499

Note. This analysis included a dummy-coded variable for the counterfactual loss manipulation: 0 = control, 1 = counterfactual loss. Additionally, prevention and promotion pride were mean-centered within this model. Estimated effect sizes reported here are unstandardized regression coefficients.

Table 8: Summary of Linear Regression Analysis Controlling for Education

Predictor	Estimate	SE	t	p
Intercept	40.39	19.46	2.08	0.039
Prevention Pride	5.54	3.50	1.58	0.115
Counterfactual Loss	0.70	4.73	0.15	0.883
Education: Some College	3.67	20.27	0.18	0.857
Education: Associate's	18.53	20.08	0.92	0.357
Education: Bachelor's	6.44	20.30	0.32	0.751
Education: Grad. Degree	8.54	19.79	0.43	0.667
Education: Doctorate	16.26	21.15	0.77	0.443
Promotion Pride	-1.04	4.67	-0.22	0.825
Prevention Pride x Counterfactual Loss	-13.53	5.27	-2.57	0.011
Promotion Pride x Counterfactual Loss	7.43	6.92	1.07	0.284

Note. This analysis included a dummy-coded variable for the counterfactual loss manipulation: 0 = control, 1 = counterfactual loss. Additionally, prevention and promotion pride were mean-centered within this model. Estimated effect sizes reported here are unstandardized regression coefficients.

Exploratory Moderated Mediation Analysis: Missing Out

Table 9: Summary of Exploratory Mediation Analysis

Predictor	Estimate	SE	z	p	CI.lower	CI.upper
Model 1 (DV = Missed Out)						
Intercept	-0.05	0.07	-0.80	0.423	-0.1817	0.0771
Prevention Pride	-0.08	0.06	-1.35	0.178	-0.1983	0.0432
Counterfactual Loss	-0.10	0.06	-1.61	0.108	-0.2286	0.0216
Prev. Pride x CF Loss	-0.12	0.06	-1.93	0.054	-0.2365	0.0039
Promotion Pride	-0.12	0.06	-1.98	0.048	-0.2317	-0.0009
Prom. Pride x CF Loss	0.04	0.06	0.71	0.475	-0.0712	0.1582
Model 2 (DV = Bitcoin Allocation)						
Intercept	0.01	0.07	0.13	0.896	-0.1236	0.1377
Prevention Pride	0.01	0.06	0.18	0.861	-0.1082	0.1388
Counterfactual Loss	0.04	0.07	0.65	0.518	-0.0850	0.1706
Prev. Pride x CF Loss	-0.11	0.06	-1.69	0.091	-0.2322	0.0175
Promotion Pride	0.14	0.06	2.08	0.037	0.0109	0.2662
Prom. Pride x CF Loss	0.05	0.06	0.82	0.412	-0.0748	0.1763
Missed Out	0.29	0.07	4.30	$< .001$	0.1528	0.4121
Bootstrapped Conditional Indirect Effects (Prev. Pride x CF Loss → Missed Out → Bitcoin Allocation)						
Control Condition	0.01	0.02	0.39	0.694	-0.0403	0.0603
Counterfactual Loss Condition	-0.06	0.03	-2.02	0.043	-0.1162	-0.0069

Note: This analysis included an effect-coded variable for the counterfactual loss experience: -1 = control, 1 = counterfactual loss. Additionally, all other variables were standardized (M = 0, SD = 1) within this model. Estimated effect sizes for the models reported here are standardized regression coefficients.

When we control for promotion pride and the interaction between promotion and counterfactual loss, the interaction between prevention pride and counterfactual loss was only *marginally* associated with the degree to which participants reported they missed out by not investing in Bitcoin earlier ($\beta = -0.12$, $p = 0.054$), while the effect of participants reporting they missed out by not investing earlier ($\beta = 0.29$, $p < .001$) on Bitcoin allocation was significant. (See Table 9 for full model output.)

Given the marginal significance of the a path, we concluded that our interaction of interest is not mediated by missing out.

Exploratory Moderated Mediation Analysis: Regret

Table 10: Summary of Exploratory Mediation Analysis

Predictor	Estimate	SE	z	p	CI.lower	CI.upper
Model 1 (DV = Regret)						
Intercept	-0.10	0.06	-1.52	0.128	-0.2171	0.0310
Prevention Pride	-0.07	0.06	-1.09	0.276	-0.1821	0.0530
Counterfactual Loss	-0.14	0.06	-2.22	0.026	-0.2585	-0.0164
Prev. Pride x CF Loss	-0.08	0.06	-1.35	0.177	-0.1974	0.0389
Promotion Pride	-0.09	0.06	-1.40	0.160	-0.2103	0.0353
Prom. Pride x CF Loss	0.01	0.06	0.10	0.922	-0.1147	0.1300
Model 2 (DV = Bitcoin Allocation)						
Intercept	0.02	0.07	0.35	0.729	-0.1087	0.1505
Prevention Pride	0.01	0.06	0.12	0.907	-0.1124	0.1368
Counterfactual Loss	0.06	0.07	0.84	0.403	-0.0736	0.1860
Prev. Pride x CF Loss	-0.12	0.06	-1.81	0.070	-0.2417	0.0112
Promotion Pride	0.13	0.07	1.97	0.049	0.0057	0.2609
Prom. Pride x CF Loss	0.06	0.06	0.98	0.328	-0.0630	0.1875
Regret	0.31	0.07	4.55	$< .001$	0.1760	0.4388
Bootstrapped Conditional Indirect Effects (Prev. Pride x CF Loss → Regret → Bitcoin Allocation)						
Control Condition	0.00	0.03	0.19	0.853	-0.0510	0.0584
Counterfactual Loss Condition	-0.05	0.03	-1.62	0.105	-0.1025	0.0064

Note: This analysis included an effect-coded variable for the counterfactual loss experience: -1 = control, 1 = counterfactual loss. Additionally, all other variables were standardized (M = 0, SD = 1) within this model. Estimated effect sizes for the models reported here are standardized regression coefficients.

The interaction between prevention and counterfactual loss was not significantly associated with the degree to which participants reported they regretted not investing in Bitcoin earlier (n.s.), so we concluded that our interaction of interest is not mediated by regret. (See Table 10 for full model output.)

Exploratory Moderated Mediation Analysis: Hypothetical Happiness

Table 11: Summary of Exploratory Mediation Analysis

Predictor	Estimate	SE	z	p	CI.lower	CI.upper
Model 1 (DV = Hypothetical Happiness)						
Intercept	-0.15	0.06	-2.25	0.024	-0.2701	-0.0174
Prevention Pride	-0.01	0.06	-0.09	0.930	-0.1276	0.1137
Counterfactual Loss	-0.01	0.06	-0.09	0.929	-0.1291	0.1241
Prev. Pride x CF Loss	-0.10	0.06	-1.58	0.115	-0.2154	0.0256
Promotion Pride	-0.08	0.06	-1.31	0.191	-0.2049	0.0433
Prom. Pride x CF Loss	0.01	0.06	0.17	0.868	-0.1119	0.1371
Model 2 (DV = Bitcoin Allocation)						
Intercept	0.05	0.07	0.71	0.478	-0.0826	0.1720
Prevention Pride	-0.01	0.06	-0.17	0.864	-0.1287	0.1165
Counterfactual Loss	0.02	0.07	0.23	0.815	-0.1116	0.1427
Prev. Pride x CF Loss	-0.11	0.06	-1.67	0.094	-0.2310	0.0187
Promotion Pride	0.13	0.07	2.01	0.045	0.0080	0.2642
Prom. Pride x CF Loss	0.06	0.06	0.94	0.347	-0.0678	0.1846
Hypothetical Happiness	0.36	0.07	5.54	$< .001$	0.2305	0.4928
Bootstrapped Conditional Indirect Effects (Prev. Pride x CF Loss → Hypothetical Happiness → Bitcoin Allocation)						
Control Condition	0.03	0.03	1.10	0.270	-0.0265	0.0945
Counterfactual Loss Condition	-0.04	0.03	-1.08	0.282	-0.1074	0.0302

Note: This analysis included an effect-coded variable for the counterfactual loss experience: -1 = control, 1 = counterfactual loss. Additionally, all other variables were standardized (M = 0, SD = 1) within this model. Estimated effect sizes for the models reported here are standardized regression coefficients.

The interaction between prevention and counterfactual loss was not significantly associated with the degree to which participants reported they imagine they would be happier if they had invested in Bitcoin earlier (n.s.), so we concluded that our interaction of interest is not mediated by hypothetical happiness. (See Table 11 for full model output.)

Exploratory Moderated Mediation Analysis: Hypothetical Relief

Table 12: Summary of Exploratory Mediation Analysis

Predictor	Estimate	SE	z	p	CI.lower	CI.upper
Model 1 (DV = Hypothetical Relief)						
Intercept	-0.16	0.06	-2.58	0.010	-0.2793	-0.0383
Prevention Pride	-0.07	0.06	-1.20	0.232	-0.1819	0.0469
Counterfactual Loss	-0.07	0.06	-1.05	0.293	-0.1843	0.0614
Prev. Pride x CF Loss	-0.13	0.06	-2.28	0.022	-0.2458	-0.0162
Promotion Pride	-0.11	0.06	-1.85	0.064	-0.2282	0.0084
Prom. Pride x CF Loss	0.02	0.06	0.29	0.772	-0.1007	0.1371
Model 2 (DV = Bitcoin Allocation)						
Intercept	0.06	0.06	0.97	0.334	-0.0654	0.1812
Prevention Pride	0.02	0.06	0.28	0.782	-0.0973	0.1416
Counterfactual Loss	0.04	0.06	0.64	0.523	-0.0825	0.1654
Prev. Pride x CF Loss	-0.08	0.06	-1.41	0.160	-0.2031	0.0368
Promotion Pride	0.15	0.06	2.36	0.018	0.0285	0.2761
Prom. Pride x CF Loss	0.06	0.06	0.92	0.356	-0.0654	0.1783
Hypothetical Relief	0.42	0.07	6.44	$< .001$	0.2888	0.5510
Bootstrapped Conditional Indirect Effects (Prev. Pride x CF Loss → Hypothetical Relief → Bitcoin Allocation)						
Control Condition	0.03	0.03	0.77	0.440	-0.0421	0.0923
Counterfactual Loss Condition	-0.09	0.04	-2.30	0.021	-0.1614	-0.0141

Note: This analysis included an effect-coded variable for the counterfactual loss experience: -1 = control, 1 = counterfactual loss. Additionally, all other variables were standardized (M = 0, SD = 1) within this model. Estimated effect sizes for the models reported here are standardized regression coefficients.

When we control for promotion pride and the interaction between promotion and counterfactual loss, the interaction between prevention and counterfactual loss was significantly associated with the degree to which participants reported they imagine they would be relieved if they had invested in Bitcoin earlier ($\beta = -0.13$, $p < .05$), and the effect of participants reporting they imagined being relieved if they had invested earlier ($\beta = 0.42$, $p < .001$) on Bitcoin allocation was also significant. (See Table 12 and the article for full model output.)

Rerunning with Participants Who Learned About Study from Other M-Turk Workers

Primary Linear Analysis

The direction and significance of our primary linear analysis does not change when rerunning the analysis to include participants who learned about the study from other M-Turk workers (see Table 13 and Figure 2).

Table 13: RERUN: Summary of Linear Regression Analysis

Predictor	Estimate	SE	t	p
Intercept	49.96	3.07	16.25	< .001
Prevention Pride	4.42	3.39	1.31	0.193
Counterfactual Loss	1.69	4.49	0.38	0.707
Prevention Pride x Counterfactual Loss	-12.77	5.15	-2.48	0.014
Promotion Pride	1.25	4.36	0.29	0.774
Promotion Pride x Counterfactual Loss	5.70	6.66	0.86	0.393

Note. This analysis included a dummy-coded variable for the counterfactual loss manipulation: 0 = control, 1 = counterfactual loss. Additionally, prevention and promotion pride were mean-centered within this model. Estimated effect sizes reported here are unstandardized regression coefficients.

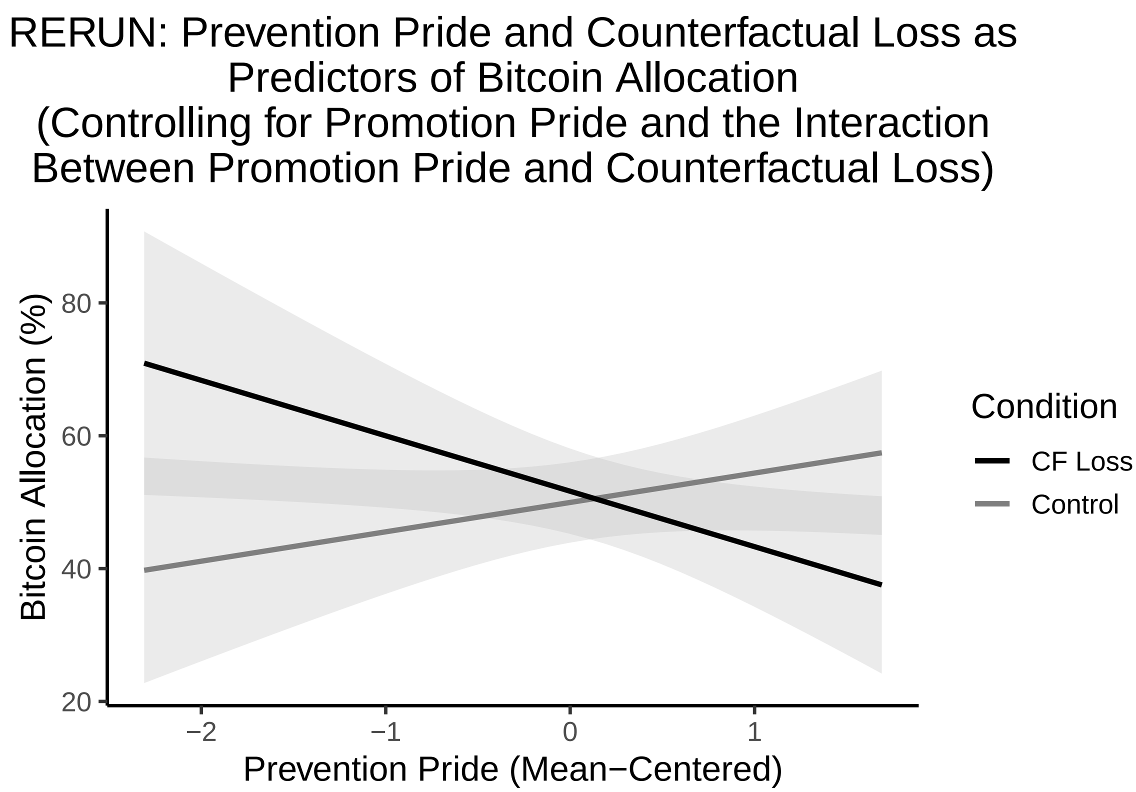


Figure 2: RERUN: Predicted Bitcoin allocation by prevention pride and counterfactual loss experience, controlling for promotion pride and the interaction between promotion pride and counterfactual loss.

Simple Slopes Analysis

When rerunning our simple slopes analysis, the direction and significance of our results do not change. The effect of prevention pride on Bitcoin allocation was still significant in the counterfactual loss condition ($B = -8.35, SE = 3.88, t = -2.15, p < .05$; 95% CI [-15.9856, -0.7073]) but non-significant in the control condition.

Exploratory Mediation Analysis (Hayes PROCESS Model 8): Counterfactual Relief

Table 14: Summary of Exploratory Mediation Analysis

Predictor	Estimate	SE	z	p	CI.lower	CI.upper
Model 1 (DV = Hypothetical Relief)						
Intercept	-0.16	0.06	-2.59	0.010	-0.2787	-0.0421
Prevention Pride	-0.07	0.06	-1.20	0.230	-0.1845	0.0451
Counterfactual Loss	-0.07	0.06	-1.06	0.291	-0.1896	0.0553
Prev. Pride x CF Loss	-0.13	0.06	-2.31	0.021	-0.2461	-0.0216
Promotion Pride	-0.11	0.06	-1.85	0.064	-0.2334	0.0040
Prom. Pride x CF Loss	0.02	0.06	0.30	0.766	-0.1012	0.1391
Model 2 (DV = Bitcoin Allocation)						
Intercept	0.06	0.06	0.97	0.333	-0.0634	0.1798
Prevention Pride	0.02	0.06	0.28	0.782	-0.1010	0.1361
Counterfactual Loss	0.04	0.06	0.66	0.511	-0.0791	0.1639
Prev. Pride x CF Loss	-0.08	0.06	-1.40	0.163	-0.2068	0.0300
Promotion Pride	0.15	0.06	2.41	0.016	0.0314	0.2748
Prom. Pride x CF Loss	0.06	0.06	0.91	0.361	-0.0672	0.1801
Hypothetical Relief	0.42	0.07	6.37	$< .001$	0.2874	0.5525
Bootstrapped Conditional Indirect Effects (Prev. Pride x CF Loss → Hypothetical Relief → Bitcoin Allocation)						
Control Condition	0.03	0.03	0.78	0.435	-0.0423	0.0924
Counterfactual Loss Condition	-0.09	0.04	-2.34	0.019	-0.1600	-0.0158

Note: This analysis included an effect-coded variable for the counterfactual loss experience: -1 = control, 1 = counterfactual loss. Additionally, all other variables were standardized (M = 0, SD = 1) within this model. Estimated effect sizes for the models reported here are standardized regression coefficients.

When we control for promotion pride and the interaction between promotion and counterfactual loss, the interaction between prevention and counterfactual loss was still significantly associated with the degree to which participants reported they would be relieved if they had invested in Bitcoin earlier ($\beta = -0.13$, $p < .05$), and the effect of participants reporting they would be relieved if they had invested earlier ($\beta = 0.42$, $p < .001$) on Bitcoin allocation was also significant.

The indirect effect of prevention on Bitcoin allocation through reporting relief if they had invested earlier was significant and negative for individuals in the counterfactual loss condition ($\beta = -0.09$, $SE = 0.04$, 95% $CI = -0.1600, -0.0158$), but not for individuals in the control condition (n.s.). This indicates that the moderation is still fully mediated.

Table 15: RERUN (ALL): Summary of Linear Regression Analysis

Predictor	Estimate	SE	t	p
Intercept	51.13	2.24	22.79	$< .001$
Prevention Pride	0.27	2.67	0.10	0.918
Counterfactual Loss	0.09	3.18	0.03	0.976
Prevention Pride x Counterfactual Loss	-7.98	3.99	-2.00	0.046
Promotion Pride	0.85	3.53	0.24	0.811
Promotion Pride x Counterfactual Loss	4.87	5.25	0.93	0.354

Note. This analysis included a dummy-coded variable for the counterfactual loss manipulation: 0 = control, 1 = counterfactual loss. Additionally, prevention and promotion pride were mean-centered within this model. Estimated effect sizes reported here are unstandardized regression coefficients.

Rerunning with All Participants Who Completed Independent Measure (Regulatory Focus Questionnaire) and Dependent Measure (Bitcoin Allocation)

Primary Linear Analysis

The direction and significance of our primary linear analysis does not change when rerunning the analysis to include every single participant who completed our independent and dependent measures, even those whose data had questionable validity due to IP spoofing issues as described above (see Table 15 and Figure 3).

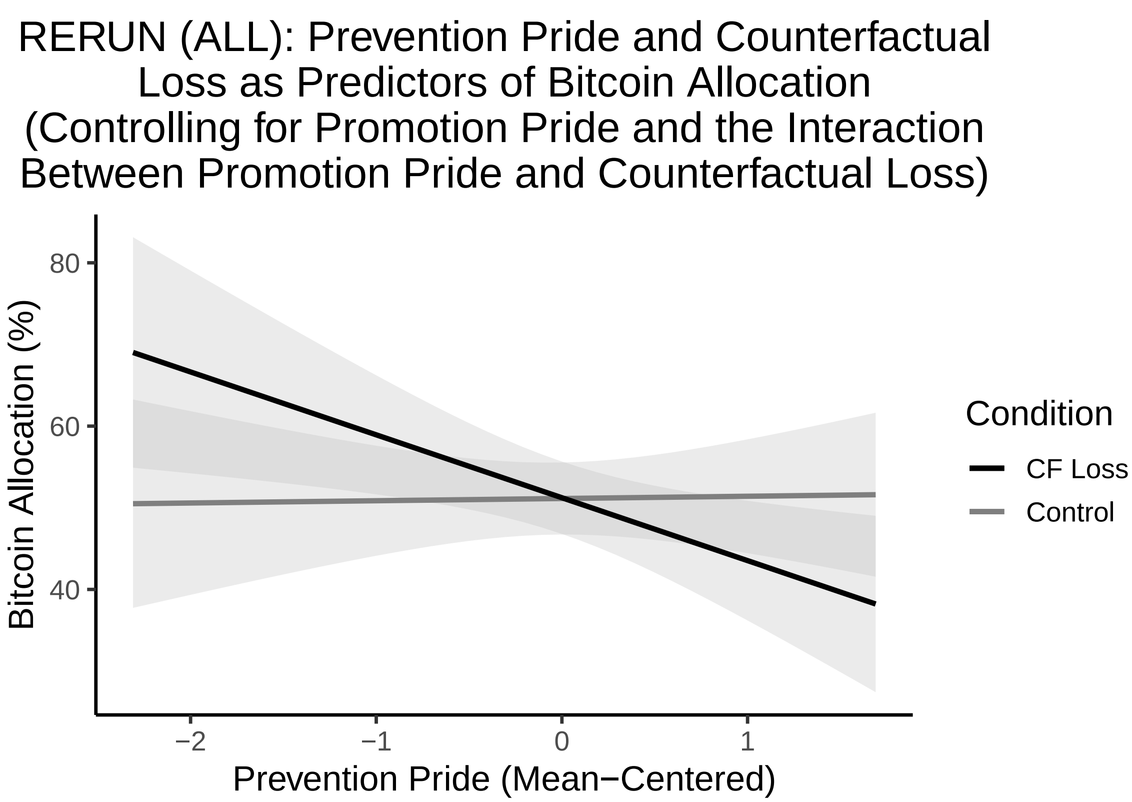


Figure 3: RERUN (ALL): Predicted Bitcoin allocation by prevention pride and counterfactual loss experience, controlling for promotion pride and the interaction between promotion pride and counterfactual loss.

Simple Slopes Analysis

When rerunning our simple slopes analysis to include all participants who completed our independent and dependent measures, the direction and significance of our results do not change. The effect of prevention pride on Bitcoin allocation was still significant in the counterfactual loss condition ($B = -7.70, SE = 2.96, t = -2.60, p < .01$; 95% CI [-13.5132, -1.8898]) but non-significant in the control condition.

Exploratory Mediation Analysis (Hayes PROCESS Model 8): Counterfactual Relief

Table 16: Summary of Exploratory Mediation Analysis

Predictor	Estimate	SE	z	p	CI.lower	CI.upper
Model 1 (DV = Hypothetical Relief)						
Intercept	0.01	0.05	0.29	0.775	-0.0854	0.1162
Prevention Pride	-0.10	0.05	-1.75	0.079	-0.1998	0.0106
Counterfactual Loss	-0.05	0.05	-0.92	0.358	-0.1564	0.0531
Prev. Pride x CF Loss	-0.11	0.05	-2.12	0.034	-0.2135	-0.0092
Promotion Pride	-0.08	0.06	-1.45	0.147	-0.1858	0.0275
Prom. Pride x CF Loss	-0.01	0.06	-0.16	0.876	-0.1148	0.1020
Model 2 (DV = Bitcoin Allocation)						
Intercept	-0.03	0.05	-0.59	0.556	-0.1324	0.0699
Prevention Pride	0.01	0.06	0.11	0.909	-0.1013	0.1201
Counterfactual Loss	0.03	0.05	0.54	0.592	-0.0759	0.1238
Prev. Pride x CF Loss	-0.07	0.06	-1.22	0.224	-0.1756	0.0419
Promotion Pride	0.11	0.05	2.02	0.043	0.0024	0.2109
Prom. Pride x CF Loss	0.05	0.05	0.88	0.380	-0.0570	0.1493
Hypothetical Relief	0.33	0.06	6.03	$< .001$	0.2188	0.4369
Bootstrapped Conditional Indirect Effects						
(Prev. Pride x CF Loss → Hypothetical Relief → Bitcoin Allocation)						
Control Condition	0.01	0.02	0.22	0.824	-0.0448	0.0526
Counterfactual Loss Condition	-0.07	0.03	-2.45	0.014	-0.1289	-0.0168

Note: This analysis included an effect-coded variable for the counterfactual loss experience: -1 = control, 1 = counterfactual loss. Additionally, all other variables were standardized (M = 0, SD = 1) within this model. Estimated effect sizes for the models reported here are standardized regression coefficients.

When we control for promotion pride and the interaction between promotion and counterfactual loss, the interaction between prevention and counterfactual loss was still significantly associated with the degree to which participants reported they would be relieved if they had invested in Bitcoin earlier ($\beta = -0.11$, $p < .05$), and the effect of participants reporting they would be relieved if they had invested earlier ($\beta = 0.33$, $p < .001$) on Bitcoin allocation was also significant.

The indirect effect of prevention on Bitcoin allocation through reporting relief if they had invested earlier was significant and negative for individuals in the counterfactual loss condition ($\beta = -0.07$, $SE = 0.03$, 95% $CI = -0.1289, -0.0168$), but not for individuals in the control condition (n.s.). This indicates that the moderation is still fully mediated.

Summary Table

Table 17: Effect of Interest (Prevention Pride x Counterfactual Loss Interaction) Across All Linear Regression Analyses

Model	Estimate	SE	t	p
Original Model	-13.41	5.22	-2.57	0.011
Controlling for Gender	-13.68	5.21	-2.62	0.009
Controlling for Age	-13.03	5.26	-2.48	0.014
Controlling for Ethnicity	-12.97	5.25	-2.47	0.014
Controlling for Income	-13.32	5.26	-2.53	0.012
Controlling for Education	-13.53	5.27	-2.57	0.011
Not Controlling for Prom. Pride x CF Loss Interaction	-12.51	5.10	-2.45	0.015
Not Controlling for Prom. Pride or Prom. Pride x CF Loss Interaction	-12.61	5.11	-2.47	0.014
Rerun with Ps Who Learned About Study from Others	-12.77	5.15	-2.48	0.014
Rerun with All Ps Who Completed IV and DV	-7.98	3.99	-2.00	0.046

Note: This analysis included a dummy-coded variable for the counterfactual loss manipulation: 0 = control, 1 = counterfactual loss. Estimated effect sizes reported here are unstandardized regression coefficients.

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