Beneficiaries' Misery: How Serendipitously Benefitting from a Crisis Affects Perceptions toward Companies' Crisis Relief Actions

by

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Abstract

At times of crisis, companies strategically communicate their CSR initiatives, expecting benefits from such communication. Results from six studies indicate that the benefits a company receives from CSR communication during a crisis depend on their perceived status as "beneficiary" or "losing." Differentiating from other works, this paper shows that serendipitously benefiting from a crisis for a firm can lead to negative reactions from the public to the firm's crisis-relief actions. Using six studies of various crisis scenarios, such as the COVID pandemic, the Brazilian supply crisis, Turkey's wildfires, and the Ukraine-Russo war, we showed that when "beneficiary" (compared to "losing") companies in a crisis communicated their CSR activities, they faced less willingness from consumers to spread positive word-of-mouth and less willingness to help the company in public. The perceived sincerity of those companies mediated this negative effect, and larger firms suffered more from it as they would be perceived as less sincere. However, when large "beneficiary" companies communicate their in-kind (material) rather than monetary (financial) donations during a crisis, the negative effect of the company's status on the public's attitudes towards the firm decreases.

Keywords

CSR, perceived sincerity, COVID, big data, company status, crises, crisis relief, disaster management.

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TABLE 1

DISTRIBUTION OF COMPANY TWEETS AND USER REPLIES BASED ON INDUSTRY TYPE AND COMPANY ACCOUNT WITHIN THE FOCAL DATE RANGE

Twitter Account Tag	Industry	Number of tweets posted	Number of user replies received
Microsoft	Software and Computer Services	80	903
amazon	General Retailers	37	1024
Facebook	Software and Computer Services	22	1412
Walmart	General Retailers	90	2129
JNJNews	Pharmaceuticals and Biotechnology	22	98
Procter gamble	Personal Goods	51	255
intel	Technology Hardware and Equipment	44	430
Verizon	Fixed Line Telecommunications	50	370
LiveNation	Media	140	1537
BankofAmerica	Banks	28	436
ATT	Fixed Line Telecommunications	175	1619
CocaCola	Beverages	39	1022
HomeDepot	General Retailers	37	533
Merck	Pharmaceuticals and Biotechnology	31	86
PepsiCo	Beverages	21	71
Netflix	Media	115	8286
WaltDisneyCo	Media	15	320
Pfizer	Pharmaceuticals and Biotechnology	41	161
Cisco	Technology Hardware and Equipment	58	133
Nvidia	Technology Hardware and Equipment	13	64

Adobe	Software and Computer Services	70	212
AbbottNews	Pharmaceuticals and Biotechnology	29	235
McDonalds	Travel and Leisure	16	1615
WellsFargo	Banks	44	519
TMobile	Fixed Line Telecommunications	67	3292
LillyPad	Pharmaceuticals and Biotechnology	14	74
cms news	Pharmaceuticals and Biotechnology	15	23
Amgen	Pharmaceuticals and Biotechnology	21	58
IBM	Software and Computer Services	22	202
Nike	Personal Goods	3	131
abbvie	Pharmaceuticals and Biotechnology	12	16
InsidePMI	Tobacco	41	57
Gilead sciences	Pharmaceuticals and Biotechnology	21	253
3M	General Industrials	22	391
Ford	Automobiles and Parts	25	907
Starbucks	Travel and Leisure	51	3212
CVSHealth	Food and Drug Retailers	37	119
MDLZ	Food Producers	9	11
Lowes	General Retailers	28	125
AltriaNews	Tobacco	1	2
general electric	General Industrials	12	97
UPS	Industrial Transportation	108	1321
Target	General Retailers	41	2942
BookingHoldings	Travel and Leisure	1	2
Intuit	Software and Computer Services	21	53
CP_News	Personal Goods	13	18
VertexPharma	Pharmaceuticals and Biotechnology	5	17
AND	Technology Hardware and Equipment	23	332

Allergan	Pharmaceuticals and Biotechnology	2	6
biogen	Pharmaceuticals and Biotechnology	7	26
usbank	Banks	38	397
GM	Automobiles and Parts	28	295
KraftHeinzCo	Food Producers	7	31
Microtech	Technology Hardware and Equipment	21	26
Chubb	Nonlife Insurance	4	4
Regeneron	Pharmaceuticals and Biotechnology	16	51
Aon_plc	Nonlife Insurance	9	38
KeyCorp	Personal Goods	9	16
Progressive	Nonlife Insurance	17	303
Walgreens	Food and Drug Retailers	18	254
BBT	Banks	17	91
PNCBank	Banks	6	84
monster energy	Beverages	78	320
Kroger	Food and Drug Retailers	33	1383
GeneralMills	Food Producers	9	27
LasVegasSands	Travel and Leisure	4	19
Marriott Intl	Travel and Leisure	25	101
MetLife	Life Insurance	13	38
Allstate	Nonlife Insurance	7	193
Prudential	Life Insurance	5	16
yum brands	Travel and Leisure	16	22
Aflac	Life Insurance	3	4
brands	Beverages	14	30
Delta	Travel and Leisure	40	2419
eBay	General Retailers	63	795
Twitter	Software and Computer Services	49	4883
FedEx	Industrial Transportation	45	591
Travelers	Nonlife Insurance	16	63
Kelloggs	Food Producers	3	36
insurance	Nonlife Insurance	4	4
HormelFoods	Food Producers	16	29
SouthwestAir	Travel and Leisure	61	1552

HP	Technology Hardware and Equipment	13	77
BestBuy	General Retailers	46	839
VFCorp	Personal Goods	7	8
WTWcorporate	Nonlife Insurance	3	3
AutoZone	General Retailers	2	23
AlexionPharma	Pharmaceuticals and Biotechnology	5	6
ChipotleTweets	Travel and Leisure	51	3402
brownforman	Beverages	6	9
DollarTree	General Retailers	26	78
AmericanAir	Travel and Leisure	49	1465
Clorox	Household Goods and Home Construction	4	153
first republic	Banks	1	1
Hersheys	Food Producers	2	16
oreillyauto	General Retailers	12	33
Tyson foods	Food Producers	16	224
McCormickCorp	Food Producers	17	29
CampbellSoupCo	Food Producers	18	25
carnival cruise	Travel and Leisure	12	464
united	Travel and Leisure	59	1277
ConagraBrands	Food Producers	4	5
Incyte	Pharmaceuticals and Biotechnology	8	17
GallagherGlobal	Nonlife Insurance	3	4
cardinal health	Pharmaceuticals and Biotechnology	2	4
CDWCorp	Technology Hardware and Equipment	5	7
Copart	General Retailers	9	21
CenturyLink	Fixed Line Telecommunications	37	108
Lennar	Household Goods and Home Construction	45	78
DR Horton	Household Goods and Home Construction	9	14
Garmin	Leisure Goods	32	75
MandT_Bank	Banks	9	54

MylanNews	Pharmaceuticals and Biotechnology	7	16
Seagate	Technology Hardware and Equipment	40	669
westerndigital	Technology Hardware and Equipment	19	69
Discover	Banks	15	141
FifthThird	Banks	16	56
the Hartford	Nonlife Insurance	3	8
Hasbro	Leisure Goods	52	320
CitizensBank	Banks	28	119
Smuckers	Food Producers	4	10
NortonLifelock	Software and Computer Services	5	16
WhirlpoolCorp	Household Goods and Home Construction	32	48
CarMax	General Retailers	2	5
genuinepartsco	Automobiles and Parts	1	1
KeyBank	Banks	17	71
GlobeLife	Life Insurance	2	2
MGMResortsIntl	Travel and Leisure	32	162
MolsonCoors	Beverages	73	132
Pulte homes	Household Goods and Home Construction	53	83
askRegions	Banks	16	82
Ralcorp	Travel and Leisure	10	50
tractor supply	General Retailers	12	54
ultabeauty	General Retailers	37	402
WynnLasVegas	Travel and Leisure	24	133
AdvanceAuto	General Retailers	22	57
Alaska air	Travel and Leisure	63	2577
Assurant	Nonlife Insurance	6	9
Discovery	Media	160	919
Gap	General Retailers	2	14
HRBlock	General Retailers	25	402
harleydavidson	Automobiles and Parts	48	666
Huntington_Bank	Banks	2	5
Kohls	General Retailers	20	206
L_Brands	General Retailers	2	3

lincolnfingroup	Life Insurance	2	4
NewsCorp	Media	5	16
Nordstrom	General Retailers	10	114
CruiseNorwegian	Travel and Leisure	34	318
PerrigoCompany	Pharmaceuticals and Biotechnology	3	3
Xerox	Technology Hardware and Equipment	15	100
ZionsBank	Banks	8	17
ComericaBank	Banks	8	40
HanesBrands	Personal Goods	2	3
Nielsen	Media	29	44
PeoplesUnited	Banks	8	23
PVHCorp	Personal Goods	3	3
RalphLauren	Personal Goods	38	146
principal	Life Insurance	1	1
UnderArmour	Personal Goods	9	55
Darden	Travel and Leisure	1	6
Total		4122	68191

TABLE 2

PARTICIPANTS' RATINGS OF INDUSTRY LEVEL BENEFICIARY STATUS

Industry and Company Information	Average Ratings of Company Status
Software and Computer Services (Microsoft, Facebook, Twitter)	5.67
General Retailers (Amazon, Walmart, Home Depot)	5.47
Pharmaceuticals and Biotechnology (Pfizer, Johnson and Johnson, Amgen)	5.80
Personal Goods (Procter and Gamble, Colgate-Palmolive, Nike, Under Armour)	4.80
Technology Hardware and Equipment (Apple, HP, Intel)	5.13
Fixed Line Telecommunications (Verizon, AT&T, T-Mobile)	5.40
Media (Netflix, Disney, Discovery)	6.10
Banks (Bank of America, Zions Banks, People's United Financial)	5.40
Beverages (Coca Cola, Pepsi, Monster)	4.90
Travel and Leisure (Hilton, Delta Air, Booking.com, McDonalds, Starbucks)	4.13
Tobacco (Philip Morris, Altria)	4.93
General Industrials (3M, General Electric, Honeywell)	4.90
Automobiles and Parts (General Motors, Ford, Harley-Davidson)	4.43
Food and Drug Retailers (CVS Health, Walgreens, Kroger)	5.43
Food Producers (Mondelez, Kraft Heinz, Kellogg)	4.97
Industrial Transportation (UPS, FedEx, Old Dominion)	5.10
Nonlife Insurance (Chubb, AON, Loews)	4.63
Life Insurance (Metlife, Aflac, Principal Financial Group)	4.73
Household Goods and Home Construction (Clorox, Whirlpool, D.R. Horton)	4.73
Leisure Goods (Garmin, Hasbro)	4.87

TABLE 3

TOPIC NUMBERS AND MOST FREQUENT TEN WORDS IN EACH TOPIC

Topic Number	**Topic Details and Words Weights**
0	0.110*"bank" + 0.090*"space" + 0.088*"deliv" + 0.065*"process" + 0.060*"minut" + 0.058*"easi" + 0.056*"anniversari" + 0.052*"futur" + 0.041*"sustain" + 0.035*"park"
1	0.174*"thank" + 0.160*"learn" + 0.129*"readi" + 0.075*"impact" + 0.072*"book" + 0.039*"execut" + 0.031*"trip" + 0.014*"role" + 0.008*"frontlin" + 0.003*"ralph"
2	0.191*"avail" + 0.088*"honor" + 0.079*"near" + 0.073*"past" + 0.072*"adventur" + 0.044*"safeti" + 0.042*"oper" + 0.041*"gener" + 0.033*"mobil" + 0.030*"concern"
3	0.145*"design" + 0.115*"content" + 0.087*"photo" + 0.073*"view" + 0.068*"add" + 0.062*"compani" + 0.057*"worker" + 0.043*"serv" + 0.042*"drop" + 0.013*"pickup"
4	0.218*"feel" + 0.154*"tonight" + 0.077*"servic" + 0.064*"fall" + 0.047*"stop" + 0.043*"wednesday" + 0.039*"hero" + 0.035*"prepar" + 0.030*"instagram" + 0.023*"leader"
5	0.174*"visit" + 0.147*"black" + 0.060*"king" + 0.056*"perfect" + 0.047*"grow" + 0.046*"origin" + 0.042*"card" + 0.033*"mark" + 0.029*"cost" + 0.027*"approach"

6	0.235*"home" + 0.114*"mind" + 0.095*"plan" + 0.062*"icon" + 0.041*"stage" + 0.039*"level" + 0.034*"activ" + 0.031*"ensur" + 0.027*"remain" + 0.012*"time"
7	0.265*"local" + 0.088*"read" + 0.060*"hope" + 0.044*"transform" + 0.040*"recogn" + 0.038*"long" + 0.033*"enter" + 0.028*"difficult" + 0.024*"network" + 0.024*"sign"
8	0.286*"tour" + 0.152*"presal" + 0.074*"start" + 0.068*"color" + 0.047*"social" + 0.023*"face" + 0.023*"today" + 0.022*"reflect" + 0.022*"heart" + 0.021*"host"
9	0.137*"lauren" + 0.102*"insid" + 0.083*"winter" + 0.058*"road" + 0.057*"return" + 0.056*"februari" + 0.044*"januari" + 0.036*"extra" + 0.027*"weather" + 0.025*"waiver"
10	0.120*"edit" + 0.114*"summer" + 0.086*"join" + 0.083*"employe" + 0.064*"order" + 0.058*"nation" + 0.049*"addit" + 0.044*"roll" + 0.032*"essenti" + 0.022*"press"
11	0.162*"work" + 0.097*"chang" + 0.063*"data" + 0.060*"idea" + 0.053*"respons" + 0.052*"repli" + 0.050*"corpor" + 0.050*"hand" + 0.037*"incred" + 0.028*"children"
12	0.150*"info" + 0.108*"sale" + 0.107*"free" + 0.076*"worldwid" + 0.069*"flight" + 0.046*"player" + 0.043*"congrat" + 0.041*"small" + 0.038*"receiv" + 0.029*"rise"
13	0.106*"room" + 0.092*"experi" + 0.089*"hear" + 0.070*"debut" + 0.063*"launch" + 0.048*"current" + 0.035*"comment" + 0.035*"round" + 0.026*"investig" + 0.026*"ask"

14	0.136*"good" + 0.108*"video" + 0.080*"option" + 0.060*"financi" + 0.057*"dream" + 0.040*"forget" + 0.037*"relief" + 0.036*"twitter" + 0.034*"trend" + 0.029*"applic"
15	0.133*"excit" + 0.112*"follow" + 0.091*"stream" + 0.091*"travel" + 0.076*"kitchen" + 0.066*"tell" + 0.063*"wish" + 0.037*"state" + 0.028*"especi" + 0.013*"convers"
16	0.101*"complet" + 0.083*"stimulu" + 0.073*"safe" + 0.065*"coronaviru" + 0.053*"health" + 0.047*"test" + 0.042*"extend" + 0.037*"statu" + 0.034*"simpl" + 0.034*"treat"
17	0.146*"know" + 0.123*"want" + 0.117*"spend" + 0.086*"brand" + 0.071*"beer" + 0.060*"begin" + 0.044*"offer" + 0.044*"question" + 0.040*"discuss" + 0.034*"lead"
18	0.165*"custom" + 0.086*"night" + 0.077*"newest" + 0.076*"stand" + 0.046*"number" + 0.044*"virtual" + 0.036*"base" + 0.035*"assist" + 0.035*"birthday" + 0.032*"reduc"
19	0.148*"celebr" + 0.105*"covid" + 0.098*"guest" + 0.078*"onlin" + 0.059*"true" + 0.059*"david" + 0.057*"mean" + 0.043*"answer" + 0.035*"believ" + 0.029*"platform"
20	0.256*"look" + 0.069*"exclus" + 0.064*"seri" + 0.061*"great" + 0.056*"protect" + 0.044*"reveal" + 0.040*"parti" + 0.036*"cover" + 0.032*"unit" + 0.029*"possibl"

21	0.221*"today" + 0.154*"collect" + 0.110*"friday" + 0.079*"sunday" + 0.059*"save" + 0.050*"place" + 0.033*"journey" + 0.022*"benefit" + 0.022*"increas" + 0.014*"vote"
22	0.072*"limit" + 0.064*"say" + 0.059*"mile" + 0.055*"foundat" + 0.049*"kick" + 0.045*"money" + 0.045*"digit" + 0.040*"insight" + 0.038*"solut" + 0.037*"medic"
23	0.157*"make" + 0.094*"proud" + 0.092*"hour" + 0.082*"tip" + 0.044*"program" + 0.044*"focu" + 0.036*"branch" + 0.030*"direct" + 0.027*"resourc" + 0.027*"ship"
24	0.140*"music" + 0.076*"think" + 0.074*"donat" + 0.058*"produc" + 0.055*"drive" + 0.051*"tune" + 0.047*"appli" + 0.035*"connect" + 0.032*"manag" + 0.031*"purchas"
25	0.136*"come" + 0.099*"classic" + 0.098*"favorit" + 0.085*"take" + 0.085*"singl" + 0.064*"relat" + 0.043*"away" + 0.042*"prioriti" + 0.040*"member" + 0.029*"tomorrow"
26	0.432*"year" + 0.105*"life" + 0.078*"famili" + 0.053*"pick" + 0.027*"explor" + 0.019*"speak" + 0.012*"passion" + 0.004*"ralph" + 0.003*"caption" + 0.000*"cisco"
27	0.144*"star" + 0.094*"littl" + 0.083*"month" + 0.078*"select" + 0.076*"offic" + 0.067*"latest" + 0.064*"sure" + 0.047*"legend" + 0.036*"person" + 0.031*"technolog"

28	0.177*"store" + 0.149*"best" + 0.062*"access" + 0.057*"friend" + 0.053*"deposit" + 0.048*"way" + 0.045*"intern" + 0.027*"hous" + 0.022*"pandem" + 0.018*"partnership"
29	0.117*"issu" + 0.096*"creat" + 0.071*"continu" + 0.068*"presid" + 0.064*"break" + 0.056*"fund" + 0.052*"distanc" + 0.052*"keep" + 0.051*"care" + 0.037*"champion"
30	0.181*"discoveri" + 0.158*"watch" + 0.133*"featur" + 0.099*"meet" + 0.087*"episod" + 0.070*"chanc" + 0.045*"date" + 0.025*"final" + 0.017*"uniqu" + 0.008*"govern"
31	0.206*"like" + 0.120*"peopl" + 0.081*"award" + 0.078*"welcom" + 0.050*"reason" + 0.040*"american" + 0.032*"guid" + 0.031*"choos" + 0.028*"plu" + 0.022*"divers"
32	0.122*"game" + 0.113*"beauti" + 0.107*"busi" + 0.084*"vega" + 0.080*"million" + 0.074*"land" + 0.055*"women" + 0.030*"pledg" + 0.027*"credit" + 0.020*"vehicl"
33	0.145*"go" + 0.138*"listen" + 0.086*"play" + 0.068*"fan" + 0.059*"innov" + 0.057*"global" + 0.035*"word" + 0.031*"human" + 0.020*"gender" + 0.019*"auto"
34	0.211*"announc" + 0.132*"special" + 0.107*"album" + 0.071*"import" + 0.066*"detail" + 0.039*"clean" + 0.038*"femal" + 0.038*"blog" + 0.033*"expect" + 0.019*"run"

35	0.226*"check" + 0.095*"time" + 0.078*"spring" + 0.076*"bring" + 0.075*"introduc" + 0.061*"high" + 0.035*"equal" + 0.035*"chief" + 0.031*"power" + 0.022*"equip"
36	0.196*"help" + 0.158*"wear" + 0.099*"provid" + 0.063*"build" + 0.059*"get" + 0.040*"suppli" + 0.039*"result" + 0.033*"hospit" + 0.028*"tool" + 0.023*"chain"
37	0.299*"ticket" + 0.081*"inspir" + 0.050*"inform" + 0.049*"offici" + 0.044*"crisi" + 0.042*"water" + 0.042*"call" + 0.041*"enjoy" + 0.035*"releas" + 0.021*"affect"
38	0.168*"miss" + 0.127*"week" + 0.089*"share" + 0.067*"give" + 0.049*"commit" + 0.045*"leav" + 0.044*"drink" + 0.040*"effort" + 0.039*"monday" + 0.023*"area"
39	0.197*"world" + 0.136*"updat" + 0.082*"song" + 0.054*"soon" + 0.047*"tweet" + 0.040*"amaz" + 0.036*"measur" + 0.031*"happen" + 0.028*"account" + 0.028*"booth"
40	0.207*"love" + 0.129*"start" + 0.097*"stori" + 0.082*"discov" + 0.080*"right" + 0.062*"thing" + 0.047*"expert" + 0.025*"daili" + 0.023*"real" + 0.012*"film"
41	0.163*"need" + 0.123*"see" + 0.109*"team" + 0.096*"product" + 0.079*"includ" + 0.047*"locat" + 0.038*"organ" + 0.020*"remot" + 0.020*"fast" + 0.003*"ralph"
42	0.148*"citi" + 0.073*"action" + 0.058*"healthcar" + 0.050*"lose" + 0.050*"practic" + 0.047*"click" + 0.046*"explain" + 0.043*"center" + 0.041*"fight" + 0.041*"mask"

43	0.120*"happi" + 0.114*"time" + 0.094*"angel" + 0.048*"march" + 0.046*"hard" + 0.045*"earn" + 0.042*"name" + 0.038*"crew" + 0.029*"workplac" + 0.028*"secur"
44	0.099*"support" + 0.093*"partner" + 0.090*"stay" + 0.087*"artist" + 0.079*"regist" + 0.073*"winner" + 0.059*"payment" + 0.042*"gift" + 0.027*"abl" + 0.026*"north"
45	0.244*"live" + 0.184*"head" + 0.056*"food" + 0.041*"present" + 0.036*"board" + 0.033*"spot" + 0.033*"second" + 0.028*"histori" + 0.025*"deserv" + 0.022*"deal"
46	0.134*"weekend" + 0.083*"resort" + 0.069*"line" + 0.069*"market" + 0.060*"catch" + 0.049*"america" + 0.048*"cheer" + 0.043*"countri" + 0.041*"moment" + 0.039*"april"
47	0.141*"commun" + 0.130*"shop" + 0.112*"perform" + 0.078*"light" + 0.066*"challeng" + 0.051*"industri" + 0.048*"talk" + 0.042*"valentin" + 0.022*"scientist" + 0.017*"collabor"
48	0.110*"open" + 0.102*"attend" + 0.061*"wait" + 0.057*"spread" + 0.055*"smart" + 0.050*"list" + 0.040*"goal" + 0.038*"step" + 0.037*"learn" + 0.036*"forward"
49	0.193*"style" + 0.077*"better" + 0.066*"day" + 0.065*"season" + 0.062*"news" + 0.061*"differ" + 0.059*"premier" + 0.055*"consum" + 0.041*"arriv" + 0.036*"situat"

Note: Words are lemmatized.

TABLE 4

NUMBER OF STATEMENTS MATCHED WITH MONEY CONTRIBUTION RELATED KEYWORDS IN EACH TOPIC AND THEIR RATIOS TO THE OVERALL NUMBER OF TWEETS IN CORRESPONDING TWEETS IN EACH TOPIC

(M_{Ratio}=.005, SD_{Ratio}=.009)

Topic Number	**# of Matched Statements**	**Ratio**
0	0	0.000
1	2	0.014
2	0	0.000
3	0	0.000
4	0	0.000
5	0	0.000
6	0	0.000
7	1	0.018
8	0	0.000
9	0	0.000
10	*1*	0.022
11	1	0.008
12	0	0.000
13	0	0.000
14	1	0.017
15	0	0.000

16	0	0.000
17	0	0.000
18	0	0.000
19	2	0.026
20	2	0.021
21	0	0.000
22	1	0.022
23	1	0.011
24	*0*	0.000
25	*0*	0.000
26	0	0.000
27	0	0.000
28	0	0.000
29	0	0.000
30	*0*	0.000
31	0	0.000
32	5	0.041
33	1	0.013
34	0	0.000
35	0	0.000
36	1	0.012
37	0	0.000
38	0	0.000

39	0	0.000
40	0	0.000
41	2	0.014
42	1	0.022
43	0	0.000
44	0	0.000
45	1	0.009
46	0	0.000
47	0	0.000
48	0	0.000
49	0	0.000

TABLE 5

NUMBER OF STATEMENTS MATCHED WITH IN-KIND CONTRIBUTION RELATED KEYWORDS IN EACH TOPIC AND THEIR RATIOS TO THE OVERALL NUMBER OF TWEETS IN CORRESPONDING TWEETS IN EACH TOPIC

(MRatio=.003, SDRatio=.01)

Topic Number	**# of Matched Statements**	**Ratio**
0	0	0
1	0	0
2	0	0
3	0	0
4	0	0
5	0	0
6	0	0
7	0	0
8	0	0
9	0	0
10	0	0
11	0	0
12	0	0
13	1	0.016
14	0	0
15	0	0

16	1	0.014
17	0	0
18	0	0
19	0	0
20	0	0
21	0	0
22	0	0
23	0	0
24	0	0
25	0	0
26	0	0
27	0	0
28	0	0
29	0	0
30	0	0
31	0	0
32	1	0.008
33	0	0
34	0	0
35	0	0
36	6	0.071
37	0	0
38	0	0

39	0	0
40	0	0
41	1	0.007
42	0	0
43	0	0
44	0	0
45	1	0.009
46	0	0
47	1	0.011
48	0	0
49	0	0

TABLE 6

VARIABLES AND CORRESPONDING VIF SCORES

Variables	VIF Scores
Firm Size	1.24
Contribution Type (-1:Money, 0:Neutral, :1:In-kind)	1.02
Log (Daily Infections)	1.06
Location	1.34
Number of Words	1.30
Analytical Thinking	1.14
Clout	1.16
Authenticity	1.08
Sentiment	1.12
Popularity	2.25
Number of Followers per day	1.19
Number of Followings per day	2.96
Number of Likes per day	1.33
Number of Tweets per day	2.13
Number of Media per day	1.36
Age of the Account	1.17
Status Score (Company Status)	1.47

TABLE 7

VARIABLES AND BIVARIATE CORRELATIONS

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
1	1																
2	.01	1															
3	.001	.02	1														
4	.1**	.03*	-.004	1													
5	-.04**	-.01	.2**	-.01	1												
6	-.03	-.02	-.01	.1**	.3**	1											
7	-.004	-.01	.1**	-.03*	.2**	-.1**	1										
8	-.1**	-.02	-.04*	-.03	-.04**	.1**	-.2**	1									
9	.02	-.01	.03	.002	.2**	.1**	.2**	-.1**	1								
10	.2**	-.02	.01	.02	.000	.1**	-.1**	.1**	-.03	1							
11	.1**	.002	.03*	.1**	-.2**	-.1**	-.1**	.1**	-.1**	.2**	1						
12	-.1**	.01	-.1**	-.1**	-.1**	-.1**	.1**	.000	.01	-.6**	-.02	1					
13	.1**	-.02	.01	-.2**	-.1**	-.1**	.004	.02	.03	.2**	-.1**	-.1**	1				
14	-.1**	-.02	-.03	-.4**	-.1**	-.1**	.03*	.1**	-.02	.03	-.03*	.5**	.2**	1			
15	.2**	-.003	-.1**	-.04*	-.1**	-.1**	-.01	.1**	.002	.1**	-.004	.2**	.4**	.2**	1		
16	.1**	.01	-.02	.2**	-.1**	-.1**	-.03	.05**	-.03	.1**	.2**	.2**	.1**	.1**	.1**	1	
17	.3**	.04**	.1**	.1**	-.03	.02	-.1**	.05**	-.1**	.1**	.2**	-.3**	-.1**	-.4**	.01	.1**	1

Note. The variables are given and numbered in the same order as presented in Table 6.
†p<0.1. *p < .05. **p < .01. ***p < .001

TABLE 8

REGRESSION RESULTS

	Dependent variable:	
	Sentiment Score of User Responses	
	(1)	(2)
Firm Size		-0.34
		(0.33)
Contribution Type (D1) (1:Money)		.10
		(1.24)
Contribution Type (D2) (1:In-Kind)		1.44
		(1.89)
Log Transformed Daily Infections		0.36†
		(0.22)
Location Information (0:Other, 1:US)		3.06*
		(1.34)
Number of Words in Company's tweet (LIWC)		0.02
		(0.04)
Analytical Thinking Score of Company's Tweet (LIWC)		0.02†
		(0.01)
Clout Score of Company's Tweet (LIWC)		0.01
		(0.02)
Authenticity Score of Company's Tweet (LIWC)		-0.02
		(0.01)
Sentiment Score of Company's Tweet (LIWC)		0.06***
		(0.01)
The popularity of the Company		30.8**
		(10.2)

Number of Followers Gained per Day		-0.00
		(0.00)
Number of Followings Done per Day		0.15
		(0.12)
Number of Likings Done per Day		-0.35***
		(0.10)
Number of Tweets posted per Day		-0.01
		(0.01)
Number of Media posted per Day		0.24
		(0.15)
Age of the Company's Twitter Account		-0.00†
		(0.00)
Status score	-1.745*	-1.78*
	(0.72)	(0.87)
Constant	62.0***	34.6**
	(3.76)	(11.2)
Df	4,120	4,096
R^2	0.001	0.022
Adjusted R^2	0.001	0.017

Note. The table shows standardized regression coefficients, with standard errors in parentheses and adjusted R-squared values for each step to compare model fits between steps. †p<0.1. *p < .05. **p < .01. ***p < .001.

TABLE 8

SUMMARY OF THE CURRENT RESEARCH

Hypotheses	**Studies**	**Crisis Contexts (respectively)**	**Results**
H1a:People's willingness to spread positive WOM for the beneficiary companies will be less than other (losing and non-specified status) companies communicating the same CSR messagesduring a crisis.	1a, 1b, 3, 4, 5	COVID, Brazilian Fuel Oil Crisis, Turkey's Wildfires, Ukraine - Russia War.	Supported in studies 1a, 1b, 3, 4, 5.
H1b:People's willingness to help the beneficiary companies will be less than other (losing and non-specified status) companies that communicate the same CSR message during a crisis.	2,3,4,5	COVID, Turkey's Wildfires, Ukraine - Russia War.	Supported in Studies 2, 4, 5. Partially supported in study 3.
H2a: Perceived sincerity will mediate the relationship between the company status and consumers' willingness to spread positive WOM for those companies in a way that the perceived sincerity of beneficiary companies' CSR messages will be lower than other (losing and non- specified status) companies during a crisis which in turn, will make people less willing to spread positive WOM for beneficiary companies than others.	2,3,4,5	COVID, Turkey's Wildfires, Ukraine - Russia War.	Supported in studies 2, 3, 4, 5.
H2b: Perceived sincerity will mediate the relationship between the company status and consumers' willingness to help those companies in a way that the perceived sincerity of beneficiary companies' CSR messages will be lower than other (losing and non-specified status) companies during a crisis which in turn will make people less willing to help beneficiary companies than others.	2,3,4,5	COVID, Turkey's Wildfires, Ukraine - Russia War.	Supported in studies 2, 3, 4, 5.
H3a: Mediation of perceived sincerity between company status and willingness to spread positive WOM is moderated by perceived company size in a way that when the company size is perceived to be large (vs small), it leads beneficiary companies' perceived sincerity and people's willingness to	4,5	COVID, Turkey's Wildfires, Ukraine - Russia War.	Supported in study 4, yet not supported in study 5.

spread positive WOM for those companies to be the lowest compared to other companies.			
H3b: Mediation of perceived sincerity between company status and willingness to help the company is moderated by perceived company size in a way that when the company size is perceived to be large (vs small), it leads beneficiary companies' perceived sincerity and people's willingness to help the company to be the lowest compared to other companies.	4,5	COVID, Turkey's Wildfires, Ukraine - Russia War.	Supported in study 4, yet not supported in study 5.
H4a: When company size is perceived to be large (vs small), perceived sincerity and subsequently people's willingness to spread positive WOM about beneficiary companies should be higher when the company makes in-kind donations compared to monetary contributions or when no specific contribution type mentioned.	5	COVID, Turkey's Wildfires, Ukraine - Russia War.	Supported in study 5.
H4b: When company size is perceived to be large (vs small), perceived sincerity and subsequently people's willingness to help beneficiary companies should be higher when the company makes in-kind donations compared to monetary donations or when no specific contribution type mentioned.	5	COVID, Turkey's Wildfires, Ukraine - Russia War.	Supported in study 5.

Note. Study 1a used secondary data collected from Twitter in a cross-sectional setting, whereas other studies used primary data in an experimental setting.

List of Figures

FIGURE 1

MODERATED MEDIATION MODEL WITH WILLINGNESS FOR POSITIVE WOM

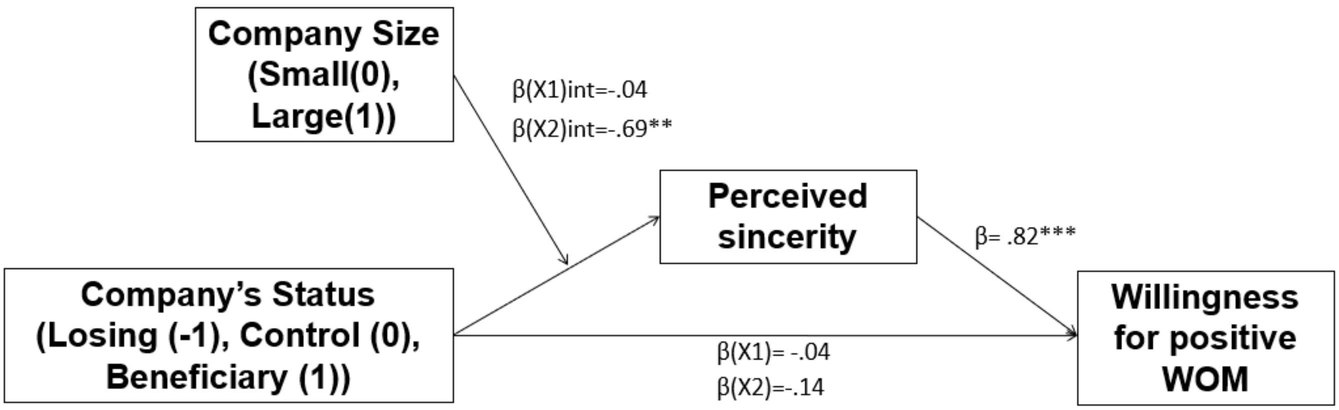


FIGURE 2

MODERATED MEDIATION MODEL WITH WILLINGNESS TO SUPPORT

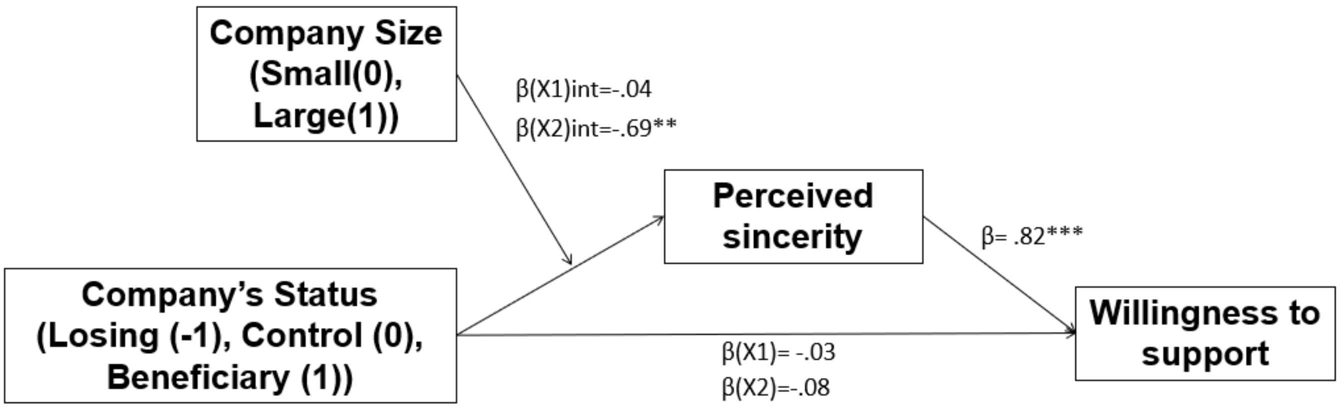
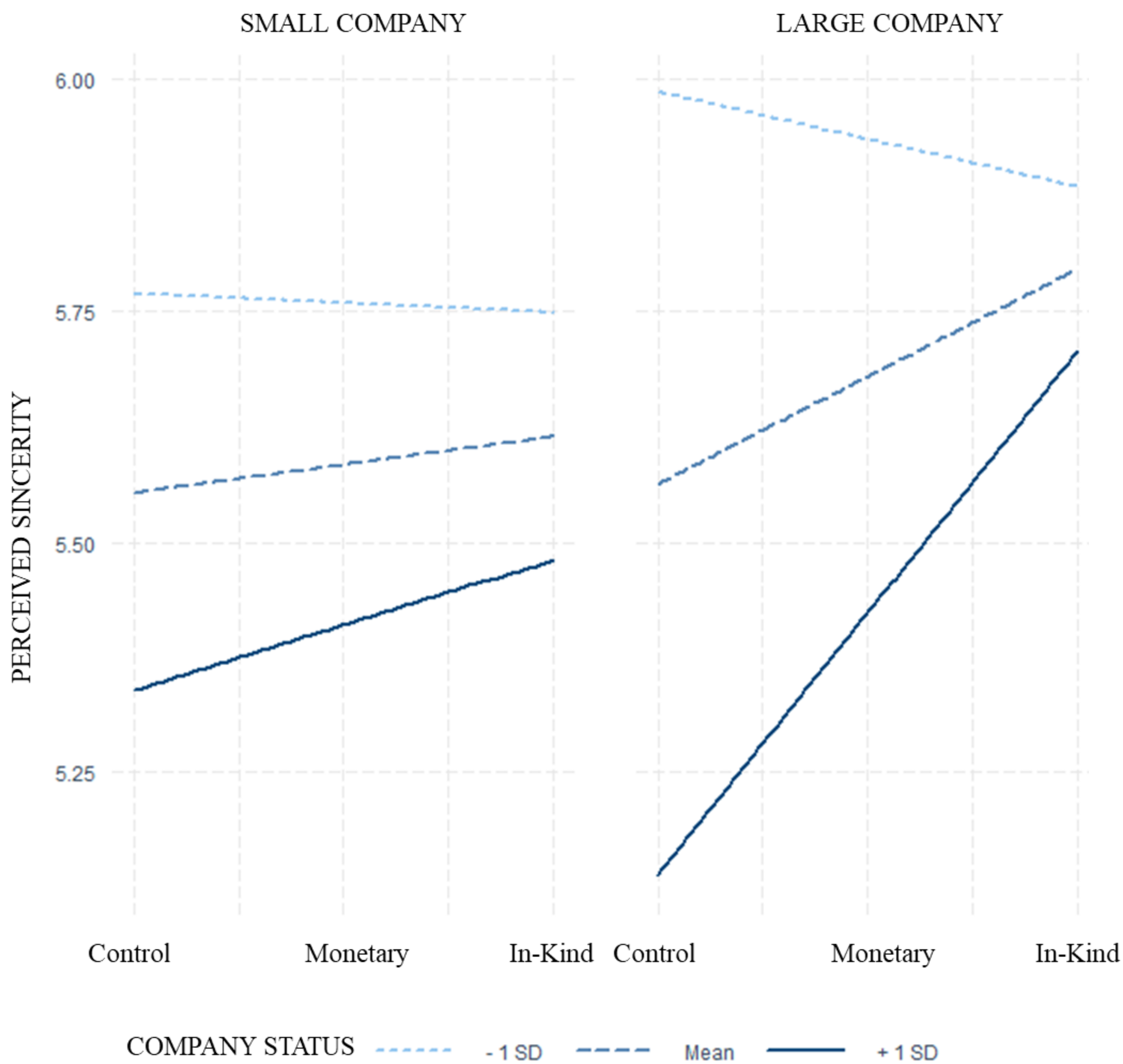


FIGURE 3

THREE WAY INTERACTION BETWEEN COMPANY STATUS, COMPANYS SIZE, AND CONTRIBUTION TYPE ON PERCEIVED SINCERITY



Chapter I: Introduction

"*We are in the movement you fear the most, and in fear, you will fail after fail. You are not used to being cornered up. Now, bleed.*"

In March 2020, a Twitter user posted this provocative statement in response to a corporate social responsibility (CSR) tweet from Microsoft, wherein the company introduced some of its crisis relief efforts during the COVID pandemic. Microsoft offered resources to aid businesses and schools in transitioning to remote work during challenging times (Microsoft, 2020). However, this gesture of goodwill was met with negative reactions from some users, exemplified by the user's statement. This incident suggests that it is not uncommon for companies to face backlash for their CSR efforts during crises. For example, during the British Columbia floods, Air Canada announced on Twitter that the company would match all donations made to the Canadian Red Cross by Canadians to support impacted communities. Yet, this tweet received adverse reactions, as users accused the company of seeking a tax break by ostensibly displaying altruistic behavior (Air Canada, 2021). Likewise, Intel's communications regarding their relief efforts to address the microchip crisis in 2021 sparked criticism among social media users, who claimed that the company was too late and incompetent to resolve the issue (Intel, 2021). These incidents raise questions about the factors that trigger consumers' adverse reactions to some companies' CSR communications during crises and the mechanism that explains their ill-fated CSR communications. The current research sets out to explore this unique phenomenon which was labeled as "beneficiaries' misery." firstly in this research.

In all these cases, the "beneficiary" companies financially benefited from the crises they were responding to, while other industries and the general public suffered. For instance, during the COVID pandemic, Microsoft's profits increased significantly due to the high demand for cloud computing (O’brien, 2021). Similarly, Air Canada saw an increase in profits as a result of the higher demand for air transportation during the British Columbia floods (Reynolds, 2021). Additionally, Intel's revenue rose by $1 billion during the microchip shortage, as the demand for microchips reached unprecedented levels (Gartenberg, 2021).

These observations prompt important questions regarding why consumers may react negatively to a company's CSR communications, particularly when the crisis is exogenous to the company. For instance, would consumers exhibit the same negativity towards a company that suffered a financial loss as a result of a crisis? Additionally, would a small company face the same skepticism and criticism if it financially gained from a crisis? Furthermore, if a beneficiary company made material rather than monetary contributions as part of their CSR actions, would it still suffer from the same "beneficiaries’ misery" status? These critical questions guide the current research, which aims to provide a deeper understanding of the complex relationship between companies, crises, and CSR, and to identify effective strategies for managing these relationships ethically, transparently, and responsibly. By examining these factors, this research endeavors to illuminate the "beneficiaries’ misery" phenomenon and its implications for CSR communications during times of crisis.

Specifically, the present research seeks to investigate the impact of the perceived status (beneficiary or losing) of the company on public’s response to a firm's CSR communication in the context of a crisis. Previous studies on CSR have investigated diverse factors that may influence the public's attitudes toward companies' CSR communications, including the fit between the company and the cause they support (Simmons and Becker-Olsen, 2006), the size and positioning of the company (Kirmani et al., 2017; Yang and Aggarwal, 2019), the perception of corporate greed (Lee et al., 2017), the perceived level of altruism (Rim et al., 2016), the perceived sincerity of the company (Yoon et al., 2006), the perceived authenticity of corporate communication (Walker and Wan, 2012), and the type of contribution made by the company to social causes (Hildebrand et al., 2017; Langan and Kumar, 2019). Indeed, some prior research has suggested a positive relationship between a company's CSR actions and the public's attitudes toward the firm (Ellen et al., 2000; Sen and Bhattacharya, 2001), as consumers have come to expect companies to fulfill their CSR-related obligations (Nickerson et al., 2022).

Nonetheless, the present study constitutes a significant departure from prior research by introducing and demonstrating that, in a crisis situation, the public's evaluation of a company's CSR communication not only depends on its CSR actions but also on its perceived "status" during the crisis. This innovative and critical determinant, the perceived status of a company within a crisis, has been largely neglected in previous research. Findings of this research indicate that when a company is perceived as benefiting from a crisis, even if such gains are coincidental, it can evoke negative public attitudes and amplify suspicions regarding the sincerity of its CSR actions. This research contrasts with previous studies that propose that people generally identify with beneficiaries as they symbolize strength and capability (Cialdini et al., 1976). For instance, leading brands are thought to possess a greater probability of meeting expectations, which may result in positive public attitudes under certain circumstances (Woolley et al., 2022). However, findings of this research suggest that the beneficial effects linked to beneficiary companies, as observed in prior research, could be reversed during crises, leading to "misery" rather than advantage.

Most importantly, “beneficiaries’ misery”, the effect uncovered in this paper, takes place in a unique context where companies neither caused the crisis nor had any control over how it would impact their business, either positively or negatively. Therefore, they are not culpable for the crisis. In such a scenario, it can be argued that consumers may discredit the CSR efforts of beneficiary companies, as successful companies are already expected to undertake CSR actions (Mowen, 2012), and their efforts merely serve to confirm existing expectations. The expectation confirmation theory posits that behavior aligned with existing expectations carries less significance (Meyers-Levy and Tybout, 1989) and is therefore less likely to yield substantial reputational benefits (Settle and Golden, 1974; Smith and Hunt, 1978). Conversely, performing CSR actions may not signal sufficient corporate effort for beneficiary companies, as these efforts are perceived to be less burdensome for them compared to losing companies (Langan and Kumar, 2019). As a result, consumers may evaluate the CSR actions of beneficiary companies negatively (Nowak and Sigmund, 2005).

Building on this theoretical framework, current research unveils a novel effect termed "beneficiaries' misery," which signifies a negative public attitude towards a firm's CSR efforts during a crisis when the company is perceived to be in a beneficiary position. This finding underscores the need for companies to carefully consider their CSR communication strategies during times of crisis, taking their perceived status into account when designing and implementing CSR actions.

Theoretically, this research contributes to existing research on crisis management and corporate CSR communications by examining crisis scenarios in which companies are not culpable (Klein and Dawar, 2004). In contexts such as pandemics, wildfires, supply shortages and wars, society and companies together can indeed be considered as victims of the crises altogether but to different extents (Coombs, 2007). The primary focus of this research is on crisis scenarios where no company or organization is responsible for causing them. This unique context offers opportunities to investigate perceived company status (beneficiary vs. losing vs.

not specified) during a crisis as a novel predictor of the success of CSR communications. This research posits that a company's beneficiary status during crises results in less support, as beneficiary companies are perceived to be less sincere when communicating their CSR efforts. A moderator and a boundary condition for this suggested mediation path are also proposed and tested as perceived company size and company's contribution type respectively. It was observed that large beneficiary companies may suffer from the effect of beneficiaries' misery the most, yet when they perform material donations (in-kind donations) as a part of their CSR contributions, this effect is muted.

Managerially, using CSR communications as strategic tools to derive reputational benefits such as positive word-of-mouth (WOM) (Jalilvand et al., 2017) and support from society (McGlone et al. 2011) is a common practice adopted by companies. However, the COVID-19 pandemic changed the marketplace drastically as global lockdowns affected various industries differently and the connection between CSR communications and reputational returns of those communications to companies (e.g. positive WOM willingness to help/support the company) is not self-evident. This research capitalized on this unique phenomenon and uncovered companies' perceived status during a crisis as an antecedent to companies' success in CSR communications and perceived sincerity as a mediating factor. Starting from the COVID pandemic but extending to various crisis scenarios such as the 2020 wildfires in Turkey and the 2022 Ukraine-Russia war this work provides important insight into companies' CSR communication strategies during a crisis.

Chapter II: Literature Review

An Altruistic Consumer Bias: Attitudes toward Beneficiary Companies in a Crisis Environment

Consumers process CSR information in conjunction with other company-related information they can access in the environment (Torelli et al., 2012). This means that consumers evaluate firms' CSR messages based on not only what the message communicates but also what kind of company communicates the message (Simmons and Becker-Olsen, 2006; Szykman et al., 2004). Prior work argues that when firms have advantages such as power and status they are more susceptible to CSR-related criticism and scrutiny (Paharia et al., 2014; Yang and Aggarwal, 2019). For example, Godfrey (2005) found that companies known to be financially advantaged come under greater public pressure to perform CSR actions. Similarly, CSR messages of luxury brands are more likely to be evaluated poorly since luxury brands represent self-enhancement values such as power over others and dominance over resources (Torelli et al., 2012). In addition, non-family firms' CSR messages are approached more negatively than family firms' CSR messages because non-family firms are perceived to be more advantaged than family firms in the competition (Nekhili et al., 2017)

As prior research has documented there seems to be a general tendency of consumers to "punish" the beneficiaries and the powerful and empathize with the losers and the powerless. However, this research stretches this notion of altruistic consumers further and examines whether this bias still holds when the beneficiary or losing status of a company is simply a result of unpredictable accidents or natural causes.

Consumers seem to be sophisticated yet paradoxical in granting credits to company's CSR behaviors. On the one hand, performing CSR actions is "expected" from companies that hold advantaged positions during crises (Mowen, 1980). For example, companies who hold more advantageous positions than their competitors (such as hotels with higher price points) are expected to take on more CRS activities related to the environmental problems (Wang et al., 2017). On the other hand, when beneficiary companies perform the CSR actions that are expected of them, consumers do not value their CSR behaviors adequately (Ajzen, 1971; Nickerson et al., 2022), because it can be argued that these CSR actions confirming expectations are considered to be less important (Meyers-Levy and Tybout, 1989), and thus, they are less likely to generate positive attitudes from consumers (Settle and Golden, 1974; Smith and Hunt, 1978). A similar line of work suggests that when corporate behavior exceeds expectations, a positive disconfirmation effect will occur, and the company will be evaluated more positively, whereas when corporate actions match the expectations, evaluations become neutral (Lau and Russel, 1980; Nickerson et al., 2022; Oliver, 1980). This paper argues that consumers reward the CSR actions of a firm when these actions are disconfirming expectations, hence carrying more informational value (Ajzen, 1971) and the unexpected actions are deemed to be more credible than the expected ones (Meyers-Levy and Tybout, 1989; Smith and Hunt, 1978).

Furthermore, prior work indicates that consumers' evaluations of a firm's CSR actions depend on their perceived motivation of a firm's CSR actions. For instance, if consumers believe that a company's prosocial actions are simply fulfilling what is expected of them, rather than being freely chosen out of genuine concern for others, they may view these actions as insincere and lacking in authenticity. In other words, if prosocial behavior is perceived as being involuntary or compelled, rather than a voluntary expression of the company's values, it may be viewed as inauthentic (Groza et al., 2011) and as "box-checking" attempts (Nickerson et al., 2022). Hence, those actions may lead to negative company evaluations (Ellen et al., 2006).

Consumers also use “cost” and “effort” to engage in CSR actions as a proxy of a company’s motivations. For example, Nowak and Sigmund (2005) found that altruistic behavior is evaluated negatively if performing the behavior does not inflict a substantial cost on the actor. Similarly, researchers found that CSR actions are perceived to be less costly for advantaged companies, therefore for the advantaged companies who perform CSR, they are perceived to be not trying hard enough or not trying their best (Du, Bhattacharya, and Sen, 2007; Langan and Kumar, 2019).

Building on these perspectives, this research proposes that when a company’s status is perceived to be “beneficiary" in a crisis environment, consumers' willingness to spread positive WOM (Brown et al., 2005) and their willingness to help the company will be lower than other companies because consumers make important attributions as to why the company performs CSR actions based on its perceived status. Formally:

H1a: People’s willingness to spread positive WOM for the beneficiary companies will be less than other (losing and non-specified status) companies communicating the same CSR messages during a crisis.

H1b: People’s willingness to help the beneficiary companies will be less than other (losing and non-specified status) companies that communicate the same CSR message during a crisis.

As prior work indicated, consumers make inferences about a company's motivation and efforts when they evaluate its CSR actions. One piece of information consumers rely on when they make inferences of a company’s CSR actions is a company’s perceived status. For example, beneficiary companies’ attempts to engage in CSR and to meet public expectations are attributed to self-serving reasons such as protecting the company’s image; hence they are discounted (Lau and Russel, 1980). Consumers may cast doubt on the perceived sincerity of the CSR actions based on the beneficiary (or losing) status of these companies. Therefore, the perceived sincerity of the firm should mediate the effect of a firm's perceived status in a crisis environment on consumers' attitudes toward the firm. The following section conceptualizes this mechanism.

Perceived Sincerity as a Mediator

Prior research discussed that crises give consumers reasons to think badly about organizations (Coombs, 2007). Primarily when a company performs CSR-related behavior during a crisis, consumers show a greater tendency to attribute the company's CSR efforts to self-serving (selfish) motivations (Nekhili et al., 2017; Sen and Bhattacharya, 2001) and they use their persuasion knowledge more extensively when they investigate motivations of those companies (Groza et al., 2011). For example, companies' relief efforts come under greater scrutiny during crises, and the size of their donations is questioned more widely when consumers attribute selfish motivations to those efforts, particularly when those efforts are announced and made public (Hildebrand et al., 2017; Yoon et al., 2006).

Attributions of selfish motivations to CSR behavior diminish the desired reputational effects of CSR actions and harm the company's image (Becker-Olsen et al., 2006). Some of the selfish motivations that customers attribute to a company’s CSR efforts include increasing sales and market share (Auger et al., 2003), reducing business risks (Orlitzky and Benjamin, 2001), and elevating employee commitment (Greening and Turban, 2000). When these ulterior motivations are attributed to a company's CSR actions, the perceived sincerity of CSR efforts and hence the company itself will come under attack. Therefore, when selfish reasons are attributed to a company's CSR actions, consumers tend to negatively evaluate the company's sincerity (Szykman et al., 2004).

The past research also delineated a path between sincerity and brand attitude. When brands are perceived as insincere in their CSR actions, they become subject to greater suspicion and, eventually, more negative attitudes and evaluations (Becker-Olsen et al., 2006). When the perceived sincerity is high, consumers' support for companies' CSR actions, their loyalty to the company, and their willingness to spread positive WOM about the company increase (Groza et al., 2011; Nickerson et al., 2022). Therefore, consumer reactions to CSR actions are primarily driven by the perceived sincerity of those actions. In addition, in CSR-related domains, consumers are very sensitive to sincerity cues (Lin-Healy and Small, 2012). Some researchers argue that sincerity is a morality construct (Kirmani et al., 2017), and people generally are more attentive to companies' moral qualities than other qualities (Ybarra et al., 2001). Conceptually, this situation further establishes that perceived sincerity is critical for a company and its stakeholders regarding CSR-related actions during crises.

The current research argues that when the beneficiary (vs. losing) companies perform CSR actions during crises, their motivations are more likely to be attributed to selfish reasons. As evidenced in prior work, when firms' CSR behaviors were perceived to be self-serving, such as performed to match stakeholder expectations, these efforts are perceived to be less sincere (Ellen et al., 2006). This research argues that companies that are perceived to be in a beneficiary status during a crisis are more expected to engage in CSR related activities by the public and their CSR actions are more like to be attributed to situational pressures rather than the freewill of those companies.

Hence, it is proposed that the perceived sincerity of the companies' CSR actions during crises should mediate the effect of companies' perceived status on consumers' willingness to spread positive WOM and their willingness to help the company. Therefore, beneficiary (vs.

losing) companies in a crisis environment should be perceived to be less sincere in their CSR communications. In turn, low sincerity perceptions emerging from the attribution of selfish motivations should deter consumers' willingness to spread positive WOM and their willingness to help the company. Formally:

H2a: Perceived sincerity will mediate the relationship between the company status and consumers' willingness to spread positive WOM for those companies in a way that the perceived sincerity of beneficiary companies' CSR messages will be lower than other (losing and non-specified status) companies during a crisis which in turn, will make people less willing to spread positive WOM for beneficiary companies than others.

H2b: Perceived sincerity will mediate the relationship between the company status and consumers' willingness to help those companies in a way that the perceived sincerity of beneficiary companies' CSR messages will be lower than other (losing and non-specified status) companies during a crisis which in turn will make people less willing to help beneficiary companies than others.

The next goal of this research is to uncover a potential moderation for these proposed mediation effects. Understanding what can improve or exacerbate the effect of beneficiary status on people's perceptions is crucial for companies, because the negative effect of beneficiary status during a crisis may not be universal. Therefore, both theoretically and managerially, it is important to understand what corporate features can cause firms to experience the negative effect of beneficiary status to a lesser or greater extent. In the next section, it has been identified that company size can be such a feature that when it is large, it can signify the advantaged position of a beneficiary company, which can exacerbate the negative effect of its beneficiary status further.

Perceived Company Size: A Moderating Role

Consumers are mostly aware of a company's size while making decisions concerning that company (Woolley et al., 2022). Prior research suggests that a company's size is associated with its ability to satisfy public expectations (Yang and Aggarwal, 2019). Hence, larger firms are under greater public pressure and expectations to perform CSR activities than smaller firms (Attig et al., 2016) as they are perceived to have greater resources (Fatemi, 1984) and greater social impact and visibility (Udayasankar, 2008). At the same time, smaller firms are less likely to perform CSR behaviors due to resource restrictions during crises, and their CSR actions tend to have less visibility (Uhlaner et al., 2004). This situation gives small firms an underdog position in the eyes of the public and causes them to be subjected to less public pressure to perform CSR actions during crises compared to large firms (Hoch and Deighton, 1989).

The underdog position of small firms can work in their favor when they compete with larger firms (Kirmani et al., 2017), as people show greater appreciation of small firms' efforts in general (Paharia et al., 2014). This support largely stems from people's tendency to identify with underdog companies' struggles to survive against adversities (Paharia et al., 2011). Researchers also discovered that people's favoritsm toward small companies largely results from the innate empathy and altruism toward those companies (Batson et al. 1981).

Therefore, small firm size functions as a buffer against the negative effect of a beneficiary status for a company. Perceived underdog status of a company due to its smaller size, or any other disadvantaged position compared to other actors, are often associated with determination, passion, and greater efforts to perform their corporate obligations adequately (Paharia et al., 2011). It can further be argued that compared to large firms, small firms can win empathy and appreciation even when they are in a beneficiary position and their efforts in CSR are perceived to be more sincere.

In contrast, the pressure on beneficiary companies to engage in CSR actions during a crisis should intensify when they are large. As discussed previously, when a large (vs. small) firm is in a beneficiary position during a crisis, the expectation of their CSR efforts is higher. According to financial resources lay theory, consumers tend to perceive that larger companies have greater power to fund R&D activities; hence their quality expectations from large companies' products and services tend to be higher (Woolley et al., 2022).

Therefore, it is expected to observe a gap between large and small companies of the beneficiary status in terms of their perceived sincerity and, subsequently, people's willingness to spread positive WOM about those companies and their willingness to help. Formally:

H3a: Mediation of perceived sincerity between company status and willingness to spread positive WOM is moderated by perceived company size in a way that when the company size is perceived to be large (vs small), it leads beneficiary companies' perceived sincerity and people's willingness to spread positive WOM for those companies to be the lowest compared to other companies.

H3b: Mediation of perceived sincerity between company status and willingness to help the company is moderated by perceived company size in a way that when the company size is perceived to be large (vs small), it leads beneficiary companies' perceived sincerity and people's willingness to help the company to be the lowest compared to other companies.

The last task of this research is to find a boundary condition where a large beneficiary company can be less penalized when they communicate their CSR efforts during a crisis. As discussed earlier, large beneficiary firms are under constant scrutiny and pressure from the public to engage in CSR actions (Groza et al., 2011). The current research intends to explore a CSR strategy that can solve this dilemma for large and beneficiary companies during a crisis. Past research showed that when a large company makes non-monetary contributions such as investing corporate time (Langan and Kumar, 2019) and providing supplies (Hildebrand et al., 2017) as a part of their CSR actions, the public's evaluations of the company improve, since non-monetary (monetary) contributions signal greater (less) effort and investment for large companies. Therefore, it has been proposed that "communicating in-kind contributions" as a strategy can attenuate the negative attitudes toward large and beneficiary firms' CSR communications.

In-Kind Donations: A Boundary Condition

Limited work on the impact of the type of CSR contributions on people's evaluations of the company showed that monetary contributions are often perceived as less emotionally expressive, more rational (Liu and Aaker, 2008), and more transactional (Macdonnell and White, 2015). Langan and Kumar's work (2019) showed that the company size and contribution type can interact in a way that large companies' money contributions are evaluated more poorly than the same amount of monetary contributions from small firms. They argue that monetary contributions do not signal as much corporate effort for large companies as for small companies (Langan and Kumar, 2019). From their work, it can be inferred that consumers associate large companies with abundant financial resources; therefore, when large companies make monetary contributions, these contributions are perceived to be less effortful and hence less sincere.

However, when large companies make in-kind contributions such as food, materials, or even time (e.g., employee volunteering activities) for the impacted communities during crises, their efforts are evaluated more positively than small companies performing the same actions

(Langan and Kumar, 2019). For example, prior work showed that in-kind donations such as delivering meals signal greater care and efforts for the emotional well-being of others than monetary contributions (Hildebrand et al., 2017; Liu and Aaker, 2008). Researchers argue that large firms are often perceived to be too busy to invest corporate time in coordinating non-monetary contributions (e.g., delivering meals) (Hildebrand et al., 2017; Langan and Kumar, 2019). Therefore, in-kind contributions are the less expected type of contributions from large firms (Yang and Aggarwal, 2019).

In a similar vein, researchers also found that consumers make motivational attributions to a firm's CSR actions based on the cost of a CSR action relative to the company's status (Folse et al., 2010). Therefore, this research argues that large beneficiary companies, when they communicate their in-kind donations, are more likely to receive greater support from the public than when they do not mention any specific contribution type or when they communicate their monetary contributions (Ellen et al., 2000) as in-kind donations are a less expected type of CSR behavior from these companies, and these activities signal greater corporate effort for large beneficiaries when performed. From this perspective, making in-kind contributions should mute the negative impact of their beneficiary status for large beneficiaries on their perceived sincerity, thus, consumers' willingness to spread positive WOM and their willingness to help those companies should significantly increase compared to when they do not mention any specific contribution type or when they communicate their monetary contributions. More formally:

H4a: When company size is perceived to be large (vs small), perceived sincerity and subsequently people's willingness to spread positive WOM about beneficiary companies should be higher when the company makes in-kind donations compared to monetary contributions or when no specific contribution type mentioned.

H4b: When company size is perceived to be large (vs small), perceived sincerity and subsequently people's willingness to help beneficiary companies should be higher when the company makes in-kind donations compared to monetary donations or when no specific contribution type mentioned.

Chapter III: Methods

Current research has examined the presented hypotheses with one big data study, and five experiments, and showed that when a company has a beneficiary status during a crisis and communicates their CSR actions, people become less likely to spread positive WOM about the company (H1a) (Study1a, Study 1b, Study 3, Study 4, and Study 5), and their willingness to help the company (H1b) reduced significantly (Study 2, Study 3, Study 4, and Study 5). From a marketing perspective, we define crises as negative events that have a detrimental impact on the marketplace, affecting not only corporations but also the general public. Consequently, in our process of selecting crises, we made decisions based on whether these two conditions were satisfied. As a result, we considered scenarios such as the COVID pandemic (Study 1a, Study 2, Study 3), the Brazilian fuel oil crisis (Study 1b), wildfires in Turkey (Study 4), and Ukraine-Russia war (Study 5).

Study 1a was a big data study in which we analyzed user reactions to tweets posted by selected companies from the S&P 500 list during the early days of the COVID-19 pandemic using sentiment analysis. We scraped the tweets of these companies, as well as the user responses they received, and collected other relevant control variables that could be accessed through their company profile pages. To operationalize our independent variable, we asked 30 Mturkers to rate the beneficiary status of each company within their respective industries using a 7-point Likert scale.Our results indicated that the beneficiary status of companies had a negative impact on the sentiment scores of user responses. This mechanism has been repeated experimentally in Study 1b. It has also been showed that perceived sincerity mediates this relationship as an underlying psychological mechanism in a way that beneficiary companies' CSR messages are perceived to be less sincere during crises, and in turn, people showed less willingness to spread positive WOM (H2a) and less willingness to help those companies (H2b) (Study 2, Study 3, Study 4, and Study 5).

Moreover, the perceived size of the company moderated this mediation path in a way that large beneficiaries are perceived to be significantly less sincere in their CSR communications and, in turn, willingness to spread positive WOM (H3a) and consumers' willingness to help (H3b) for these companies was significantly lower than other companies (Study 4).

Finally, it has been found that the communicated contribution type can be used as a strategic tool to moderate the negative effect for large beneficiary companies. When a large beneficiary company communicates their material donations (vs. monetary contributions or no specific contribution type mentioned) as a crisis relief effort, the negative effect of size and status on perceived sincerity dissipates where people's willingness to spread positive WOM (H4a) and willingness to help the company (H4b) becomes higher than when the company makes monetary contributions or mentions no specific contribution type (Study 5). Thus, this research shows that in-kind donations can function as a buffer against the negative interaction effect between company status and company size on the perceived sincerity of a company and the subsequent evaluations of the company.

Study 1a: Sentiment of User Responses to Companies During COVID Pandemic

In study 1a, a python program has been compiled to scrape data from the Twitter accounts of selected companies from the S&P 500 list. The corresponding code can be found in the Appendix.

Preprocessing. As the only criterion to select the companies, it has been focused on whether companies had an active Twitter account. That said, in the initial dataset, 166 such companies have been collected. Between January 1, 2020, and April 22, 2020, during the early stages of the COVID pandemic, 9435 tweets from these companies' Twitter accounts with 73485 direct user replies that they had received have been scraped. It has been aimed to analyze tweets posted by companies and the replies they received from users on Linguistic Inquiry and Word Count (LIWC) algorithm (Pennebaker et al., 2015). Applying data cleaning methods suggested by Pennebaker et al. (2015), the hashtags, mentions, URLs, and email addresses in those tweets have been standardized by replacing them with SubTwitterHashtag, SubTwitterName, SubUrl, and SubEmailAddress, respectively. Further, using the *langid* package (Lui, 2011) from the python library, non-English tweets have been detected, since LIWC is not programmed to analyze nonenglish texts. Nonreadable tweets due to format differences in encoding and those company tweets that have received no replies from users have also been eliminated. For example, some users used alphabetic characters to draw figures and shapes rather than forming meaningful sentences. When they are scraped, those statements are encoded in nonreadable formats and thus had to be eliminated. Most importantly, only direct statements from the companies have been collected.

Therefore, there were 4122 company tweets in the final data set with 68191 user replies from 161 companies represented by 20 different industries (5 companies are eliminated naturally during data curation processes). These replies were from 68191 unique users. To remove duplicates, account IDs were used as the reference for this operation, as they serve as unique identifiers on the platform. Therefore, only the first comment made by each user has been taken into account. Table 1 shows those companies together with the number of tweets and user replies to those tweets in the final dataset.

Insert Table 1 about here.

Variables of Interest

Average sentiment scores of user replies. The dependent variable was the average sentiment scores of user replies. Average sentiment scores of user replies have been used as a proxy to examine users' willingness to spread positive WOM about each company. Sentiments of user replies have been analyzed on the Linguistic Inquiry and Word Count (LIWC) algorithm (Pennebaker et al., 2015) and the average of total sentiment scores for each company tweet has been taken. LIWC assigns a positivity score for each statement on a scale from 0 to 100, as greater positivity corresponds to greater numerical values in the scale.

Company status. Using the same method implemented by Woolley et al. (2022), independent variable (company status) has been created by asking 30 Mturkers (40% Female; M_{age}= 41) their opinion about companies' status in the changing market environment (e.g., lockdown, social distancing, travel restrictions) during the COVID pandemic on a 7-point Likert scale ranging from "Complete Loss" to "Complete Benefit". Participants received $1 for their participation. Participants were given the industry information and names of a few companies operating within each corresponding industry as a reference (see Table 2) to eliminate the potential effects of participants' unfamiliarity with certain industries and company names. It has been assumed that people assessed the status of companies based on industry information rather than company-level information since COVID's effects varied at the industry level rather than the company level. Therefore, the averages of participant ratings for each industry have been taken and been used as a proxy to assess the status of companies as the independent variable (see Table 2).

Insert Table 2 about here.

Control Variables

Firm size. Previously, Saxton et al. (2019) employed a firm's assets as a proxy to measure firm size, and Attig et al. (2016) used the logarithm of a company's total sales to create a size variable. Following the procedures of the past research in using objective measures to create a size variable (Woolley et al., 2022), natural logarithm of market equity has been used for each firm by calculating the product of stock price and the number of shares outstanding at the end of the month (Fama and French, 1995).

Contribution type in tweet content. It has also been examined whether the content of company tweets made any difference in the sentiments of user replies. The contribution type mentioned in the tweets has been examined by coding each tweet according to whether they are neutral (no contribution information) or mention either money or in-kind contributions. To perform content analyses, a Latent Dirichlet Allocation (LDA) algorithm has been compiled adapting the corresponding python algorithm code from Li (2018). Each company tweet has been split into the words they contain and tokens out of each word have been derived by lemmatizing them. In the topic analyses, the term frequency-inverse document frequency (tf-idf) model has been adopted as a summarizer since the results of prior work showed the superiority of this model's accuracy compared to other models (Christian, Agus, and Suhartono, 2016). Tf-idf model takes not only the frequency of a token's appearance in a single statement but also its frequency of appearance in the whole corpus. Thus, it reflects the corpus level and statement-level importance of each token (Salton et al., 1988).

As the most important stage in building the LDA algorithm, the most feasible α and β values had to be assessed to finetune the algorithm for the most coherent allocation results. In the context of topic modeling, α indicates the density of topics in a document, while β indicates the density of words in a topic. A higher value of alpha indicates that a document covers a larger number of topics, whereas a lower alpha value implies that the document focuses on fewer topics. Similarly, a high beta value indicates that a topic contains a larger number of words across the corpus, while a low beta value implies that the topic is represented by only a few words (Griffiths and Steyvers, 2004). Therefore, finding feasible α and β values is crucial since these values specify the assumptions that the algorithm will follow in allocating topics. For example, an α value smaller than 1 means that topics are significantly separate from each other (Lu, Mei, and Zhai, 2011), whereas large β values are expected to increase the similarity between topics, making them more heavily accumulate on certain areas as different topics consist of similar words (Griffiths and Steyvers, 2004). As a rule of thumb, the existing literature suggests that the most feasible α value can be calculated as α =50/K, where K is the number of topics to be generated and β can be taken as 0.1 as a fixed value (Griffiths and Steyvers, 2004; Stevyers and Griffiths, 2007). That said, the number of topics to create has been assessed as 50, although Griffiths and Steyvers (2004) previously showed that creating 300 topics provides the most accurate results according to log likelihood accuracy comparisons. However, due to the technical limitations of the tools used in this research (computing power), it has been decided to select a smaller topic number, such as 50 (See Table 3).

<u>Insert Table 3 about here.</u>

After the algorithm processed the data, each company tweet was assigned 50 different probability scores according to their likelihood of being associated with each created topic. To each tweet among these 50 topics, to which each tweet was associated with different probabilities, the topic to which the tweet was associated with the greatest probability score has been allocated. Later, another python program has been created to scan particular key statements in each tweet to heuristically allocate those tweets to either of the contribution types as money or in-kind when an associated key statement match is detected and neutral when there was no match. Those keywords have been selected by observing randomly selected 1000 tweets and scanning the most relevant words to each contribution type using intuition, such as "money donation, relief fund, financial help" for money contributions or "food donation, equipment donation, supplies" in-kind contributions.

Next, tweets have been seperated according to their content (contribution types) into two data sets to divide the topics according to their relatedness to money contributions or in-kind contributions. To do so, for each data set, the ratio of the number of tweet matches detected by the code in each topic to the total number of tweets allocated to that particular topic have been calculated. Values of mean($ratio_i$) + standard deviation($ratio_i$) for each dataset have been calculated, where i represents one of two datasets created. Only those topics with ratios greater than the calculated mean(ratio) + standard deviation(ratio) value for each dataset are assumed to be associated with that particular dataset and assigned the corresponding content label as either money, in-kind, or neutral. That said, topics 7, 10, 14, 19, 20, 22, 32, and 42 have been found to be more related to money contributions (N_{money}=544 tweets), whereas topics 13,16 and 36 have been found to be more related to in-kind contributions (N_{inkind}=218 tweets). The rest of the tweets were labeled as "neutral." (See Tables 4, and 5).

<u>Insert Table 4 about here.</u>

<u>Insert Table 5 about here.</u>

Location information. The effectiveness of CSR communications in leveraging company reputation may be highly dependent on the company's location (Nekhili et al., 2017). The location of a company's headquarters is found to be affecting the perceived fit between CSR actions performed by the company and the company's operations. For example, locally performed CSR actions increase consumer support for corporate CSR activities by improving attitudes toward the organization (Grau and Folse, 2007), since people prefer local CSR initiatives to a greater extent (Drumwright, 1996; Ross, Stutts, and Patterson, 1991; Smith and Alcorn, 1991). Therefore, location information provided by companies could impact the sentiment of customer responses. Location information has been operationalized by collecting companies' disseminated location from their Twitter account biographies and coding this information as (1) if the location is within US borders and (0) if the given location is not in US borders or no location information is publicly given.

Daily infection cases. The daily number of new COVID infections have been extracted from John Hopkins University's COVID tracking website (Johns Hopkins Coronavirus Resource Center, 2020) to control for the potential effects of increasing mortality salience with increasing infection rates on the sentiment of user responses (Evers, Greenfield, and Evers, 2021). To standardize, this variable has been log-transformed by taking the logarithmic base as 10.

LIWC dimensions. Four main linguistic dimensions (Analytical Thinking, Clout, Authenticity, Sentiment) and one word count variable (Number of words in a company's tweet) from Pennebaker's LIWC (Pennebaker et al., 2015) have been employed to generate content-level covariates. LIWC assigns scores to each statement ranging between 0 and 100 based on statements' associations with these four linguistic dimensions.

The number of words in a company's tweet may explain how deeply the company elaborates itself. Therefore, it could have an impact on user replies. Considering this possibility, the number of words in the company's tweet have been employed as a control variable.

The analytical thinking dimension of linguistics reflects the degree to which the author thinks in formal, logical, and hierarchical formats. Low values in this linguistic dimension imply that the author communicates more personally and intimately, whereas high values show greater formality in communications (Boyd and Pennebaker, 2015; Jordan et al., 2019: Pennebaker et al., 2014). Analytical thinking can be rewarded in formal settings yet punished in others (liwc.app/help/liwc). Therefore, analytical thinking has been examined in company tweets as a covariate in the analyses.

The clout of a statement is related to the author's self-confidence, social power, and leadership (liwc.app/help/liwc). This dimension reflects the author's social status in the corresponding social setting (Drouin et al., 2017; Fox and Royne Stafford, 2021; Kacewicz et al., 2014). For this reason, the clout of company tweets can have a differential impact on the sentiment of user replies, as high values of this dimension signal greater leadership during the COVID crisis.

The authenticity of a statement communicates the author’s sincerity (Langon and Kumar, 2019). Therefore, tweets’ authenticity on LIWC has been analyzed and LIWC-assigned authenticity scores have been used as a covariate to measure the impact of this dimension on the sentiment of user replies.

A tweet's tone could affect the tone of responses it would receive since people are more likely to respond positively to positive emotions (Monzani et al., 2021). Therefore, sentiment scores assigned by the LIWC algorithm to company tweets have been employed as another potential covariate to examine in the analyses.

The popularity of the company on Twitter. People are more likely to respond to popular accounts more positively on social media (Kim et al., 2016). Therefore, the popularity of companies' Twitter accounts has been calculated using the following formula adapted from McCord and Chuah (2011);

$$P(j)=\frac{n_i(j)}{n_i(j)+n_o(j)} \tag{1}$$

where P(j) is the individual popularity score of company j, and $n_i(j)$ and $n_0(j)$ are the number of followers and followees that the company j has, respectively.

Covariates related to companies' twitter activity. The activity levels of a Twitter account reveal a significant amount of evidence about the account's legitimacy. For instance, the number of tweets posted per day by Twitter accounts can be used as a parameter to distinguish between Twitter bots and actual users (Haustein et al., 2016). In a similar vein, greater intensity of social media use indicates stronger social connections with others in the same network (Chen et al., 2010), generating greater positive attitudes toward the account. Therefore, building on past research (Alrubaian et al., 2016; Haustein et al., 2016), companies' activities on Twitter have been calculated based on the number of tweets and media (pictures and videos) they posted daily, the number of followings they made and the number of followers they gained per day as well as the daily number of likes they sent to other users' tweets. Each of these metrics has been operationalized separately and been employed as separate covariates by dividing their total number as given on companies' accounts by the company's age in days.

Age of the companies' twitter accounts. ***F***inally, age of the companies' Twitter accounts has been calculated in days based on the given information regarding the account's creation date on their Twitter pages as the last control variable. Employing account age as an additional covariate was important since older company accounts could be known for longer by Twitter users, which could create familiarity-related biases in users' responses to company tweets.

Results. To examine the effect of companies' perceived status on the sentiment of user responses, a two-steps linear regression approach has been adopted in which the first step only included the focal variable, company status scores, and in step 2, control variables entered in the equation. Multicollinearity test result were given in the Table 6. To check for potential multicollinearity between variables, variance inflation factors (vif) for each variable have been analyzed. The maximum value of vif scores was 2.96 (See, Table 6. Previously, Nekhili et al. (2017) considered VIF values below 3 to be within an acceptable range. Therefore, it has been concluded that multicollinearity is not a concern in the analyses. Bivariate correlations between the variables can be seen on Table 7.

Insert Table 6 about here.

Insert Table 7 about here

Main effect. Results of the linear regression analysis showed that the beneficiary status of companies had a significant negative effect on the sentiment of user replies (β= -1.74, *SE* = .72, $p<.05$), showing that as companies' perceived status became more "beneficiary" (as companies are perceived to be benefitting more from the COVID crisis), the user replies to their Twitter communications became significantly more negative. This effect remained significant even after control variables were entered in the equation in step 2 (β= -1.78, *SE* = .87, $p<.05$) (See Table 8). That said, every 1-unit increase in the perceived status of the company led positivity of user responses to decrease 1.78 units. Thus, hypothesis H1a. The results of covariate analyses have been discussed in the next section under "Other Analyses."

Insert Table 8 about here.

Other analyses. Besides the main effect, other intriguing results have been obtained. For example, to analyze the effect of contribution type two dummy variables have been created where money (D1) and in-kind (D2) contribution factors are labeled as 1 and other factors as 0, separately. Both D1 (β= .10, *SE* = 1.24, *p*>.1) and D2 (β= 1.44, *SE* = 1.89, *p*>.1) gave nonsignificant results. These results suggest that communicated contribution type does not directly affect the sentiment of user responses.

Objective firm size variable also did not show any significant direct effect on user sentiments (β= -.34, *SE* = .33, *p*>.1). On the other hand, the location information showed a significant positive effect on the sentiment of user replies, suggesting that when a US company disseminated on their Twitter account that they were located in the US, their likelihood of receiving positive replies to their communications increased (β= 3.06, *SE* = 1.34, *p*<.05). Similarly, the positivity of company tweets (β= .06, *SE* = .01, *p*<.001) and the popularity of the company on Twitter (β= 30.8, *SE* = 10.2, *p*<.01) increased the likelihood of company tweets receiving more positive responses. Finally, the number of likes a company sends to other users' posts showed a negative association with the sentiment of user replies (β= -.35, *SE* = .01, *p*<.001). This effect may have emerged because users may have made attributions of sycophancy to the companies that like the posts of other users. However, this suggestion requires further research to make solid inferences.

Discussion. With a big data analysis on Twitter, this study showed that beneficiary status negatively affects WOM as people showed a greater inclination to respond to company tweets negatively. Using the sentiment of user replies as a proxy to explain users' willingness to spread positive WOM, this study showed that these results support the hypothesis, H1a. While using sentiment analysis as a proxy has its advantages, it also has certain limitations. For instance, it provides only a limited insight into people's real behavioral patterns as it mainly focuses on emotions and may not always reflect the actual attitude or behavior. Additionally, sentiment analysis relies on a machine learning approach which can miss the context and intended meaning of certain statements. The sentiment analysis used in this research was limited to the English language, which means that it may not capture the sentiments of non-English speakers. These limitations need to be taken into account when evaluating Study 1a.

Study 1a focused on companies from the United States and used convenience sampling, which has limitations that may reduce the generalizability of our results to other companies from different countries and increase the risk of bias (Jager, Putnick, and Bornstein, 2017). Additionally, the possibility of outliers in the data is higher with convenience sampling, which can contribute to potential biases (Etikan, Musa, and Alkassim, 2016). To address these limitations and validate our findings under a different scenario, we conducted an experimental study using the 2018 supply crisis in Brazil as the stimulus material.

Study 1b: Supply Crisis in Brazil

Study 1b focuses on another crisis scenario, yet this time from Brazil. In 2018, Brazil underwent a prolonged supply crisis, as truckers went on strike and blocked highways for days to protest government policies that increased fuel oil prices. Because of the strike, supply chains of many essential items, including fuel oil, were disrupted (Rapoza, 2018). This situation caused fuel prices to increase further and placed fuel oil companies in a beneficiary position from this crisis even though those companies did not do anything, in particular, to increase fuel prices as price increase was a government sanction (Phillips, 2018).

With this scenario, in study 1b, the effect of a company's status on people's willingness to spread positive WOM about the company has been examined under experimental conditions using a different crisis scenario in a foreign country setting to increase the generalizability of the results from Study 1a.

Design and Procedure. 200 participants from Amazon MTURK have been recruited (40% Female; Mage= 38.49) and randomly assigned to one of the three conditions (-1: Losing Company; 0:Control Condition; 1: Beneficiary Company) in a between subjects design. Participants received $1 as compensation for their participation, and no data were eliminated from the dataset.

Regardless of what condition they were randomly assigned to, participants firstly read the following information about the Brazilian supply crisis of 2018, which was adapted from Rapoza (2018):

"The strike created a crisis of supply in almost each product category between April and June 2018. Supply shortage changed the market conditions drastically, making people from all ages and all social backgrounds suffer negative consequences since the shortage prevented them from accessing essential products. For example, during the crisis, fuel prices have risen 12 times more due to the supply shortage. Luckily, this price increase benefitted fuel oil companies increasing their profit. However, other companies such as transportation companies were not that lucky since their services were disrupted due to road barricades, and they lost money."

After participants read the common information, they were either informed that the tweet they were about to read was posted by a Brazilian fuel oil company that was known to be making profit during the supply crisis (beneficiary condition), a Brazilian transportation company which is known to be losing profit due to supply crisis (losing condition), or a Brazilian company without any further information (control condition).

Next, all the participants read the same tweet, which was adapted from a real tweet posted by Amazon during the COVID crisis (Amazon 2020); "We are making every effort to support those directly and indirectly impacted by the supply crisis and to give back to our community.". This tweet was particularly selected because it was making a salient emphasis on company effort, and it was posted by a relatively large real company.

People's willingness to spread positive WOM about companies was measured on 7-point Likert scale using four items such as "I would speak highly about this company.", "I would recommend this company to others.", "I would speak favorably about this company to others." and "I would talk about this company positively." (α=.87).

To check the manipulation of company status, participants have been asked to rate to what extent they agree/disagree with the following statements on a 7-point Likert scale, "Supply crisis helped the company make more money than before.", "Supply crisis became profitable for this company.", "Supply crisis enabled the company to prosper.", "Due to supply crisis, the company has lost a lot of money." (R), and "Supply crisis became disastrous for the company's business." (R) (α=.62).

Results

Manipulation check. The results of a Tukey test showed that people perceived the company in the beneficiary condition to be benefitting to a greater extent than the losing company (β_{B-L}= .88, SE = .15, p<.001), and the company in the control condition was perceived to be benefitting to a greater extent than the losing company (β_{C-L}= .37, SE = .15, p<.05). Finally, the difference between the beneficiary company and the company in the control condition was also significant

($\beta_{B\text{-}C}$= .51, *SE* = .15, *p*<.01). Thus, these analyses showed that company status manipulation was successful.

Main effect. Contrast analyses through the Tukey test showed that people's willingness to spread positive WOM about beneficiary companies was significantly less than both control ($\beta_{B\text{-}C}$= -.58, *SE* = .19, *p*<.01) and losing company ($\beta_{B\text{-}L}$= -.64, *SE* = .19, *p*<.01) conditions. These results suggest that people were significantly less willing to spread positive WOM about beneficiary companies than others, even though other companies communicated the same CSR statements as the beneficiary company. Therefore, H1a gained further support in an experimental setting.

Discussion. Experiment A showed that beneficiary companies generate significantly less willingness to spread positive WOM compared to losing company and control conditions. This way, these results further support H1a in an experimental setting.

Study 2: Is the Support for Small Businesses Unconditional during Crises?

Study 2 investigated people's willingness to help small businesses during the COVID pandemic. During the COVID pandemic supporting local businesses was highly endorsed by policymakers and charities (Frazier, 2021). Study 2 was inspired by the "Code Red" status many North American cities had adopted in the early stages of the pandemic (Rosen, 2020). During the Red Code period, many small-size firms such as local restaurants had to close their stores until further notice (Bartik et al., 2020). Therefore, in study 2, the effect of company status on people's willingness to help small local companies and the mediating role of perceived sincerity in this relationship have been examined.

Design and Procedure. The study was conducted in 2021. Participants were 194 students enrolled in an introductory marketing course at a large Canadian University in return for course credit (56 % Female; M_{age}= 21.72). Participants were randomly assigned to one of three conditions (-1: Losing Company; 0:Control Condition; 1: Beneficiary Company) in a between subjects design. Regardless of what condition they were randomly assigned to, participants first read the following hypothetical information:

“During the COVID crisis, most North American cities underwent several restriction phases. The following information is taken from the website of the municipality of a small North American Town; ‘Provincial government declared code 'Red' which issues stricter restrictions on public gatherings. With code 'Red,' all public gatherings will be limited further. Cafes and restaurants that do not have delivery channels will be indefinitely closed. Only those that have delivery channels will remain in operation as only options for citizens in lockdown.’”

After participants read the common information, they were all informed that the tweet they were about to read was posted by "Jenny's" a local restaurant in town. In addition to that, participants in the beneficiary condition were told that Jenny's was the only restaurant in town that had delivery channels; therefore, it remained open and could continue selling during the Code Red period. In contrast, participants in the losing condition were told that Jenny's was the only restaurant in town that did not have delivery channels and therefore remained closed and could not continue selling during the Code Red period. Participants in the control condition did not have any additional information about the restaurant called "Jenny's". All the participants read the following tweet as it was ostensibly portrayed as sent by the company during the cirsis period; "We are making every effort to support those directly and indirectly impacted by the COVID crisis and to give back to our community." as in Study 1b.

Participants’ willingness to help the company has been measured with a single item by asking them to indicate on a 7-point Likert scale to what extent they would agree/disagree with the following statement: “I would like to engage in actions that can help this company.” (*M* =

5.05, *SD* = 1.16). The scale items to measure the perceived sincerity of the company were adapted from Rifon et al. (2004). Participants were asked to indicate their agreement or disagreement with the following statements: "This company truly cares about the public.", "This company has a genuine concern for the welfare of the public." and "This company really cares about providing a better market environment for the public." (α=.78). An alternative mediation path has also been tested by using a scale to measure people's felt compassion towards the company (Hwang et al., 2008). To do so, the items such as "I feel compassion for this company." and "I got tender feelings toward this company." have been used (r=.63). To check the manipulation of company status, the same manipulation check questions as in study 1b has been used.

Results

Manipulation check. The manipulation was successful. People perceived the company to be benefitting from the crisis in the beneficiary condition to a greater extent than the losing condition ($\beta_{B\text{-}L}$= 1.92, *SE* = .19, p<.001), and the company in the control condition was perceived to be benefitting to a greater extent than in the losing condition ($\beta_{C\text{-}L}$= .54, *SE* = .19, p<.01). Finally, the difference in the perceived status of the company in the beneficiary and in the control condition was also significant ($\beta_{B\text{-}C}$ = 1.38, *SE* = .19, p<.001). Therefore, it has been concluded that the company status manipulation was successful.

Main effect. Post-hoc tests in a one-way ANOVA showed that people's willingness to help the restaurant in the beneficiary company condition was significantly less than the control ($\beta_{B\text{-}C}$= -.70, *SE* = .20, p<.01) and losing conditions ($\beta_{B\text{-}L}$= -.48, *SE* = .20, p<.05). These results suggest that people were significantly less willing to support small-sized local companies when they are in the beneficiary side in a crisis environment than when they are in the losing side, or when no such information was provided. Therefore, findings here supported H1b.

Mediation of perceived sincerity. Mediation analyses has been conducted on SPSS using model 4 on Hayes's PROCESS module (Hayes, 2012) with two dummy variables, X1 (Control condition =1) and X2 (Beneficiary condition=1), to code the status variable.

First, the effect of company status on perceived sincerity was negative and significant, yet only for dummy variable X2 (β_{X2} = -.60, *SE* = .20, *p*<.01). The same effect did not reach significance for X1 (β_{X2} = -.03, *SE* = .20, *p*>.1). Additionally, the effect of perceived sincerity on people's willingness to help the company was positively significant ($\beta_{Sincerity}$ = .61, *SE* = .06, p<.001). The analyses of indirect effects showed that perceived sincerity mediates the relationship between company status and people's willingness to help the company, yet only for the second dummy variable (X2), since indirect effect of perceived sincerity was significant only for X2 (β_{X1} = -.02, *SE* = .12, CI = [-.25, .22]; β_{X2} = -.36, *SE* = .13, CI = [-.63, -.13]). The direct effect of X2 on willingness to help became nonsignificant when perceived sincerity was added as a mediator to this equation (β = -.11, *SE* = .16, *p*>.1). Therefore, perceived sincerity mediated the effect of company status on people's willingness to help a company. That is, despite being small-local companies, beneficiary companies were perceived to be less sincere, which in turn led to less willingness from public to help those companies than other companies (losing companies and control conditions). Here, hypothesis H2b has been supported.

Alternative mediation path. The compassion for the company has been tested as an alternative mediation by entering this variable as a parallel mediator to perceived sincerity with company status coded as two dummy variables. The results showed that both perceived sincerity and compassion mediated the effect of company status on willingness to help the company together.

However, indirect effects were only significant for X2 (Beneficiary condition =1) for both mediation paths ($\beta_{X1Sincerity}$ = -.01, *SE* = .07, CI = [-.15, .14]; $\beta_{X2Sincerity}$= -.21, *SE* = .08, CI = [-.40, -.06]; $\beta_{X1Compassion}$ = .09, *SE* = .08, CI = [-.05, .28]; $\beta_{X2Compassion}$ = -.15, *SE* = .09, CI = [-.34, -.001]). Both people's perceived sincerity and their felt compassion in beneficiary company conditions were significantly less than losing and control conditions, which, in turn, led to people's willingness to help those companies to be significantly lower. These results suggest that mediation through perceived sincerity is robust and remains significant even after a potential alternative explanation such as compassion is added to the equation. The mediating effect of compassion is discussed in the next section.

Discussion. Study 2 showed that even for small businesses, people's willingness to help beneficiary companies during a crisis is significantly lower than other companies because beneficiary companies were perceived to be significantly less sincere when they communicated their CSR efforts. These results challenged the "go local, eat local" mantra during the COVID crisis. Consumers made fine distinctions as to who is beneficiary and who is losing during the crisis and the status of the company alone affected the perceived sincerity of the firm's CSR communication and consumers' willingness to help.

In addition, it has been found that compassion was a parallel mediator that mediated the effect of company status on people's willingness to help the company together with perceived sincerity. This result suggests that while consumers questioned beneficiary companies' sincerity in relief efforts during the pandemic, they also felt significantly less compassionate for these companies compared to the companies in the losing and control conditions.

Study 3 focuses on large companies in the same COVID context yet employing a scenario regarding a different industry, car insurance.

Study 3: Large Companies during COVID Pandemic

Focusing on large companies, in Study 3, COVID context has been readdressed with companies from a different sector, insurance. This study was conducted in 2021.

Design and Procedure. 120 participants from Amazon MTURK have been recruited (45% Female; M_{age}= 36.39). Participants received $1 as compensation for their participation. No data were eliminated from the dataset. Besides employing the same scales that was employed in study 2, people's willingness to spread positive WOM has also been measured as an additional dependent variable employing the same scale used in study 1b. Again, following the same procedure as in other studies, participants first read a mutual information regardless of what condition they were randomly assigned to. However, this time the informative text did not contain any information regarding what makes companies advantaged or disadvantaged in this crisis. The information is adapted from web (Sharma, 2020) as follows:

"Please read the given information about the effects of the COVID pandemic on society. The information has been taken from the web as it is.

'Millions of enterprises face an existential threat. Nearly half of the world's 3.3 billion global workforce are at risk of losing their livelihoods. Informal economy workers are particularly vulnerable because the majority lack social protection and access to quality health care and have lost access to productive assets. Without the means to earn an income during lockdowns, many are unable to feed themselves and their families. For most, no income means no food, or, at best, less food and less nutritious food.'"

This information did not include any hint about the type of companies being investigated. Next, all the participants were informed that the social media post they were about to read was posted by "Autocov", a large car insurance company. In addition to that, participants in the beneficiary company condition were given that Autocov is known to be making profit during the pandemic due to significantly fewer accident claims filed by drivers. In contrast, participants in the losing condition were given that Autocov is known to be losing profit due to significantly fewer additional coverages purchased by drivers. Participants in the control condition did not have any additional information about Autocov. All the participants read the adapted version of the same social media post used in previous studies.

Results

Manipulation check. Manipualtion tests using a one-way ANOVA showed that manipulation of the company status was successful (F= 1.24, df_1 = 2, df_2=117, p<.001). Pairwise contrasts through the Tukey test showed that people perceived the beneficiary company as benefitting from the crisis to a greater extent than the losing condition ($M_{B\text{-}L}$= 1.22, SE = .21, p<.001), and the company in the control condition was perceived to be benefitting to a greater extent than the losing company ($M_{C\text{-}L}$= .53, SE = .22, p<.05). Moreover, the difference between the beneficiary company and the company in the control condition was also significant ($M_{B\text{-}C}$ = .70, SE = .21, p<.01). This indicated that applied manipulation was successful.

Main Effects. The main effect of beneficiary status on willingness to spread positive WOM was significant as people showed less willingness to spread positive WOM when Autocov was perceived as a beneficiary company compared to control ($\beta_{B\text{-}C}$= -.77, SE = .24, p<.01) and losing company conditions ($\beta_{B\text{-}L}$= -.71, SE = .23, p<.01). Thus, H1a has been confirmed for the third time. Further analyses showed that the difference between the effects of beneficiary and control conditions on participants' willingness to help the company was significant ($\beta_{B\text{-}C}$= -.74, SE = .28, p<.05), yet the difference between the beneficiary and losing conditions was only marginally significant ($\beta_{B\text{-}L}$= -.65, SE = .27, p<.1). This way, H1b has been only partially supported in Study 3. This result will be addressed in the discussion part of this study.

Mediation of perceived sincerity. Mediation analyses have been conducted on SPSS using PROCESS and by creating two dummy variables, X1 (Control condition =1) and X2 (Beneficiary condition=1), to code company status in each model: willingness to spread positive WOM (Model 1) and willingness to help the company (Model 2). The effect of company status on perceived sincerity was negative and significant, yet only for X2 ($\beta_{X2} = -.72$, $SE = .25$, $p<.01$). The effect of X1 on perceived sincerity of the company was nonsignificant ($\beta_{X1} = -.15$, $SE = .25$, $p>.1$). Moreover, the effect of perceived sincerity was positively significant on both people's willingness to spread positive WOM ($\beta_{Sincerity} = .72$, $SE = .06$, $p<.001$) and their willingness to help the company ($\beta_{Sincerity} = .68$, $SE = .08$, $p<.001$).

Further analyses showed that perceived sincerity mediates the relationship between company status and people's willingness to spread positive WOM about the company, but only for the second dummy variable (X2), since indirect effect of perceived sincerity was significant only for X2 ($\beta_{X1} = -.11$, $SE = .15$, CI = [-.39, .18]; $\beta_{X2} = -.52$, $SE = .21$, CI = [-.95, -.14]). The effect of X2 on willingness to spread positive WOM about the company when perceived sincerity is added as a mediator to this equation became nonsignificant ($\beta = -.19$, $SE = .16$, $p>.1$). Therefore, perceived sincerity fully mediated the effect of company status on people's willingness to spread positive WOM about the company, in a way that beneficiary companies were perceived to be less sincere and, in turn, the public's willingness to spread positive WOM about these companies was significantly lower than others. That said, H2a has been supported.

On the other hand, perceived sincerity also mediated the relationship between company status and people's willingness to help the company, again only for the second dummy variable (X2), since indirect effect of perceived sincerity was significant only for X2 ($\beta_{X1} = -.10$, $SE = .14$, CI = [-.35, .18]; $\beta_{X2} = -.49$, $SE = .19$, CI = [-.88, -.14]). The significant mediation path indicated that beneficiary companies were perceived to be less sincere. In turn, the public's willingness to help those companies was significantly lower than other companies. Hence, H2b found support once more.

Discussion. Study 3 focused on large companies. People were less willing to spread positive WOM about beneficiary companies and less willing to help them, although, for the latter variable, the evidence was weak. Moreover, perceived sincerity mediated this path in a way that beneficiary companies' perceived sincerity was significantly lower than other companies. Hence,further support for the proposed mediation path has been obtained. This study’s weakness in supporting H1b in Model 2 may have occurred due to the companies' industry. Participants may already have existing negative attitudes toward insurance companies (Ghasemaghaei et al., 2016); therefore, their losing status may have not stimulated significantly more willingness to help losing companies than beneficiary companies. However, this suggestion needs further investigation.

Study 4: Turkey’s Wildfires

Study 4 examines the moderating effect of company size on the mediating effect of perceived sincerity of the company in its CSR communications. In this study, a new scenario has been employed as wildfires in Turkey in 2021. When wildfires broke out in the coastal Turkey in the summer of 2021, Turkish society and the impacted communities were very skeptical of the support efforts from authorities, scrutinizing the sincerity of those efforts (Guzel and Bilginsoy, 2021). Therefore, this particular scenario has been employed to extend the hypothesis testing to a new crisis context to render stronger external validity.

Design and Procedure. Three hundred and fifty workers from Amazon MTURK (38 % Female; M_{age}= 40.17) participated in this study. Participants received $1 as compensation for their participation. The scales used in this study were taken from previous studies. Additionally, the perceived size of the companies has been manipulated as “small” and “large”. Participants again read a piece of mutual information regardless of what condition they were randomly assigned to. This information was adapted from a website article (Ertan, 2021) as follows;

“Turkey’s wildfires, which started on July 28, 2021, killed at least eight people and countless animals and turned hundreds of hectares to ashes. In the country's touristic south, known as the Turkish Riviera, villagers and tourists had to be evacuated, and some rescued by sea. In Bodrum alone, more than 4,000 tourists and staff were saved by the coast guard. Wildfires in Turkey's south coast delivered a fresh blow to the already struggling tourism sector as tourists abandoned the region." and the rest was fabricated to manipulate company status during the crisis. The fabricated information read as follows:

“However, fate smiled upon some other sectors, such as the real estate industry, since the property values of the affected fields along the coastline now greatly increased as deforestation by wildfires left large open fields with a scenic view for residential construction."

Next, depending on the company status and size manipulation conditions they were assigned to, participants read the following information:

Beneficiary-large:

“Below you will find an Instagram post, during wildfires by Viva, a large real estate company that owns lands along now-deforested open areas on the coastline. Viva is known to be a large corporate organization.”

Beneficiary-small:

“Below you will find an Instagram post during wildfires by Viva, a small real estate company that owns lands along now-deforested open areas on the coastline. Viva is known to be a small local company.”

Losing-large:

“Below you will find an Instagram post during wildfires by Viva, a large tourism company. Viva is known to be a large corporate organization.”

Losing-small:

“Below you will find an Instagram post during the wildfires by Viva, a small tourism company. Viva is known to be a small local company.”

Control-large:

“Below you will find an Instagram post during wildfires by Viva, a large company from Turkey. Viva is known to be a large corporate organization.”

Control-small:

“Below you will find an Instagram post during wildfires by Viva, a small company from Turkey. Viva is known to be a small local company.”

Finally, regardless of the condition they were assigned, the participants were informed that the company posted the same social media post used in previous studies.

Results

Manipulation check. Contrast analyses through the Tukey test in a one-way ANOVA showed that this study was only partially successful at manipulating the company status. The difference between the beneficiary and control conditions was significant ($M_{B\text{-}C}$= 1.02, SE = .13, p<.001). Similarly, the difference between the beneficiary and losing company conditions was also significant (M_{B-L}= 1.24, SE = .13, p<.001). However, the difference between control and losing company conditions was only marginally significant (M_{C-L}= .22, SE = .13, p<.1).

Second, the size manipulation has been tested by asking participants, "What is the size of the company?" on a 7-point Likert scale from "Very Small" to "Very Big." The result of an independent samples t-test showed that in large size condition, companies were perceived to be larger than in the small size condition (M_{small}= 4.04, M_{large}= 5.51, t= -9.55, df=289.5, p<.001). Therefore, the size of these hypothetical companies was successfully manipulated.

Main effects. Since variances were not homogenously distributed according to Levene's test statistic (F=15.6, df_1=2, df_2=347, p<.001), Welch test has been used to compare different company status conditions in terms of people's willingness to spread positive WOM. The results manifested that there was a significant difference between conditions (F=17.7, df_1=2, df_2=221.02, p<.001). Next, posthoc comparisons with the Tukey test showed that people had less willingness to spread positive WOM when Viva was positioned as a beneficiary company and communicated its CSR efforts during the wildfires than when it was positioned as a losing company (β_{B-L}= -.86, *SE* = .14, *p*<.001). Similarly, the difference between the beneficiary company and control condition was also significant (β_{B-C}= -.63, *SE* = .14, *p*<.001). Therefore, H1a was confirmed once more.

Next, people's willingness to support the companies has been examined. The analysis through the Welch test demonstrated that there was a significant difference between conditions (F=11.58, df_1=2, df_2=226.64, p<.001). People's willingness to help the beneficiary company was significantly less than the losing company (β_{B-L}= -.80, *SE* = .16, *p*<.001), and the control condition (β_{B-C}= -.58, *SE* = .16, *p*<.01). This way, further support has been found for H1b in Study 4.

Mediation of perceived sincerity. Mediation analyses have been conducted on SPSS using PROCESS and by creating two dummy variables, X1 (Control condition =1) and X2 (Beneficiary condition=1), to code company status in each model: Model 1 (DV: willingness to spread positive WOM), and Model 2 (DV: willingness to help the company). The results showed that only the effect of X2 was significant on perceived sincerity (β_{X2} = -.88, *SE* = .13, p<.001). The effect of the first dummy variable, X1, was only marginally significant (β_{X1} = -.24, *SE* = .13, p<.1). Therefore, for the rest of the analyses in Model 1, X2 was the only focus.

Further analyses showed that perceived sincerity mediated the relationship between company status and people's willingness to spread positive WOM about the company for dummy variable X2 (β_{X2} = -.72, *SE* = .12, CI = [-.96, -.49]). The effect of X2 on willingness to spread positive WOM about the company became nonsignificant when perceived sincerity was added as a mediator to this equation (β = -.14, *SE* = .09, p>.1). Therefore, perceived sincerity mediated the effect of company status on people's willingness to spread positive WOM about the company, in a way that beneficiary companies were perceived to be less sincere and, in turn, the public's willingness to spread positive WOM about these companies was significantly lower than others. That said, H2a has been supported.

On the other hand, perceived sincerity mediated the relationship between company status and people's willingness to help the company for X2 (β_{X2} = -.57, *SE* = .08, CI = [-.74, -.41]). Again, the direct effect of X2 became nonsignificant after perceived sincerity was added to the mediation path (β = -.08, *SE* = .12, p>.1). Therefore, perceived sincerity mediated the effect of company status on people's willingness to help a company in a way that beneficiary companies were perceived to be less sincere and in turn, the public's willingness to help those companies was significantly lower than other companies. Hence, H2b has been supported.

Moderation of company size. Next, the moderating effect of company size on the mediation path from company status to willingness to spread positive WOM (Model 1) and willingness to help the company (Model 2) through perceived sincerity have been analyzed. Two dummy variables, X1 (Control condition =1) and X2 (Beneficiary condition=1) have been created to code companystatus in each model and the analyses have been run through model 7 of PROCESS (Hayes, 2012) on SPSS. It has been found that the interaction effect between company status and company size was significant for X2 (β = -.69, SE= .26, p<.01). The same effect did not reach significance for X1 (β = -.04, SE= .26, p>.1). In both small and large size conditions, the beneficiary company perceived to be less sincere and generated significantly less willingness to spread positive WOM (βX2 = -.47, BootSE = .14, BootCI=[-.74, -.20] for small size; βX2 = -1.03, BootSE = .18, BootCI= [-1.39, -.70] for large size) (See, Figure 1) and less willingness to support the company (βX2= -.47, BootSE = .14, CI=[-.74, -.20] for small size; βX2 = -1.03, BootSE = .18, BootCI= [-1.39, -.70] for large size) (See, Figure 2).

Insert Figure 1 about here.

Insert Figure 2 about here.

More importantly, the proposed moderated mediation paths were significant only for dummy variable X2, with significant indices of moderated mediation in both model 1 (Index = -.56, BootSE= .22, BootCI=[-1.01, -.13]) and model 2 (Index = -.56, BootSE= .23, BootCI=[-1.04, -.13]). The negative signs of moderated mediation indices indicate that from small to large company conditions indirect effects through perceived sincerity decreases. Therefore, in large-beneficiary condition, the company was perceived to be less sincere than all other company-size combinations such that people's willingness to spread positive WOM and their willingness to help these companies were significantly lower than small-beneficiary, large-control, smallcontrol, large-losing, and small-losing company conditions. Hence, H3a and H3b have been supported in Study 4.

Discussion. In Study 4, hypotheses H3a and H3b gained further support as it has been shown that large size beneficiary companies are perceived to be less sincere and, in turn, generate significantly less willingness to spread positive WOM and less willingness to help the company. Additionally, the main effect of company status on people's willingness to spread positive WOM and help the company has been replicated as well as the mediating role of perceived sincerity between company status and dependent variables of both willingness to spread the WOM and to help the company. Hence, H2a and H2b gained further support in this study. However, results also showed that the difference between control and losing company conditions in manipulation tests was nonsignificant. This may be because the nature of wildfire crisis in Turkey falsely primed participants that all companies are on the losing side even in the control condition where no sector information was given. Therefore, results concerning the differences between control and losing conditions should be approached with caution in this study.

Study 5: Ukraine-Russo War

In Study 4, it was observed that large-beneficiary companies are perceived to be less sincere; thus, they generate significantly less willingness to spread positive WOM and elicit less willingness to help in public than other companies when they communicate the same CSR message during a crisis. Study 5 aims to uncover a communication strategy for large beneficiaries to eliminate or weaken this negative effect. Taking note of the humanitarian crisis that emerged during the Ukraine-Russo war in 2022, Study 5 used this crisis as the stimuli and introduced the "contribution type" as a potentially strategical tool in CSR communications.

There are a few differences in Study 5. First, company status has been measured as a continuous variable rather than being manipulated as in previous studies. Second, instead of social media, news media has been used as a platform to disseminate the company's CSR.

statement regarding the crisis. Third, in study 5, new variables have been explored such as schadenfreude (malicious jealousy) for companies, participants' identification with the victims of the crisis, perceived effort of companies from their CSR statements, and expectedness of companies' CSR behavior. Finally, for exploratory purposes, people's willingness to purchase the company's products and services has been analyzed as an additional dependent variable.

Design and Procedure. One thousand MTURK workers from amazon MTURK platform participated in this study in return for $1 as compensation for their participation. However, four data points have been removed as they came from the same IP addresses with the same numerical values, which increases the possibility that a worker might have taken the questionnaire more than once. Therefore, in the final dataset, the data of 996 Mturkers has remained for the final analyses (43.3% Female; M_{age}= 41).

A 2 (size: small (0) vs large (1)) X 3 (contribution: control (0) vs monetary (1) vs in-kind (2)) between-subjects design has been created. The company size has been manipulated with the following fictional information about a hypothetical camping gear manufacturing company; BearClaw, in which the company was either defined as a start-up (small) or a global company (large);

“Bearclaw is a start-up (global) company that has been operating in Ukraine and manufacturing every kind of camping equipment, including tents, air beds, heating tools, and other equipment for long-term survival in non-urban conditions."

Next, depending on the contribution condition they were randomly assigned to, participants read either one of the following information and were informed that the information had been taken from an interview with a representative from BearClaw:

Control:

"We are making every effort to support those directly and indirectly impacted by the war against Russia and to give back to the community."

Monetary:

"We are making every effort to support those directly and indirectly impacted by the war against Russia and to give back to the community. So far, we donated 10 million US dollars for those who had to abandon their houses to escape the war."

In-kind:

"We are making every effort to support those directly and indirectly impacted by the war against Russia and to give back to the community. So far, we donated 10 million dollars worth of food, medicine, and other survival equipment for those who had to abandon their houses to escape the war."

In this study, independent variable, company status, has been measured with the following three scale items adapted from the manipulation check questions in previous studies; "The war enabled the company to prosper", "Due to the war, the company has lost a lot of money." (R), and "The war became disastrous for the company's business." (R). All scales were shortened to three items to avoid potential attention problems (Hauser et al., 2019).

For exploratory reasons, adapting the scale items from Dalakas and Malancon (2012), malicious envy (schadenfreude) towards beneficiary status has been measured with three items such as "I would feel joy if this company went out of business.", "I would feel joy if this company faced legal consequences.", and "I would feel joy if this company suffered financial losses." (α=.93). Identification with the victims was measured through the following items adapted from Cairns et al. (2006): "As a person, I empathize with the victims of the war mentioned in the passage.", "As a person, I can feel the suffering of the victims of the war mentioned in the passage.", "As a person, I consider myself siding with the victims of the war mentioned in the passage." (α=.70). Perceived effort from the company's statement has also been measured with the following items, "The company puts a lot of effort toward helping the community during this crisis." and "The company works hard to help/support the community." (r=.47) and expectedness of company's CSR behavior with "I would not expect this company to help the society. (R)", "This company's helping behavior surprised me. (R)", and "Helping society is an unexpected behavior from such a company. (R)" (α=.77). Finally, people's preference of the company's products and services over others has been measured with the following items: "I would prefer this company's products/services over others.", "I would consider choosing this company's product and services over others.", and "The likelihood that I would purchase this company's product and services are higher than others." (α=.71). The rest of the scales in the survey were used as they were used in the previous studies.

Results

Manipulation check. The result of an independent samples t-test showed that in large-size conditions, companies were perceived to be larger than the small-size condition (t=7.5, df=994, p<.001).

Main effect. The effect of company status has been analyzed by creating three linear regression models on the dependent variables, willingness to spread positive WOM (Model 1), willingness to support the company (Model 2), and preference for the company's products (Model 3). The results were negatively significant for all three models; Model 1 (β= -.23, SE=.03, p<.001), Model 2 (β= -.19, SE=.04, p<.001), and Model 3 (β= -.30, SE=.03, p<.001), which indicates that as the company is perceived to be benefitting from the crisis more, people's willingness to spread positive WOM about the company, their willingness to support the company, and their preference of the company's products over those of others significantly decreased. These results supported H1a and H1b one more time.

Mediation of perceived sincerity. Similarly, the mediation of perceived sincerity has been examined with three dependent variables in three separate models, as done in the analysis of the main effect. The effect of company status on perceived sincerity was negative and significant ($\beta = -.29$, $SE = .03$, $p<.001$). Increased perceptions of beneficiary status decreased the perceived sincerity of the companies. Further analysis conducted through Hayes's Model 4 on PROCESS (Hayes, 2012), showed that perceived sincerity mediated the effect of perceived company status on dependent variables with significant indirect effects in Model 1 ($\beta = -.21$, $SE = .04$, CI = [-.28, -.14]), Model 2 ($\beta = -.17$, $SE = .03$, CI = [-.24, -.12]), and Model 3 ($\beta = -.21$, $SE = .04$, CI = [-.28, -.14]) in a way that as the companies are perceived to be in a beneficiary status to a greater extent, their perceived sincerity in their CSR communications decreased which, in turn, lowered people's willingness to spread positive WOM (Model 1), willingness to support the company (Model 2), and their preferences of the company's products over those of others (Model 3). Only in model 3, the direct effect of company status remained significant ($\beta = -.09$, $SE = .02$, $p<.001$). That said, this study manifested support for hypotheses H2a and H2b.

Moderation of company size. The proposed moderated mediation paths in the models have been tested using Model 7 from Hayes's PROCESS module (Hayes, 2012). Firstly, the effect of interaction between perceived company status and company size on perceived sincerity was significant ($\beta = -.13$, $SE = .07$, $p<.05$). Further analyses of indirect effects in all three models showed that as the company is perceived to be benefitting from the crisis (beneficiary) more, both in small size and large size company conditions, the company is perceived to be less sincere and people's willingness to spread positive WOM (Small size: $\beta = -.15$, $SE = .04$, CI=[-.25, -.07];

Large size: β = -.25, *SE* = .05, CI=[-.36, -.15]), willingess to support the company (Small size: β = -.13, *SE* = .04, CI=[-.21, -.06]; Large size: β = -.21, *SE* = .05, CI=[-.31, -.13]), and their preferences of the company's products over those of others (Small size: β = -.16, *SE* = .04, CI=[-.25, -.07]; Large size β = -.25, *SE* = .05, CI=[-.36, -.16]) were significantly lower.

However, the moderated mediation index was nonsignificant in each model; Model 1 (Index = -.09, BootSE= .07, CI=[-.23, .04]), Model 2 (Index = -.08, BootSE= .06, CI=[-.19, .03]), and Model 3 (Index = -.10, BootSE= .07, CI=[-.23, .04]) as in each model confidence intervals intersected with zero. Therefore, although the negative direction of indices suggests that statistically, the trend was in support of hypotheses H3a and H3b, it can be concluded that this study failed to find statistically significant support for those hypotheses. That said, the difference between large and small company information in terms of their effect on the mediation of perceived sincerity did not reach significance, even though when the company was large, the perceived sincerity followed a negative direction. It can be argued that in this study, the contribution type information may have overwritten the size information. People may have become more attentive to communicated contribution type than the company's size as they were making judgments about the company. If this is the case, this study may have employed a weak manipulation of size by using one word "start-up" or "global" to manipulate the company's size information.

Three-way interaction with contribution type. Next, the 3-way interaction between perceived company status, company size, and the contribution type in the CSR message has been analyzed. This interaction has been examined when all the other 2-way interactions are included in the model. The contribution type has been coded as 0 for control, 1 for monetary contribution, and 2 for in-kind contribution. In this way, two dummy variables were created to code contribution type as X1 (Monetary condition=1) and X2 (In-kind condition=1) to compare material and financial donation strategies with each other.

Further analyses through Model 11 of Hayes's PROCESS (Hayes, 2012) showed that there was a significant 3-way interaction between perceived company status, company size, and the contribution type on perceived sincerity (See, Figure 3), yet only for the second dummy variable X2 ($\beta_{X2} = .35$, $SE = .17$, $p<.05$). The same effect did not reach significance for the first dummy variable, X1 ($\beta_{X1} = .07$, $SE = .16$, $p>.1$). Next, employing a separate model approach, the indirect effects were tested through 3-way interaction with the dependent variables; willingness to spread positive WOM (Model 1), willingness to support the company (Model 2), and public's preference of the company's products (Model 3).

In Model 1, the results showed that increased perceptions of beneficiary status decreased perceived sincerity in small company conditions when the company mentioned no specific contribution (control) ($\beta_{smallcontrol} = -.18$, BootSE = .07, BootCI= [-.32, -.04]) and when the company made monetary contributions ($\beta_{smallmonetary} = -.19$, BootSE = .06, BootCI= [-.32, -.08]). However, when the company made in-kind contributions the effect of perceived company status became nonsignificant ($\beta_{smallinkind} = -.11$, BootSE = .09, BootCI= [-.30, .05]). Similarly, in large company conditions, increased perceptions of beneficiary status decreased perceived sincerity when the company mentioned no specific contribution (control) ($\beta_{largecontrol} = -.34$, BootSE = .07, BootCI= [-.49, -.21]) and when the company made monetary contributions ($\beta_{largemonetary} = -.31$, BootSE = .09, BootCI= [-.49, -.16]). However, again, when the company made in-kind contributions the effect of perceived company status became nonsignificant ($\beta_{largeinkind} = -.03$, BootSE = .07, BootCI= [-.18, .09]). More importantly, pairwise comparisons between conditional indirect effects showed that when large beneficiary companies make in-kind contributions, they generated significantly greater sincerity perceptions and in turn, significantly greater willingness to spread positive WOM than when they make monetary contributions ($\beta_{inkind\text{-}monetary}$ = .29, BootSE = .11, BootCI= [.06, .50]) and control condition ($\beta_{inkind\text{-}control}$ = .32, BootSE = .10, BootCI= [.12, .51]). The difference between monetary contribution and control conditions was nonsignificant ($\beta_{monetary\text{-}control}$ = .03, BootSE = .11, BootCI= [-.18, .24]).

Additionally, the same contrasts did not reach significance in small company condition ($\beta_{inkind\text{-}monetary}$ = .09, BootSE = .11, BootCI= [-.14, .28]; $\beta_{inkind\text{-}control}$ = .07, BootSE = .11, BootCI= [-.16, .28]; $\beta_{monetary\text{-}control}$ = -.02, BootSE = .09, BootCI= [-.20, .17]). In summary, making in-kind contributions increased the perceived sincerity only for large companies when they were perceived to be benefitting from the crisis environment (beneficiary), and in turn, people's willingness to spread positive WOM for those companies increased. Therefore, hypothesis H4a is supported.

In Model 2, the results manifested that increased perception of beneficiary status decreased perceived sincerity in small company conditions when the company mentioned no specific contribution (control) ($\beta_{smallcontrol}$ = -.15, BootSE = .06, BootCI= [-.27, -.04]) and when the company communicated monetary contributions ($\beta_{smallmonetary}$ = -.16, BootSE = .05, BootCI= [-.28, -.07]). Again, when the company made in-kind contributions the effect of perceived company status was nonsignificant ($\beta_{smallinkind}$ = -.09, BootSE = .08, BootCI= [-.25, .04]). In large company conditions of Model 2, increased perceptions of beneficiary status decreased perceived sincerity when the company mentioned no specific contribution (control) ($\beta_{largecontrol}$ = -.29, BootSE = .06, BootCI= [-.42, -.18]) and when the company made monetary contributions ($\beta_{largemonetary}$ = -.26, BootSE = .07, BootCI= [-.42, -.13]). When the company made in-kind contributions the effect of perceived company status became nonsignificant ($\beta_{largeinkind}$ = -.02, BootSE = .06, BootCI= [-.15, .08]). In Model 2, pairwise comparisons between conditional indirect effects showed that when large beneficiary companies make in-kind contributions they generated significantly greater sincerity perceptions and in turn, significantly greater willingness to support/help the company than both when they make monetary contributions ($\beta_{inkind-monetary}$ = .24, BootSE = .10, BootCI= [.05, .43]) and control condition ($\beta_{inkind-control}$ = .27, BootSE = .08, BootCI= [.10, .43]). The difference between monetary contribution and control conditions was statistically nonsignificant ($\beta_{monetary-control}$ = .02, BootSE = .09, BootCI= [-.15, .20]). Just like in Model 1, the same contrasts did not reach significance in small company conditions in Model 2 ($\beta_{inkind-monetary}$ = .07, BootSE = .09, BootCI= [-.11, .24]; $\beta_{inkind-control}$ = .06, BootSE = .10, BootCI= [-.14, .24]; $\beta_{monetary-control}$ = -.01, BootSE = .08, BootCI= [-.17, .14]). Therefore, this increase in perceived sincerity with in-kind contributions compared to control and monetary contributions was only peculiar to large companies. That said, making in-kind contributions increased perceived sincerity only for large companies when their beneficiary status increased, and in turn, people's willingness to help/support those companies increased. Hence, hypothesis H4b is supported.

In Model 3, people's preference for the company's products and services over those of others has been tested as an exploratory variable. The results manifested that increased perception of beneficiary status decreased perceived sincerity in small company condition when the company mentioned no specific contribution (control) ($\beta_{smallcontrol}$ = -.18, BootSE = .07, BootCI= [-.32, -.04]) and when the company made monetary contributions ($\beta_{smallmonetary}$ = -.20, BootSE = .07, BootCI= [-.34, -.08]). However, when the company made in-kind contributions the effect of perceived company status was nonsignificant ($\beta_{smallinkind}$ = -.11, BootSE = .09, BootCI= [-.30, .05]). In large company condition, increased perceptions of beneficiary status decreased perceived sincerity when the company mentioned no specific contribution (control) ($\beta_{largecontrol}$ = -.35, BootSE = .07, BootCI= [-.50, -.22]) and when the company made monetary contributions ($\beta_{largemonetary}$ = -.32, BootSE = .09, BootCI= [-.50, -.15]). In in-kind contribution condition, the effect of perceived company status became nonsignificant ($\beta_{largeinkind}$ = -.03, BootSE = .07, BootCI= [-.19, .09]). Pairwise comparison analyses showed a similar pattern to what was observed in Model 1 and Model 2 is that he analyses of contrasts between conditional indirect effects manifested that large beneficiary companies when they make in-kind contributions generated significantly greater sincerity perceptions and in turn, significantly greater preferences for company's product and services than both when they make monetary contributions ($\beta_{inkind-monetary}$ = .29, BootSE = .11, BootCI= [.06, .50]) and control condition ($\beta_{inkind-control}$ = .32, BootSE = .10, BootCI= [.12, .51]). The difference between monetary contribution and control conditions was statistically nonsignificant ($\beta_{monetary-control}$ = .03, BootSE = .11, BootCI= [-.19, .25]). The same contrasts did not reach significance in small company condition ($\beta_{inkind-monetary}$ = .09, BootSE = .11, BootCI= [-.14, .30]; $\beta_{inkind-control}$ = .07, BootSE = .12, BootCI= [-.17, .29]; $\beta_{monetary-control}$ = -.02, BootSE = .10, BootCI= [-.21, .17]). This way, it has been manifested that making in-kind contributions increased the perceived sincerity of large companies when their beneficiary status increased; this, in turn, increased people's likelihood to prefer those companies' products and services over others.

Discussion

In Study 5, it has been found that as the company was perceived to be benefitting to a greater extent, people became less willing to spread positive WOM (H1a) about the company and their willingness to help the company significantly decreased (H1b). Furthermore, perceived sincerity mediated this mechanism for both dependent variables in a way that improved company status decreased the perceived sincerity of the companies, which in turn, decreased people's willingness to spread positive WOM (H2a) and their willingness to help those companies (H2b).

Therefore, a novel mechanism has been discovered that in-kind contributions could serve as a boundary condition for negative attitudes toward large beneficiaries. As perceived beneficiary status increased for large companies, their perceived sincerity decreased significantly, yet when those companies communicated their in-kind contributions, the effect of perceived company status was muted, and those companies' perceived sincerity and, subsequently people's willingness to spread positive WOM (H4a) and their willingness to help those companies (H4b) were significantly higher than when either no contribution information given or only monetary contributions are communicated. However, this study failed to find further support for the hypotheses H3a and H3b.

Finally, in this study, another potential dependent variable has been tested, namely people's preferences for the company's products and services over those of others, for exploratory reasons. The results showed that people's likelihood to prefer beneficiary companies' products and services was significantly less than other companies' products and services. Perceived sincerity mediated this mechanism, and when it comes to large beneficiaries, making in-kind contributions muted the negative effect of company status on people's preference for company products and services through perceived sincerity.

<u>Insert Figure 3 about here.</u>

Exploratory Analyses

Effort. This study has also tested whether people’s perception of invested effort in CSR activities by companies changes based on the company's status, size, and CSR contribution, as discussed previously. Analyses through Model 3 from Hayes's PROCESS module on SPSS (Hayes, 2012) with dummy coded contribution type as X1 (Monetary condition=1) and X2 (In-kind condition=1) showed that the 3-way interaction between those variables on effort was significant, yet only with the second dummy variable, X2 ($\beta_{X2} = .36$, $SE = .17$, $p<.05$). The same effect did not reach significance for the first dummy variable, X1 ($\beta_{X1} = -.12$, $SE = .16$, $p>.1$). Further analyses showed that in small company condition, the effect of company status was nonsignificant for control ($\beta_{smallcontrol} = -.06$, BootSE = .09, BootCI= [-.23, .12]), monetary ($\beta_{smallmonetary} = -.01$, BootSE = .08, BootCI= [-.17, .14]) and in-kind ($\beta_{smallinkind} = -.07$, BootSE = .08, BootCI= [-.21, .09]) contribution conditions. In large-company condition, on the other hand, the effect was negative and significant for both control ($\beta_{largecontrol} = -.21$, BootSE = .08, BootCI= [-.36, -.06]) and monetary ($\beta_{largemonetary} = -.29$, BootSE = .07, BootCI= [-.43, -.14]) contribution conditions. This effect did not reach significance for in-kind contribution condition ($\beta_{largeinkind} = .15$, BootSE = .09, BootCI= [-.03, .39]). These results show that large companies making no contribution statement in their CSR messages (control) or communicating monetary contributions are perceived to be putting less effort for the public, as their perceived beneficiary status increased. However, the effect of the perceived status of the company on perceived corporate effort became nonsignificant when a large company communicated its in-kind contributions.

These results partially support the presented argumentation in the theory-building stage. It was claimed that in-kind contributions should activate greater effort attributions to large beneficiary companies, while no contribution statements (control) or monetary contributions should decrease perceived effort from those companies' CSR communications. These results showed that the effect for the latter group was in line with the discussed arguments as the effects of control and monetary contribution conditions for large companies resulted in significantly negative effort perceptions as those companies; percieved beneficiary status increased. However, for the in-kind contribution condition for large companies, even though the effect was on the positive direction, it did not reach significance.

Expectedness of CSR actions. The interaction between company status, company size, and contribution type on the expectedness of CSR actions has been tested. The analyses through Model 3 of Hayes's PROCESS showed that the 3-way interaction was nonsignificant for both X1 ($\beta_{X1} = .11$, $SE = .20$, $p>.1$) and X2 ($\beta_{X2} = -.15$, $SE = .21$, $p>.1$). Therefore, this study found no sufficient evidence regarding whether variations on company status, size and contribution type can confirm or disconfirm CSR-related expectancies.

Schadenfreude for companies. People's negative attitude toward beneficiary companies could be due to their jealousy toward those companies' position of advantage. Since size and company status are the indicators of a company's advantages during a crisis, this possibility has been tested by examining the interaction between perceived company status and company size on people's jealousy. There was no significant interaction ($\beta = .09$, $SE = .13$, $p>.1$). Therefore, it has been concluded that the position of advantage did not generate any significant variances in people's felt jealousy towards companies based on those companies' status and size.

Identification with victims. Finally, this study tested whether people's identification with victims can affect their sincerity judgments about companies' CSR communications. The interaction between company status and people's identification with crisis victims on perceived sincerity of those companies' communications was indeed significant ($\beta = .05$, $SE = .02$, $p<.05$). Interestingly, as people identified more with the victims, the negative effect of company status on perceived sincerity decreased (Low identification: $\beta = -.16$, $SE = .03$, $p<.001$, Moderate identification: $\beta = -.13$, $SE = .03$, $p<.001$, High identification: $\beta = -.09$, $SE = .03$, $p<.01$). The

Johnson-Neyman analyses showed that for the identification values above 6.83, the effect of company status became non-significant. This may have occurred because increased identification with victims may have simultaneously increased the participants' desperation against the negativities of the crisis, which, in turn, may prime them to be more attentive to whether there is help rather than what kind of corporation (percieved status wise) provides that help. This suggestion remains only as a speculation at this point as this topic is out of the scope of this research. Future research can investigate this possibility more extensively.

Chapter IV: General Discussion

It is no secret that companies expect returns on their CSR investments (Langan and Kumar, 2019) as disclosing CSR information may provide competitive (Jamali, 2008) and reputational advantages (Nekhili et al., 2017). The corporate expectations of positive WOM (Langan and Kumar, 2019) and increased help/support from consumers (McGlone et al., 2011; Sen and Bhattacharya, 2001) after communicating CSR actions are among some of the most fundamental expectations that motivate companies to perform and communicate their CSR actions. In addition, people show greater support for CSR initiatives when they are performed as relief actions during crises (Drumwright, 1996), which motivates companies further to communicate their CSR efforts during crises.

Therefore, in six studies (See, Table 8), this research sought answers for how, after communicating theirCSR actions, beneficiary companies in crisis environments are approached by the public; what mediates this mechanism; what qualities of those companies exacerbate this effect; and what canbe done to disrupt this negative effect in favor of the most negatively impacted company group or namely, large beneficiary companies. The results consistently showed that in a crisis environment, among companies that communicate their CSR actions, perceived beneficiary status increases the negative attitudes making people less likely to spread positive WOM about those companies and less likely to help them compared to other companies despite those companies' innocence and CSR initiatives. The low perceived sincerity of those companies mediated this mechanism. Furthermore, despite the observed failure to find further support in study 5, in study 4, the results showed evidence that among all the companies communicating their CSR initiatives during a crisis, large companies might be affected the most, as people perceived large companies to be the least sincere when those companies were perceived to be inbeneficiary status. Combining real-life data from Study 1a with experimental data from Studies1b, 2, 3, 4, and 5 was crucial for cross-validation of the results obtained under both field and controlled conditions, enhancing their generalizability compared to using only one of them (Vartanian, 2010).

Finally, this research showed that communicating their material donations or, in other words, their in-kind contributions in their CSR communications can benefit large-beneficiaries by muting the negative effect of beneficiary company status. When large-beneficiaries communicated their in-kind contributions, people's sincerity judgments and their subsequent willingness to spread positive WOM and willingness to help the company were significantly higher than when those companies communicated their money donations or made statements mentioning no specific contribution type.

Theoretical Contributions

Past research investigated the associations between companies' CSR communications and those communications' success in bringing the intended corporate benefits to the company based on firm characteristics (Nekhili et al., 2017) such as company size (Attig et al., 2016; Udayasankar, 2008), company reputation (Vanhamme and Grobben, 2009), and company's industry (Du and Vieira, 2012). Differentiating from past research, this paper brings a novel characteristic into the discussion; company status, and hence, it makes two major contributions to the existing literature.

Firstly, this research sheds light on a previously unexamined mechanism; how serendipitously benefitting from a crisis affects the public's perceptions of a company's crisis relief actions. Past research showed that there is a positive relationship between a company's CSR actions and consumers' attitudes toward that company (Ellen et al., 2000, Sen and Bhattacharya, 2001), as consumers expect companies to perform their CSR-related responsibilities adequately (Nickerson et al., 2022). However, this research shows that this is not always the case, especially during a crisis. During a crisis, people do not only consider a company's CSR actions but also its status. When a company is perceived to be beneficiary even if it is serendipitously achieved, it activates negative public attitudes toward the company, increasing sincerity-related negative judgments of the company's CSR actions. On the other hand, past research argued that people tend to identify with beneficiaries as beneficiary signals strength and capability (Cialdini et al., 1976). For example, top-dog brands signal a greater promise that they can deliver the expected (Paharia et al., 2011), which increases positive public attitudes toward those brands on certain occasions (Woolley et al., 2022). However, the results of the studies presented in this research showed that beneficiary in a crisis context increases negative attitudes toward brands, which challenges this argument's generalizability.

Secondly, to investigate the effect of firm characteristics on the perceptions of CSR communications, past research mostly focused on crisis scenarios in which the companies were culpable such as product harm (Kim, 2014) or service-harm (Gijsenberg et al., 2015) crises. The current research drew a unique context by focusing on companies' beneficiary status in crises that occur out of the company's control. In this unique context, companies neither caused the crisis nor had control over how the crisis would affect their business (benefit or loss). Therefore, this research may become a pioneer in terms of its unique scope and its potential to open new venues for further research.

Managerial Contributions

This research offers some practical contributions as well. Firstly, this research manifested how an uncontrollable factor, such as serendipitously benefitting from a crisis, can negatively affect people's willingness to spread positive WOM or to help the company. This finding emphasizes that returns on CSR communications during a crisis cannot be taken for granted, even and especially for large conglomerates.

Secondly, for managers, this research highlights the importance of understanding the public's perceptions of their companies' status during a crisis. The results presented draw a guideline for managers regarding how to configure their CSR communications, particularly when their companies are large and perceived to be benefitting from a crisis. In this vein, results showed that for large beneficiaries, the best strategy is to allocate greater resources to communicate material donations rather than financial donations as crisis-relief actions. In this way, the company can disrupt the negative attitudes emerging from its perceived advantaged position.

More importantly, in study 2, it has been found that supporting small businesses in times of crisis may not be an unconditional public reflex, as when they are perceived to be beneficiaries, small companies activated significantly less public willingness to help. This result particularly calls the attention of small business owners as it challenges the potential benefits of "underdog" positioning. Small business owners during crises should not only rely on public support but also should seek ways to sustain that support. One way to do so can be by facilitating greater underdog narratives about their brands.

Limitations and Future Research

Despite its strengths in explaining proposed relationships, this research is not without limitations. For example, the results do not explain whether perceived legitimacy plays any role in people's negative reactions to beneficiary companies. If a beneficiary company is perceived to have gained that advantage undeservingly, such as by chance, as in the focal context, people may give greater negative reactions to the company (Leach et al., 2003). Past research showed that illegitimate superiority causes companies to be evaluated more negatively (Leach et al., 2003).

Secondly, losing companies and companies in control conditions may have been perceived to be taking greater risks to engage in CSR as their business is under greater risks compared to beneficiary companies during a crisis (Du et al., 2007). This may have caused greater favoritism toward this group of companies. Therefore, negative attitudes toward beneficiary companies may be a result of alienation by the public.

On the other hand, differential treatment to beneficiary companies may also have cultural motivations. For example, American culture biasedly side with those that come from backgrounds of disadvantage, identify with their struggles more deeply, and encourage them to thrive (Paharia et al., 2011). That said, it is possible that the difference between the attitudes toward beneficiary and losing companies emerges from people's biasedness in favor of disadvantaged companies. Therefore, the mechanisms proposed in this research should be replicated in different cultural contexts.

This research also did not focus on the effects that can emerge from different types of crises. Some of the crisis contexts used in this research did not pose a direct threat to human life (as in Study 1b). This situation may lead to different attitudinal paths towards beneficiary companies in different crisis contexts. Crises can affect people's perceptions differently, priming varying levels of mortality salience (Maheswaran and Agrawal, 2004).

Finally, this research does not address the perceived controllability of the crisis scenarios. Past research shows that, in less controllable crisis situations, in-kind CSR contributions are approached more favorably than monetary contributions, whereas in more controllable crises, people prefer monetary contributions (Hildebrand et al., 2017). The potential effect of crisis controllability can open an interesting venue for future research.

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Appendix

Python Code Compiled to Collect Company Profile Information

```
from bs4 import BeautifulSoup
import time
import datetime as dt
from datetime import datetime
import urllib.request
import pandas as pd
from openpyxl import load_workbook
import sys
accountname=[]
urllist=[]
name=[]
bio=[]
date=[]
followers=[]
following=[]
location=[]
tweets=[]
likes=[]
media=[]
goza=[]
zo=[]
protected=[]
avatarexist=[]
wallpicexist=[]
pagelist=[]
```

```
bioactivity=[]
locationactivity=[]
islocationreal=[]
v=0
def request_until_succeed(url):
    req = urllib.request.Request(url, headers=headers)
    success = False
    while success is False:
        try:
            response = urllib.request.urlopen(req)
            if response.getcode() == 200:
                success = True
            if response.getcode() == 404:
                print("A problem detected in url request")
                global v
                v += 1
                return None
        except Exception as e:
            print(e)
            print("Problem occured for"+" "+str(url)+".Passing.")
            time.sleep(5)
            return None
    return  response.read().decode('utf-8')
df = pd.read_excel('GOT.xlsx', Sheet1=0) # can also index sheet by name or fetch all sheets
accountname = df['LINK'].tolist()
print(accountname)
for item in accountname:
    item=str(item)
    url="https://twitter.com/"+item
    urllist.append(url)
q=0
headers = {"Accept-Language": "en-US, en;q=0.5"}
for url in urllist:
    print(url)
    page_source =  request_until_succeed(url)
    if page_source is None:
        continue
    profile = BeautifulSoup(page_source, 'html.parser')
    all=profile.find_all('div', class_="ProfileHeaderCard")
    sall=profile.find_all('div', class_="ProfileHeaderCard-joinDate")
    for z in all:
        try:
            name.append(z.find("a", {"class":"ProfileHeaderCard-nameLink u-textInheritColor js-nav"} ).text)
        except:
            name.append(" ")
        try:
            bio.append(z.find("p", {"class":"ProfileHeaderCard-bio u-dir"} ).text)
            if(len(z.find("p", {"class":"ProfileHeaderCard-bio u-dir"} ).text))>0:
                bioactivity.append(1)
            else:
                bioactivity.append(0)
        except:
            bio.append(" ")
            bioactivity.append(0)
        try:
            location.append(z.find("span", {"class":"ProfileHeaderCard-locationText u-dir"} ).text.replace("\n        ","").replace("\n",""))
            if (len(z.find("span", {"class":"ProfileHeaderCard-locationText u-dir"} ).text.replace("\n        ","").replace("\n","")))>0:
                locationactivity.append(1)
            else:
                locationactivity.append(0)
        except:
            location.append("NoInfoGivenbyUser")
            locationactivity.append(0)
        try:
            if "Protected Tweets" in z.find("span", class_="ProfileHeaderCard-badges" ).text:
                protected.append(1)
            else:
                protected.append(0)
        except:
            protected.append(0)
    for z in sall:
```

```
    try:
        s=z.find("span", class_="ProfileHeaderCard-joinDateText js-tooltip u-dir" )["title"]
        date.append(s)
    except:
        date.append(" ")
try:
    all2=profile.find_all('div',   class_="PhotoRail")
    if len(all2)>0:
        for l in all2:
            t=l.find("a", {"class":"PhotoRail-headingWithCount js-nav"} ).text.replace(" Photos and videos", "").replace(" Photo or video",
  "").replace("\n","").replace(" ","")
            if "K" and "." in t:
                t=int(t.replace("K","").replace(".","").replace(",",""))*100
                media.append(t)
            elif "K" in t:
                t=int(t.replace("K","").replace(",",""))*1000
                media.append(t)
            elif "," in t:
                t=int(t.replace(",",""))
                media.append(t)
            else:
                media.append(t)
    else:
        media.append(" ")
except:
    media.append(" ")
try:
    all3=profile.find_all("li", class_="ProfileNav-item ProfileNav-item--tweets is-active" )
    if len(all3)>0:
        for on in all3:
            alltweet=on.find("span",     class_="ProfileNav-value")["data-count"]
            if len(alltweet)>0:
                tweets.append(alltweet)
            else:
                tweets.append(" ")
    else:
         tweets.append(" ")
except:
    tweets.append(" ")
try:
    all4=profile.find_all("li", class_="ProfileNav-item ProfileNav-item--following" )
    for on in all4:
        if len(all4)>0:
            alltweet1=on.find("span",     class_="ProfileNav-value")["data-count"]
            if len(alltweet1)>0:
                following.append(alltweet1)
            else:
                following.append(0)
                print(url+"1st else")
        else:
            following.append(0)
            print(url+"2nd else")
except:
    following.append(0)
    print(url+"Except")
try:
    all5=profile.find_all("li", class_="ProfileNav-item ProfileNav-item--followers" )
    if len(all5)>0:
        for on in all5:
            alltweet2=on.find("span",     class_="ProfileNav-value")["data-count"]
            if len(alltweet2)>0:
                followers.append(alltweet2)
            else:
                followers.append(0)
    else:
        followers.append(0)
except:
    followers.append(0)
try:

    all6=profile.find_all("li", class_="ProfileNav-item ProfileNav-item--favorites" )
```

```
        if len(all6)>0:
            for on in all6:
                alltweet3=on.find("span",     class_="ProfileNav-value")["data-count"]
                if len(alltweet3)>0:
                    likes.append(alltweet3)
                else:
                    likes.append(" ")
        else:
            likes.append(" ")
    except:
         likes.append(" ")
    try:
        all7=profile.find_all("div", class_="ProfileAvatar" )
        for on in all7:
            if len(all7)>0:
                alltweet4=on.find("img",    class_="ProfileAvatar-image")["src"]
                if "default" in alltweet4:
                    avatarexist.append(0)
                else:
                    avatarexist.append(1)
            else:

                avatarexist.append(0)
    except:
         avatarexist.append(0)

    try:
        all8=profile.find_all("div", class_="ProfileCanopy-header u-bgUserColor" )
        if len(all8)>0:
            for on in all8:
                alltweet5=on.find("div", class_="ProfileCanopy-headerBg")
                alltweet6=alltweet5.find("img")["src"]
                if len(alltweet6)>0:
                    wallpicexist.append(1)
                else:
                    wallpicexist.append(0)
        else:
            wallpicexist.append(0)

    except:
         wallpicexist.append(0)
    q += 1
    string = q/len(accountname)*100
    sys.stdout.write("\r{0}>".format("Progress %"+ str(string)))
    sys.stdout.flush()
    time.sleep(0.5)
tweets1=[]
following1=[]
followers1=[]
media1=[]
likes1=[]
protected1=[]
timepassedasdays=[]
followersratio=[]
followingratio=[]
followersperday=[]
followingperday=[]
likesperday=[]
tweetsperday=[]
mediasperday=[]
d1=datetime.now()
for i in date:
    if "PM" in i:
        k=int(i[0:4].replace(":","").replace(" ",""))+1200
        k=str(k)
        hour=k[0:1]
        minutes=k[2:3]
        hour=int(hour)
        minutes=int(minutes)
        days=i[-12:-9].replace(" ","").replace("-","")
        days=int(days)
        years=i[-5:].replace(" ","")
```

```
        years=int(years)
        if "Jan" in i:
            months=1
        if "Feb" in i:
            months=2
        if "Mar" in i:
            months=3
        if "Apr" in i:
            months=4
        if "May" in i:
            months=5
        if "Jun" in i:
            months=6
        if "Jul" in i:
            months=7
        if "Aug" in i:
            months=8
        if "Sep" in i:
            months=9
        if "Oct" in i:
            months=10
        if "Nov" in i:
            months=11
        if "Dec" in i:
            months=12
    if "AM" in i:
        k=i[0:4].replace(":","").replace("  ","")
        if len(k)==3:
            hour=k[0]
            hour=int(hour)
            minutes=k[1:2]
            minutes=int(minutes)
        else:
            hour=k[0:1]
            minutes=k[2:3]
            hour=int(hour)
            minutes=int(minutes)
        days=i[-12:-9].replace(" ","").replace("-","")
        days=int(days)
        years=i[-5:].replace(" ","")
        years=int(years)
        if "Jan" in i:
            months=1
        if "Feb" in i:
            months=2
        if "Mar" in i:
            months=3
        if "Apr" in i:
            months=4
        if "May" in i:
            months=5
        if "Jun" in i:
            months=6
        if "Jul" in i:
            months=7
        if "Aug" in i:
            months=8
        if "Sep" in i:
            months=9
        if "Oct" in i:
            months=10
        if "Nov" in i:
            months=11
        if "Dec" in i:
            months=12
    d2=dt.datetime(years,months,days,hour,minutes,0)
    timepassedasdays.append((d1-d2).days)
for i in tweets:
    i=i.replace(",","")
    try:
        k=int(i)
```

```
        weets1.append(k)
    except:
        tweets1.append(i)
for i in following:
    i=i.replace(",","")
    try:
        k=int(i)
        following1.append(k)
    except:
        following1.append(i)
for i in media:
    try:
        k=int(i)
        media1.append(k)
    except:
        media1.append(i)
for i in followers:
    i=i.replace(",","")
    try:
        k=int(i)
        followers1.append(k)
    except:
        followers1.append(i)
for i in likes:
    i=i.replace(",","")
    try:
        k=int(i)
        likes1.append(k)
    except:
        likes1.append(i)
for i,j in zip(following1,followers1):
    try:
        followingratio.append(i/(i+j))
    except:
        followingratio.append(0)
    try:
        followersratio.append(j/(i+j))
    except:
        followersratio.append(0)
for i,j,m,l,y,z  in  zip(following1,followers1,media1,likes1,tweets1,timepassedasdays):
    try:
        followersperday.append(j/z)
    except:
        followersperday.append(" ")
    try:
        followingperday.append(i/z)
    except:

        followingperday.append(" ")
    try:
        likesperday.append(l/z)
    except:
        likesperday.append(" ")
    try:
        tweetsperday.append(y/z)
    except:
        tweetsperday.append(" ")
    try:
        mediasperday.append(m/z)
    except:
        mediasperday.append(" ")


Frame=pd.DataFrame( {
      'ACCOUNT NAME':accountname,
     'NAME': name,
     'BIO INFO': bio,
     'BIO ACTIVITY': bioactivity,
     '#TWEETS': tweets1,
     '#FOLLOWING': following1,
     '#FOLLOWERS': followers1,
```

```
 '#FAVOURITES': likes1,
 '#PHOTOS/VIDEOS':  media1,
 'LOCATION': location,
 'LOCATION ACTIVITY': locationactivity,
 'JOIN DATE': date,
 'TIME PASSED AS DAYS': timepassedasdays,
 'PROTECTED(1 for yes)':protected,
 'FOLLOWERS(FOLLOWERS+FOLLOWING)':followersratio,
 'FOLLOWING(FOLLOWERS+FOLLOWING)':followingratio,
 'FOLLOWERS PER DAY':followersperday,
 'FOLLOWING PER DAY':followingperday,
 'LIKES PER DAY':likesperday,
 "TWEETS PER DAY":tweetsperday,
 "MEDIAS PER DAY":mediasperday,
 "PROFILE PIC?": avatarexist,
 "WALL PIC?":wallpicexist,
})
```