Masks, cameras and social pressure

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Introduction I

"*Descriptive norms involve perceptions of which behaviors are typically performed. They normally refer to the perception of others' behavior. These norms are based on observations of those around you.*"

Cialdini, 2003

Large literature demonstrating the power of descriptive norms (together with peer effects):

- Tax evasion (Bott et al., 2020)
- Charitable giving (Agerström et al., 2016)
- Voting choices (Gerber and Rogers, 2009)
- etc. etc.

Introduction II

Despite the importance of descriptive norms, there is little quantitative evidence on the exact relationship between the share of people who adopt an behavior and our own inclination to adopt that behavior. Typical example:

- Frey and Meier, 2004 tell students either that 64% or 46% of their peers donate to a charity.
- Findings suggest that higher beliefs lead to higher actions.
- However, this doesn't tell us what the relationship looks like over the full feasible range.

Introduction III

Why should we care about exactly how actions depend on prevalence?

- Policy motivation: the shape of this relationship reveals the returns to altering perceptions about prevalence (e.g. by disclosing information).
- Testing theories: certain economic models, e.g. those in evolutionary game theory, make distinctive predictions about the observed functional form.
- Dynamics: the shape of this relationship pins down long run equilibria in dynamic models.

Our work

We provide evidence on the shape of this relationship across two contexts:

- Experiment 1: a randomised experiment on the social determinants of face mask wearing.
- Experiment 2: a randomised experiment on the social determinant of camera use in Zoom meetings.

We deliver theoretical implications of our findings, and what models can give rise to them.

We find that

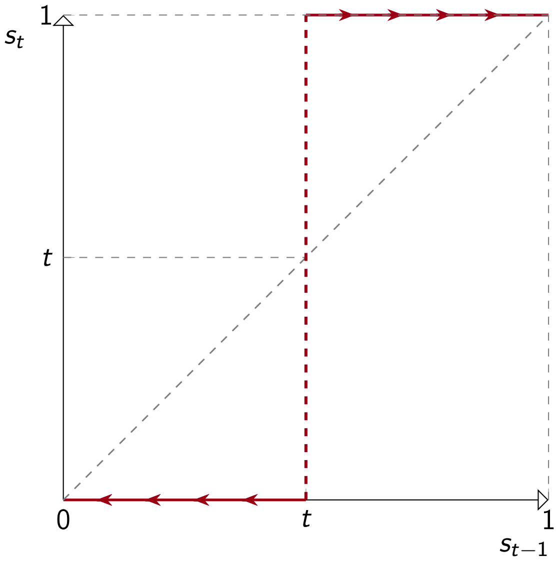
- The share of individuals taking the relevant action is monotone increasing in the share of others who take this action.
- There are some evidence of non-linearity.
- When embedded in dynamic models, our estimates predict heterogeneous behavior despite individuals' copying-like behaviour.

Theoretical Framework

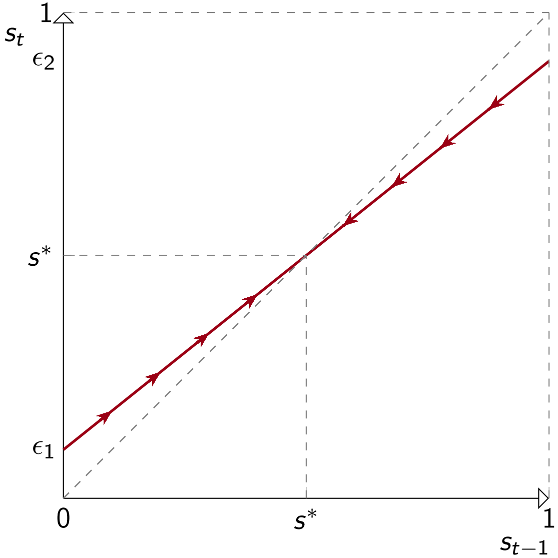
- Consider a simple dynamic setting where s_t is the share at time t of people adopting one behavior (e.g. wearing the mask).
- $s_t = f(s_{t-1}) \rightarrow$ the share of people adopting that behavior at time t depends on the share of people adopting that behavior at $t-1$.
- $f(s_{t-1})$ depends on how people respond to the different share in the population adopting the behavior.
- E.g., $f(s_{t-1})$ depends on the tipping point distribution of the population.
- Tipping point of i is t_i s.t. if $s_t \geq t_i$, i adopt the behavior.

Based on the shape of this function, the long-run prediction changes.

Theoretical framework: homogeneous tipping points



Theoretical framework: heterogeneous tipping points



Masks: experimental design I

Background:

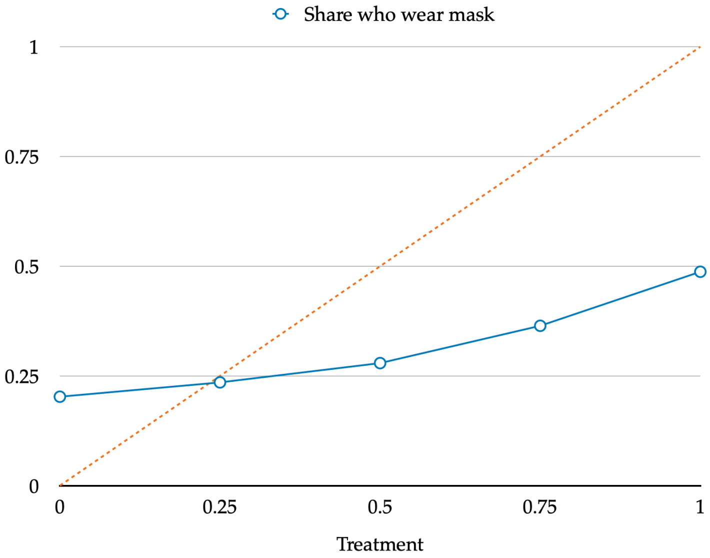
- The first experiment took place in Oxford from 25 February to 4 March 2022.
- At this time, masks were not required by either law or university rules – however, they were also not unusual.
- We conducted 14 three hour sessions in 12 different colleges.
- In total, we recruited 646 experimental subjects.
- Pre-registration: AEARCTR-0009013.

Masks: experimental design II

The details:

- Experimental subjects entered the room one by one (two minute staggered time slots).
- Before each subject entered, the number of the 4 experimenters in the room wearing a mask (and the allocation of masks to experimenters) was randomised.
- Once a subject entered, they were asked to sat at a table with a box of masks, a hand sanitizer and a box of checkers.
- All four experimenters introduced themselves by stating their name and subject of study.
- The subject was then asked some simple demographic questions, and given a decision problem involving lotteries.
- An experimenter recorded whether the subject was wearing the mask while entering or whether they chose to wear it during the experiment.
- The process then repeated... Descriptive Regressions

Masks: results I



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Masks: results II

1. The frequency of mask wearing is increasing in the share of experimenters who wear a mask $\rightarrow$ consistent with a model in which higher rates of mask wearing lead to greater social pressure to wear a mask. Mono
2. Many individuals defy social pressure: Switches
   - $f(0) = 0.20 \neq 0$ ($p = 0.000$).
   - $f(1) = 0.49 \neq 1$ ($p = 0.000$).
3. Our estimated F function appears to be non linear:
   - Estimating a model with a quadratic term suggests some convexity ($p = 0.04$). Quad
   - Large jump between the 3 and 4 treatments $\rightarrow$ potential 'everybody effect'.
4. Our estimates predict convergence to a mixed equilibrium around 23.3% $\rightarrow$ In these equilibria, around 86% of mask wearers wear the mask because they always wear one; with the remainder wearing a mask due in part to copying behaviour.

Cameras: experimental design I

The general idea resembles the masks experiment except that instead of masks, the treatments and the outcome variable were the camera usage during a Zoom meeting.

Background

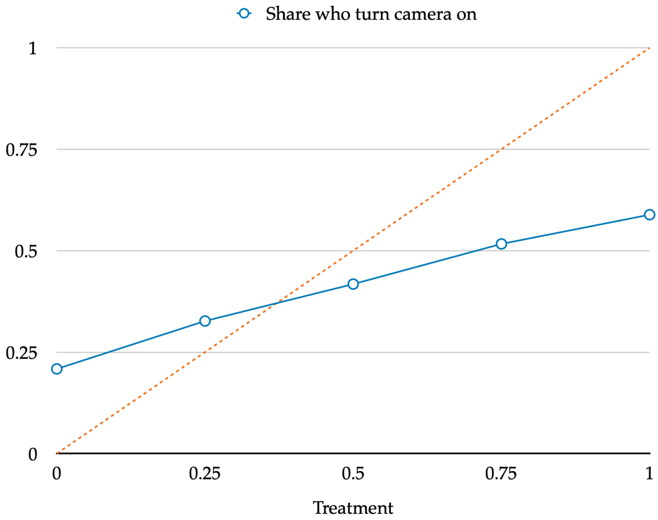
- This experiment took place online in late July and early August of 2022.
- We conducted 16 two hour sessions over the course of 8 days.
- In total, we recruited 1,115 participants (from Prolific).
- Pre-registration: https://www.socialscienceregistry.org/trials/9829.

Cameras: experimental design II

The details:

- Experimental subjects joined the Zoom call one by one (two minute staggered time slots).
- Before each subject entered, the number of the 4 experimenters in the room with their camera on (and which experimenters had their camera on) was randomised.
- Once a subject joined the call, all four experimenters introduced themselves by stating their name.
- The subject was asked for their age, and then whether they would hypothetically want to donate half of a bonus payment to the next subject on the call.
- If the subject did not turn their camera on, they were asked whether there were any issues with their camera.
- The process then repeated... Descriptive Regressions

Cameras: results I



Cameras: results II

1. We find evidence that the frequency of camera use is increasing in the share of experimenters who use a camera $\rightarrow$ again this is consistent with a model in which higher rates of camera using lead to greater social pressure to use the camera.
▸ Mono
2. Again many individuals defy social pressure: ▸ Switches
   - $f(0) = 0.209 \neq 0$ ($p = 0.000$).
   - $f(1) = 0.587 \neq 1$ ($p = 0.000$).
3. Our estimated F function appears to be roughly linear. ▸ Quad
   However, the jump between the 0 and 1 treatments is larger than the other 3 jumps.
4. Our estimates once again predict convergence to a mixed equilibrium around 37.0% $\rightarrow$ around 56% of camera users turn the camera on because they always turn it on; with the remainder turning the camera on due in part to copying behaviour.

Conclusions

In this paper, we conduct multi-treatment social norms experiments to get a quantitative understanding of how individuals' behaviour varies with the share doing an action in their immediate environment.

- Despite some differences between the estimates across our contexts (which we rationalise using a simple theory), we obtain many commonalities across the two experiments: high levels of non-compliance, monotone F functions, interior fixed points.
- Perhaps most importantly, when embedded in a dynamic model, our estimates can explain how copying can plausibly lead to heterogenous behaviour (not conformity!).

THANKS

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APPENDIX

MASKS

Masks: descriptive stats

Variable	Mean	Std. Dev.
Age	20.8	3.90
Male	.497	.500
Humanities	.283	.451
MPLS	.240	.427
Medical Sciences	.127	.333
Social Sciences	.333	.471
Wearing mask	.201	.401
n	646	

Masks: treatments

Treatment	Frequency	Percentage
0	127	19.7
1	134	20.7
2	128	19.8
3	124	19.2
4	133	20.6
Total	646	100.0

Masks: balance table

Variable	Mean	Mean	Mean	Mean	Mean	p-value
Age	21.0	21.3	20.1	20.6	20.8	.143
	[.361]	[.539]	[.165]	[.219]	[.268]	
Pre	.142	.157	.266	.242	.203	.060
	[.031]	[.032]	[.039]	[.039]	[.035]	
Male	.535	.522	.461	.548	.421	.189
	[.044]	[.043]	[.044]	[.045]	[.043]	
Humanities	.323	.246	.250	.347	.256	.237
	[.042]	[.037]	[.038]	[.043]	[.038]	
Social	.268	.403	.336	.298	.353	.177
	[.039]	[.043]	[.042]	[.041]	[.042]	
MPLS	.213	.209	.305	.242	.233	.380
	[.036]	[.035]	[.041]	[.039]	[.037]	
Medical	.181	.104	.102	.105	.143	.235
	[.034]	[.027]	[.027]	[.028]	[.030]	
Femexp	1.85	1.81	1.90	1.95	1.83	.719
	[.077]	[.071]	[.075]	[.084]	[.075]	

Masks: raw data

	Post-wearing?		
Treatment	No	Yes	Total
0	107	20	127
1	107	27	134
2	86	42	128
3	75	49	124
4	68	65	133
Total	443	203	646

back

Masks: results

Masks: empirical strategy

Our regressions take the form

$$y_i = \beta_0 + \sum_{i=1}^{4} \beta_i T_i + \gamma x_i + u_i$$

where y_i denotes whether an individual chooses to wear a mask, T_i denotes the treatment they were placed in, and x_i is a vector of covariates (including whether they entered a room wearing a mask)

Masks: regressions

VARIABLES	(1) No controls	(2) Main Specification	(3) All Controls
1.treatment	.044	.032	.020
	(.048)	(.029)	(.033)
2.treatment	.171***	.078**	.075**
	(.053)	(.032)	(.035)
3.treatment	.238***	.163***	.156***
	(.055)	(.039)	(.041)
4.treatment	.331***	.284***	.289***
	(.054)	(.043)	(.046)
pre		.757***	.741***
		(.029)	(.035)
age		.002	.001
		(.005)	(.005)
male		-.007	-.007
		(.026)	(.028)
Constant	.157***	.014	.130
	(.032)	(.107)	(.144)
Observations	646	646	646
R-squared	0.070	0.494	0.517

Notes: Robust standard errors in parentheses (*** $p<0.01$, ** $p<0.05$, * $p<0.1$).

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Masks: logits

VARIABLES	(1) No controls	(2) Main Specification	(3) All Controls
1.treatment	.044	.033	.029
	(.047)	(.030)	(.034)
2.treatment	.171***	.073**	.079**
	(.053)	(.032)	(.035)
3.treatment	.238***	.162***	.168***
	(.055)	(.040)	(.043)
4.treatment	.331***	.283***	.304***
	(.054)	(.042)	(.046)
pre		.504***	.498***
		(.030)	(.031)
age		.003	.002
		(.005)	(.004)
male		-.006	-.002
		(.026)	(.028)
Observations	646	646	620

Notes: Robust standard errors in parentheses (*** $p<0.01$, ** $p<0.05$, * $p<0.1$).

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Masks: probits

◂ back

VARIABLES	(1) No controls	(2) Main Specification	(3) All Controls
1.treatment	.044	.036	.029
	(.047)	(.031)	(.034)
2.treatment	.171***	.078**	.078**
	(.053)	(.033)	(.035)
3.treatment	.238***	.163***	.162***
	(.055)	(.040)	(.043)
4.treatment	.331***	.284***	.298***
	(.054)	(.043)	(.046)
pre		.518***	.512***
		(.024)	(.027)
age		.002	.001
		(.004)	(.004)
male		-.007	-.004
		(.026)	(.028)
Observations	646	646	620

Notes: Robust standard errors in parentheses (*** p<0.01, ** p<0.05, * p<0.1).

Masks: monotonicity (from regressions)

back

Comparison	No controls	Main specification	All controls
T0 vs T1	.355	.278	.536
T1 vs T2	.019	.205	.163
T2 vs T3	.269	.051	.068
T3 vs T4	.131	.019	.017
T0 vs T2	.001	.014	.032
T1 vs T3	.001	.002	.002
T2 vs T4	.008	.000	.000

Masks: switches

back

Table: Changes (treatment 0)

	Post-wearing	
Pre-wearing	No	Yes
No	.972	.028
Yes	.056	.944

Table: Changes (treatment 4)

	Post-wearing	
Pre-wearing	No	Yes
No	.632	.368
Yes	.037	.963

Masks: switches (2)

back

	T0	T1	T2	T3	T4
Putting mask on	.028	.080	.106	.223	.368
Taking mask off	.056	.143	.059	.067	.037

Masks: test for quadratic form

back

Variable	Linear	Quadratic	Cubic
Masks	.070***	0.008	0.024
	[-.010]	[-.028]	[-.062]
Masks^2		.016**	.004
		[-.008]	[-.045]
Masks^3			.002
			[-.008]
Pre	.752***	.757***	.757***
	[-.029]	[-.029]	[-.029]
Age	.002	.002	.002
	[-.005]	[-.005]	[-.005]
Male	-.008	-.007	-.007
	[-.026]	[-.026]	[-.026]
Constant	-.022	.016	.014
	[-.102]	[-.107]	[-.107]
Joint test	.000	.000	.000
R^2	.491	.494	.494

SURVEY

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Masks: Online Survey

We also conducted an online survey which (re-assuringly) generates similar results. Importantly, it also suggests that

1. Individual preferences have a tipping point representation.
2. Effects are driven by some social learning and social pressure mechanisms (and not mechanisms that appeal to material payoffs!).

Masks: survey explanations

Table: Explanations

Explanation	Frequency
Trying to avoid judgement	.202
Trying to cater to others' preferences	.351
Trying to follow rules	.106
Learning about COVID-risks	.011
Diminishing returns	.000
Other/not answering question	.330

Descriptive from Questionnaire I

Table: Frequency of tipping points (i.e. switches)

Switch	Frequency	Percentage
0	55	.170
1	98	.302
2	57	.176
3	45	.139
4	42	.130
5	27	.833
n		324

Descriptive from Questionnaire II

Table: Subjects wearing a mask under different treatments.

Treatment	0	1
0	.828	.172
1	.528	.472
2	.353	.647
3	.215	.785
4	.083	.917
n		1,630

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Regression from Questionnaire

VARIABLES	(1)
1.Treatment	.301***
	(.035)
2.Treatment	.475***
	(.034)
3.Treatment	.613***
	(.031)
4.Treatment	.745***
	(.026)
Constant	.172***
	(.021)
Observations	1,630
R-squared	.280

Notes: Robust standard errors in parentheses (*** $p<0.01$, ** $p<0.05$, * $p<0.1$).

CAMERAS

Cameras: treatments

◂ back

Treatment	Frequency	Percentage
0	232	20.8
1	204	18.3
2	224	20.1
3	242	21.7
4	213	19.1
Total	1115	100.0

Cameras: balance table

Variable	Mean	Mean	Mean	Mean	Mean	p-value
age	42.2	43.4	42.3	41.3	42.7	.615
	[.940]	[.931]	[.903]	[.906]	[.990]	
pre	.116	.039	.058	.074	.070	.039
	[.021]	[.014]	[.016]	[.017]	[.018]	
male	.472	.441	.439	.455	.516	.486
	[.033]	[.035]	[.033]	[.032]	[.034]	

back

Cameras: regressions

VARIABLES	(1) No controls	(2) Main Specification	(3) All Controls
1.cameras	.077*	.118***	.125***
	(.043)	(.040)	(.041)
2.cameras	.176***	.209***	.214***
	(.043)	(.039)	(.044)
3.cameras	.281***	.308***	.320***
	(.043)	(.039)	(.049)
4.cameras	.355***	.380***	.386***
	(.044)	(.041)	(.057)
pre		.579***	.581***
		(.033)	(.034)
age		.000	.000
		(.001)	(.001)
male		.024	.023
		(.027)	(.027)
Constant	0.241***	0.155***	0.0936
	(0.0282)	(0.0466)	(0.0609)
Observations	1,113	1,111	1,109
R-squared	0.069	0.161	0.183

Notes: Robust standard errors in parentheses (*** p<0.01, ** p<0.05, * p<0.1).

Cameras: logits

VARIABLES	(1) Logit No controls	(2) Main Specification	(3) Controlling for Everything
1.cameras	.0772*	.127***	.133***
	(.043)	(.039)	(.039)
2.cameras	.176***	.215***	.218***
	(.043)	(.039)	(.040)
3.cameras	.281***	.314***	.323***
	(.043)	(.039)	(.045)
4.cameras	.355***	.385***	.389***
	(.044)	(.041)	(.051)
pre		.741***	.743***
		(.092)	(.092)
age		.000	.000
		(.001)	(.001)
male		.023	.023
		(.027)	(.027)
Observations	1,113	1,111	1,109

Notes: Robust standard errors in parentheses (*** p<0.01, ** p<0.05, * p<0.1).

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Cameras: probits

back

VARIABLES	(1) No controls	(2) Main Specification	(3) All Controls
1.cameras	.077*	.125***	.130***
	(.043)	(.039)	(.039)
2.cameras	.176***	.216***	.218***
	(.043)	(.039)	(.040)
3.cameras	.281***	.312***	.321***
	(.043)	(.039)	(.046)
4.cameras	.355***	.385***	.389***
	(.044)	(.040)	(.052)
pre			.699***
			(.076)
age		.000	.000
		(.001)	(.001)
male		.024	.025
		(.027)	(.027)
Observations	1,113	1,111	1,109

Notes: Robust standard errors in parentheses (*** $p<0.01$, ** $p<0.05$, * $p<0.1$).

Cameras: monotonicity from regressions

back

Comparison	No controls	Main Specification	All Controls
T0 vs T1	.074	.003	.002
T1 vs T2	.035	.043	.051
T2 vs T3	.022	.028	.020
T3 vs T4	.116	.116	.152
T0 vs T2	.000	.000	.000
T1 vs T3	.000	.000	.000
T2 vs T4	.000	.000	.001

Cameras: switches

back

	T0	T1	T2	T3	T4
Turning camera on	0.156	0.296	0.381	0.491	0.566
Turning camera off	0.111	0.125	0.000	0.059	0.000

Cameras: test for quadratic form

back

Variable	Linear	Quadratic	Cubic
Cameras	.095***	.119***	.119
	-.009	-.032	-.074
Cameras^2		-.006	-.006
		-.008	-.049
Cameras^3			.000
			-.008
Pre	.576***	.578***	.578***
	-.033	-.033	-.033
Age	.000	.000	.000
	-.001	-.001	-.001
Male	.023	.024	.024
	-.027	-.027	-.027
Constant	.169***	.156***	.156***
	-.046	-.047	-.047
Joint test	.000	.000	.000
R^2	.161	.161	.161