Health Externalities and Policy: The Role of Social Preferences*

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February 9, 2022

Abstract

Social preferences facilitate the internalization of health externalities, for example by reducing mobility during a pandemic. We test this hypothesis using mobility data from 258 cities worldwide alongside experimentally validated measures of social preferences. Controlling for time-varying heterogeneity that could arise at the level at which mitigation policies are implemented, we find that they matter less in regions that are more altruistic, patient, or exhibit less negative reciprocity. In those regions, mobility falls ahead of lockdowns, and remains low after the lifting thereof. Our results elucidate the importance, independent of the cultural context, of social preferences in fostering cooperative behavior.

Keywords: *social preferences, pandemics, mobility, health externalities, mitigation policies.*

JEL codes: D01, D62, D64, D91, I10, I18.

* We thank Thomas Dohmen, Ruben Durante, Uwe Sunde, as well as participants at various conferences and seminars for their comments and suggestions. Saidi's research is funded by the Deutsche Forschungsgemeinschaft (DFG, German Research Foundation) under Germany's Excellence Strategy (EXC 2126/1 – 390838866). Faia gratefully acknowledges funding by the DFG under grant FA-1022-2.

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1 Introduction

Social, or other-regarding, preferences facilitate cooperation among humans, and are an important pillar for understanding under what circumstances individual behavior aligns with a concern for the greater good or social welfare (see, among others, Fehr and Fischbacher, 2002). As such, their potency is higher in situations that involve severe externalities, causing a greater divergence between private and social optimality. These considerations have led to a vast literature studying the relationship between social preferences and economic incentives (see Bowles and Polania-Reyes, 2012, for an overview), and the way in which social preferences shape individuals' response to incentives in the workplace (Bandiera et al., 2005).

The outbreak and development of the COVID-19 pandemic puts the role of social preferences in fostering cooperative behavior to the test at an unprecedented worldwide scale. This begs the question to what extent and what kind of individuals reduce their mobility in an attempt to internalize the health externalities they might impose on others. A potential concern regarding the measurement of these internalization attempts is that, at the same time, mitigation policies and other government interventions are put in place to contain mobility. Given the possibility that social preferences affect individuals' mobility decisions independently of any mitigation policies, the latter's effectiveness may be fatally misinterpreted if one does not account for the role of social preferences. In turn, neglecting individuals' behavioral response can lead to naïve policies, giving rise to an epidemiological Lucas critique.

In this paper, we use daily mobility data for 258 cities across the globe to shed light on the extent of internalization of health externalities around mitigation policies during the pandemic. We exploit cross-sectional heterogeneity across regions to mimic a counterfactual. We find that the impact of lockdowns, and the lifting thereof, on mobility is partially muted in regions in which individuals are more patient, in which they have a higher degree of altruism, and in which they exhibit less negative reciprocity. In particular, the fact that individuals in regions with varying social preferences respond differently to the same policies allows us to tease out to what degree any muted response to these policies is driven by a preceding internalization of health externalities through reduced mobility in regions that exhibit lower levels of negative reciprocity, greater altruism, or more patience. This different efficacy of policies may, however, mask other observed confounding factors or further unobserved heterogeneity. For this reason, we control for time-invariant heterogeneity at the city level. In addition, we show that our results are robust to including interactions of mitigation policies with potential confounds at the regional (or more granular city) level. Finally, we control for time-varying unobserved heterogeneity at the (typically country) level at which the mitigation policies are implemented.

For our empirical analysis, we use Apple Mobility data, which are obtained from GPS tracking. These data provide indicators on walking, driving, and transit, are daily, have a long time coverage, and offer city-level granularity for 299 cities. We create a unique dataset by merging them with regional data on social preferences. To identify the effect of social preferences across regions within countries, we consider only countries with data coverage of multiple major cities that span at least two regions within the same country. This marginally reduces our sample to 258 cities in 23 countries. We capture social preferences by using experimentally validated survey measures from the Global Preferences Survey (Falk et al., 2018). Their data are representative for the respective countries' populations, and are available at the regional level.

To explore the interaction of social preferences with mitigation policies, which vary across countries (and across states/provinces in the US, Brazil, and Canada), we use a sample period that is long enough to comprise both lockdowns and subsequent relaxations during what is commonly referred to as the first wave of the COVID-19 pandemic (late January to late June 2020). As this period was characterized by a significant degree of uncertainty, and mitigating factors such as vaccination progress were far from sight across the globe, this provides us with a relatively clean setting to test for heterogeneous effects following lockdowns and the lifting thereof as a function of average social preferences across vastly different regions in the world.

Figure 1 summarizes our main evidence on the role of social preferences for the effectiveness of lockdowns. We zoom in on transit, a mobility outcome that is most likely to generate negative externalities during a pandemic (as opposed to driving, possibly in isolation, and

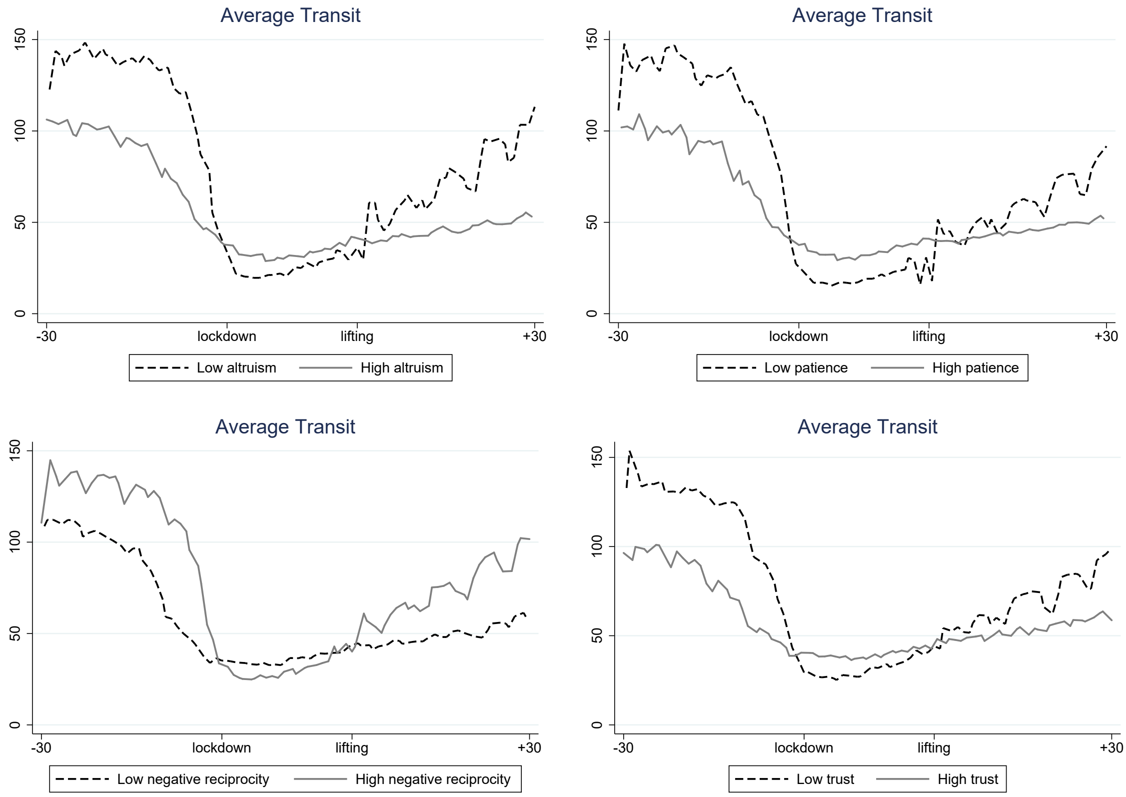

Figure 1
Mobility around Global Lockdown and Lifting Dates

Average city-level values for transit from Apple Mobility data around lockdown and lifting dates for regions in the top and bottom quartile of the distribution of the average value of altruism, patience, negative reciprocity, and trust based on the Global Preferences Survey (Falk et al., 2018). The sample starts 30 days before the beginning of a lockdown and ends 30 days after the lifting thereof. The interim period is rescaled such that one unit on the x-axis corresponds to 5% of the interim period in a given country (state/province in the US, Brazil, or Canada).

walking in less densely populated areas).[1] For regions in which individuals report different average levels of altruism, patience, negative reciprocity, and also trust, we plot average city-level values for the transit index, based on the Apple Mobility data, around lockdown and lifting dates (in our regression sample for countries with at least two cities in different regions). The latter are determined at the state/province level in the US, Brazil and Canada, and at the country level in all other cases. In the figure, we use thirty days before any lockdown measures and after the lifting thereof, thereby focusing on countries (states/provinces in the US, Brazil, and Canada) that have experienced both until the end of our sample (June 30, 2020). The interim period is rescaled to represent each country's (state's/province's) timeline.

On average, mobility is reduced in advance of lockdowns, and picks up even before the

1 While our empirical results hold for all three mobility indices, transit tends to react more than walking or driving.

lifting of mitigation policies. Importantly, lockdowns are less likely to (additionally) bring down mobility, as it is reduced well before the implementation of any stringency measures, in regions in which individuals are more altruistic, more patient, exhibit less negative reciprocity, and are more trusting. What is more, in regions with such traits, mobility is also less likely to pick up again once the mitigation measures are relaxed.

These findings are consistent with the idea that altruism captures the care for others especially in non-anonymous interactions (Bohnet and Frey, 1999), which are potentially most dangerous in a pandemic. While patience reflects time, rather than social, preferences, it can induce and reinforce socially responsible behavior in a pandemic. As patient individuals attach lower discount rates to future health risks, they internalize the future consequences of their actions, such as social contacts that affect others by helping the spread of a disease (see also Moser and Yared, 2021, for theoretical underpinnings of a similar argument). Finally, negative reciprocity reflects individuals' propensity to retaliate for unfair behavior. In the context of the pandemic, this implies that one does not restrain oneself (by reducing one's mobility) if others are seen not doing it either. Therefore, a lockdown may be necessary to bring down mobility for negative reciprocators. The bottomline is that external constraints are less needed, or even ineffective, when prosocial incentives are stronger.

A natural concern that arises in our setting and may prevent a causal interpretation is that regions with individuals that are more altruistic, patient, or exhibit less negative reciprocity also have other qualities that are correlated with these preferences and may simultaneously govern mobility choices in reaction to mitigation policies. To address this, we show that our results are robust to including interactions of mitigation policies with the number of infection cases in a given country and city-level population density, both reflecting the severity of infection risk, and also with the composition of the regional population given by recent migration movements.

Our paper is related to multiple strands of literature. We provide a more detailed literature review in Online Appendix B. Contributing to the vast literature that investigates the importance of social preferences for social interactions, social capital, and economic outcomes (e.g., Dohmen et al., 2009; Kosse and Tincani, 2020), our paper lays out the health consequences of social preferences and cooperation. For this purpose, we use the spread of the COVID-19 pandemic as a salient health risk that gives rise to externalities from mobility. As such, our paper connects with recent studies that document health behaviors and mobility in response to the pandemic in particular countries (such as Campos-Mercade et al., 2021b; Durante et al., 2021). In contrast, we shed light on how the underlying determinants of mobility—such as social preferences—interact with mitigation policies, independently of the specific context.

Our findings are in accordance with several theories in which the choice of social interactions is endogenous to agents' preferences and the environment. Alfaro et al. (2021) show in an SIR-network model that agents reduce social interactions when the time discount rate (patience) or the degree of altruism (the weight attached to other individuals' utility) increases. Our results also speak to a growing experimental literature that uses multiple games to document the consistency of behavior across contexts (Bednar et al., 2012). Cason and Gangadharan (2013) show that cooperative behavior is context dependent and, for instance, depends on whether subjects also compete in a market. Our field evidence is consistent with such cross-game spillovers, in that we show that experimentally validated measures of social and time preferences can also explain cooperation in terms of individuals' responses to health risk.

2 Data and Empirical Strategy

2.1 Data Description

In the following, we describe our various data sources. We relegate further details, especially on the treatment of the data, to Online Appendix C.

We measure mobility at the city-day level using Apple Mobility data. To capture policy responses of governments across the globe, we use dates for lockdowns and the lifting thereof at the state level for the US from the National Academy for State Health Policy, at the state/province level for Brazil and Canada from Wikipedia, and at the country level for all other countries also from Wikipedia. As an alternative, we use information on stay-at-home requirements (intensity stages 2 and 3) from the Oxford COVID-19 Government Response Tracker (OxCGRT).

Besides including city, date, and country by month fixed effects, we use control variables in our regression analysis from the following data sources: daily numbers on infections and deaths due to COVID-19 at the country level from Johns Hopkins University, which are available from January 22, 2020, the daily number of Google searches for the term "Coronavirus" in each region, as well as population density of a city and the share of new (less than ten years) foreign-born inhabitants in a region from the OECD database.

Finally, to analyze whether the effect of government responses on mobility depends on region-specific economic preferences, we rely on a set of variables from the Global Preferences Survey (Falk et al., 2018). We use their experimentally validated measures of altruism, patience, and negative reciprocity.[2] Specifically, altruism is based on questions about donation decisions and a self-assessment regarding people's willingness to give to good causes. Patience is based on a self-assessment regarding the willingness to wait and experimental questions about intertemporal-choice sequences. Negative reciprocity describes the willingness to take revenge and punish unfair behavior toward oneself and others.

Besides these social preferences, namely altruism and reciprocity, we also consider time preferences because they can foster prosocial behavior in a pandemic. Furthermore, as we show below, the timing of lockdowns is not related in any meaningful way to the variation in patience, negative reciprocity, and altruism. However, we do not find this to be the case for risk preferences (from the Global Preferences Survey), so comparing the latter's effect with those of the remaining economic preferences would be subject to a potential endogeneity bias.

The top panel of Table 1 shows summary statistics for the variables used in our regression analysis. The regression sample is limited to countries with at least two cities in different regions. This leaves us with 258 cities in 23 countries (see Table A.1 in the Online Appendix for an overview), for a sample period of more than five months in 2020, namely from January 22 to June 30. Note that (time-invariant) population density is available only for a subset

2 In the Online Appendix, we also provide results on positive reciprocity and trust, a variable based on a self-assessment as to whether individuals have only the best intentions.

of the cities, while the (time-invariant) share of new foreign-born population is available only for a subset of the regions in our analysis. We also include summary statistics for the variables we employ from the Global Preferences Survey, which are available at the (time-invariant) regional level. While altruism and patience are positively correlated (with a correlation coefficient of 0.26), both are uncorrelated with negative reciprocity (-0.01 and 0.03, respectively).

2.2 Empirical Specification

To assess whether the effect of mitigation policies on mobility varies as a function of social preferences in different cities worldwide, we exploit variation in these preferences across different regions in the same country, in which all regions typically face the same mitigation policies. By limiting the sample to countries c with at least two cities i in different regions g, we can include country by month fixed effects, thereby estimating the effect of lockdowns, or other government measures, while holding constant all remaining sources of unobserved heterogeneity at the country level in a given month.

We hypothesize that within the same country, regions with a certain preference $Preference_g$—namely greater altruism, patience, or less negative reciprocity—reduce their mobility by more preceding any government responses, thereby dampening any additional effect of $Lockdown_{ct}$ on mobility. Similarly, we conjecture that such regions increase their mobility less following the lifting of mitigation policies, captured by $Lifting_{ct}$. To test this, we estimate the following regression specification at the city-day level it:

$$\begin{aligned} \ln(Mobility)_{it} &= \beta_1 Lockdown_{ct} + \beta_2 Lockdown_{ct} \times Preference_g + \beta_3 Lifting_{ct} \\ &\quad + \beta_4 Lifting_{ct} \times Preference_g + \beta_5 \mathbf{X}_{gt-1} + \mu_i + \delta_t + \theta_{cm(t)} + \epsilon_{it}, \qquad (1) \end{aligned}$$

where the dependent variable is the natural logarithm of Apple Mobility's walking, driving, or transit index for city i at date t; $Lockdown_{ct}$ is an indicator variable for the entire post-period following a lockdown in country c (or state/province g for the US, Brazil, and Canada), and $Lifting_{ct}$ is an indicator variable for the period following the first date which marks the

Table 1
Summary Statistics

	Mean	Std. dev.	Min	Max	N
Walking	90.48	44.07	2.43	629.86	40,386
Driving	88.39	34.24	5.89	252.00	41,022
Transit	70.06	39.17	4.11	360.87	27,666
Population density (inhabitants/km^2)	628.89	646.36	23.33	4,419.33	164
Share new foreigners	32.81%	9.92%	13.40%	73.00%	91
Altruism	0.07	0.37	-2.10	0.76	150
Patience	0.44	0.49	-0.94	1.42	150
Neg. reciprocity	0.07	0.33	-1.00	1.03	150

	Patience			Neg. reciprocity			Altruism		
	low	high	p-value	low	high	p-value	low	high	p-value
Lockdown date (C)	Mar 26	Mar 20	0.46	Mar 24	Mar 22	0.89	Mar 25	Mar 19	0.20
Lockdown date (R)	Mar 26	Mar 25	0.38	Mar 26	Mar 26	0.66	Mar 25	Mar 27	0.29
LD $-$ 1$^{\text{st}}$ death (C)	9	23	0.15	17	16	0.97	21	12	0.37
LD $-$ 1$^{\text{st}}$ death (R)	22	25	0.23	24	23	0.81	22	25	0.26
Max. stringency (C)	83	77	0.15	80	82	0.57	81	79	0.66
Max. stringency (R)	81	81	0.92	80	82	0.24	82	80	0.33
Population density	680	378	0.00	371	693	0.00	662	386	0.01
Share new foreigners	36%	30%	0.00	32%	33%	0.79	33%	33%	0.99
Paid work or study	270	265	0.86	287	248	0.09	277	258	0.43
Unpaid work	204	200	0.78	214	191	0.10	194	211	0.21
Personal care	672	659	0.41	645	686	0.01	670	661	0.57
Leisure	274	300	0.13	279	295	0.36	279	295	0.38
Other time use	20	18	0.78	19	20	0.87	20	19	0.84
Google Trends spike	Mar 17	Mar 16	0.32	Mar 19	Mar 14	0.00	Mar 20	Mar 13	0.00

Based on our regression sample limited to countries (and all cities/regions therein) with at least two cities in different regions, the top panel of this table presents summary statistics at the city-day level it (comprising 258 cities from January 22 to June 30, 2020) for the three mobility indices (walking, driving, and transit from Apple Mobility), at the (time-invariant) city level i for population density (from the OECD database), and at the (time-invariant) region level g for all remaining variables (altruism, patience, and negative reciprocity from the Global Preferences Survey, and the share of new foreign-born population from the OECD database). In particular, $\textit{Population density}_i$ is the average (time-invariant) population density in city i from 2016 to 2018 in inhabitants per km^2; $\textit{Share new foreigners}_g$ is the share of new (less than 10 years) foreign-born population in region g in 2015; and $\textit{Altruism}_g$, $\textit{Patience}_g$, and $\textit{Neg. reciprocity}_g$ are the average values of the respective measures from the Global Preferences Survey in region g reported by Falk et al. (2018). In the bottom panel, we present, separately for countries/regions in the top vs. bottom half of the distribution of the respective variable from the Global Preferences Survey, average lockdown dates (LD) as well as the average period (in days) between the first death and the first day of a lockdown (at the country (C) level for all countries, using the average date for state-/province-level lockdowns in the US, Brazil, and Canada, and at the region (R) level for the US, Brazil, and Canada), the maximum stringency (during our entire sample period) from 0 to 100, based on the Oxford COVID-19 Government Response Tracker, reflecting the different policy responses that governments have taken (at the country (C) level for all countries and at the region (R) level for the US, Brazil, and Canada), as well as the average population density (city level), the average share of new foreign-born population (region level), the average no. of minutes per day (from the OECD database) for different activities (country level) and the date of the pre-lockdown maximum in the Google Trends Index for the search term "Coronavirus" (region level), alongside the p-value from a two-sided difference-in-means test.

lifting of restrictions in country c (or state/province g for the US, Brazil, and Canada). $\mathbf{X}_{gt-1}$ denotes the following control variables: the natural logarithm of the Google Trends Index for the search term "Coronavirus" in region g (of city i) and the 7-day moving averages of the number of infection cases and deaths per capita in country c (of region g) at date $t-1$. $Preference_g$ is the average value of altruism, patience, or negative reciprocity in region g (as reported by Falk et al., 2018); μ_i and δ_t denote city and date fixed effects, respectively, and $\theta_{cm(t)}$ denotes country-month fixed effects ($m(t)$ is the month for a given day t). Standard errors are double-clustered at the city and date levels.

By testing for the heterogeneous effect of, for instance, altruism at the regional level following lockdowns within countries, we mitigate the risk of picking up potential reverse causality.[3] This is because government policies are typically put in place with the entire, or rather average, population in mind. The only exceptions to this are the US, Brazil, and Canada where lockdowns are implemented at the state/province, i.e., region g, level rather than the country level. This implies that the level of variation of the economic preferences is the same as that of *Lockdown* and *Lifting*. Therefore, the more aggregate country by month fixed effects do not necessarily pick up the underlying determinants governing lockdown decisions as the latter are not taken at the country level in the US, Brazil, and Canada.[4]

Within these countries, however, the timing of the regional lockdowns does not seem to be related to the regional variation in economic preferences. In the bottom panel of Table 1, we split the lockdown dates by states/provinces (i.e., regions "R") in the bottom vs. top half in terms of patience, negative reciprocity and altruism, and find no discernible difference. This continues to hold true at the more aggregate country level for all countries ("C"), including those for which the level of variation of social preferences is more granular than that of the mitigation policies. What is more, the length of the period from the first death to the first day of a lockdown is also not related to patience, negative reciprocity, and altruism.

3 In our setup, treatment effects vary across countries and time, which can affect the magnitude of our estimates. In Online Appendix D, we present a Goodman-Bacon (2021) decomposition that quantifies the potential bias of our two-way fixed-effects estimator with staggered adoption of lockdowns to be small.

4 One way of addressing this concern is to simply drop from our analysis all cities in the US, Brazil, and Canada for which the level of variation of economic preferences matches that of mitigation policies. In spite of the US constituting a relatively large share of our sample, our results are broadly robust to doing so (see Tables A.2, A.3, and A.4 in the Online Appendix).

In our empirical analysis, we will use as an alternative source of variation in the stringency of mitigation policies a stay-at-home indicator variable, which is based on the Oxford COVID-19 Government Response Tracker (OxCGRT). To compare the maximum stringency reached across states/provinces in the US, Brazil, and Canada, we take from OxCGRT a composite index that combines several different policy responses that governments have taken. Once again, maximum stringency does not vary across regions as a function of patience, negative reciprocity, or altruism. This is also reflected in the more aggregate country-level comparisons (including all countries).

A lingering concern regarding our identification is that as social preferences can be endogenous to certain characteristics of the economy, they may capture specific features of local economies that are not necessarily highly correlated with more aggregate (country-wide) characteristics, which are captured by country-month fixed effects. Thus, other regional factors that are correlated with economic preferences at the same level of granularity could govern the mobility response to mitigation policies. In the bottom panel of Table 1, we compare the population density and the share of new foreign-born population across regions, and find that only the former correlates meaningfully with patience, negative reciprocity, and altruism. We also find no relationship with various time-use variables (from the OECD database), measured in number of minutes per day for different activities at the country level.

At last, we consider the role of policy announcements. First, Figure 1 shows that the decline in mobility takes place ahead of lockdowns, which were announced on rather short notice. Second, the impact of policy announcements is related to the degree of credibility, which typically declines in a context with high uncertainty such as the onset of the pandemic. Third, we control in all regressions for the daily number of Google searches for the term "Coronavirus" in each region. We determine the date at which the maximum pre-lockdown value for the respective Google Trends Index is reached in a given region. Earlier spikes could reflect heightened awareness. As can be seen in the last row of Table 1, the timing of the Google Trends spikes is not related to patience or negative reciprocity in a way that could explain our results.

3 Results

In Tables 2, 3, and 4, we estimate specification (1), and use as dependent variables the natural logarithm of Apple Mobility's indices for walking, driving, and transit (the latter variable being available only for a subset of our regression sample). The coefficient on $Lockdown_{ct}$ is almost always negative and highly statistically significant. This suggests that, on average, lockdowns are effective in bringing down mobility and subsequently reducing the spread of the virus (as shown by Fang et al., 2020, for the case of China). There is, however, substantial heterogeneity across regions as a function of their economic preferences.[5]

Zooming in on the role of altruism first, columns 1 to 3 of Table 2 show that in regions which exhibit greater altruism, the effect of lockdowns on mobility is reduced significantly across the board (positive coefficient on $Lockdown_{ct} \times Altruism_g$). As suggested by Figure 1, this is due to a decline in mobility ahead of lockdowns, and not a sign of government policies crowding out voluntary cooperation. In line with this rationale, we find that individuals in more altruistic regions keep their level of mobility low, and do not increase it as much after the lifting of lockdowns (negative coefficient on $Lifting_{ct} \times Altruism_g$). Thus, in more altruistic regions, mobility drops primarily ahead of any lockdowns, and stays low irrespective of subsequent relaxations. In contrast, in less altruistic regions, lockdowns are relatively more required to bring down mobility to the same level, but it increases relatively more once the mitigation measures are relaxed.

A one-standard-deviation increase in $Altruism_g$ (= 0.37, see top panel of Table 1) reduces the effectiveness of lockdowns by 24% (= (0.37 × 0.29)/0.44), 15%, and 35% for walking, driving, and transit, respectively. The extent of muting is not symmetric, however: a one-standard-deviation increase in $Altruism_g$ is associated with a reduction in the rate at which mobility picks up following the lifting of lockdowns by 57% (= (0.37 × 0.37)/0.24), 47%, and 47% for walking, driving, and transit, respectively. This attests to the relative longevity of the internalization of health externalities in more altruistic regions.

5 Our results are robust to using country-level variables from the Global Preferences Survey, thereby trading off more representative measures of social and time preferences against more granular (i.e., regional) variation.

Table 2
Effect of Government Responses on Mobility: The Role of Altruism

	Walking	Driving	Transit	Walking	Driving	Transit	Walking	Driving	Transit	Walking	Driving	Transit
Lockdown	-0.44***	-0.39***	-0.62***	-0.62***	-0.51***	-0.77***	-0.47***	-0.43***	-0.65***			
	(0.06)	(0.05)	(0.08)	(0.08)	(0.06)	(0.09)	(0.16)	(0.11)	(0.20)			
Lockdown × Altruism	0.29***	0.16**	0.59***	0.12	0.07	0.46**	0.36**	0.28***	0.65***			
	(0.11)	(0.08)	(0.16)	(0.12)	(0.07)	(0.19)	(0.14)	(0.09)	(0.16)			
Lifting	0.24***	0.18***	0.22***	0.23***	0.18***	0.21***	0.15	0.05	0.08			
	(0.03)	(0.03)	(0.04)	(0.03)	(0.03)	(0.03)	(0.15)	(0.11)	(0.14)			
Lifting × Altruism	-0.37***	-0.23***	-0.28***	-0.34***	-0.21***	-0.26***	-0.29***	-0.24***	-0.09			
	(0.06)	(0.07)	(0.08)	(0.06)	(0.06)	(0.08)	(0.09)	(0.07)	(0.09)			
Voluntary				-0.16***	-0.09***	-0.13***						
				(0.04)	(0.03)	(0.05)						
Voluntary × Altruism				-0.27**	-0.20***	-0.19						
				(0.13)	(0.07)	(0.12)						
Lockdown × Cases per capita							0.03*	0.03*	0.02			
							(0.02)	(0.01)	(0.02)			
Lifting × Cases per capita							0.02	0.01	-0.04*			
							(0.02)	(0.02)	(0.02)			
Lockdown × Population density							-0.01	-0.09*	-0.06			
							(0.09)	(0.05)	(0.09)			
Lifting × Population density							0.06	0.10**	0.08			
							(0.05)	(0.04)	(0.07)			
Lockdown × Share new foreigners							-0.22	-0.05	0.35			
							(0.45)	(0.27)	(0.58)			
Lifting × Share new foreigners							-0.23	0.12	0.82**			
							(0.27)	(0.25)	(0.39)			
Stay-at-home										-0.25***	-0.21***	-0.34***
										(0.04)	(0.03)	(0.06)
Stay-at-home × Altruism										0.28***	0.20***	0.55***
										(0.10)	(0.07)	(0.14)
City FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Date FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Country-month FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
N	38,467	39,075	26,352	38,467	39,075	26,352	19,608	19,608	14,592	38,315	38,923	26,200
Adj. R^2	0.87	0.90	0.90	0.88	0.90	0.90	0.90	0.94	0.92	0.87	0.90	0.89

The level of observation is the city-date level it, where city i is in region g of country c. The sample is limited to countries c with at least two cities i in different regions g. The dependent variable in columns 1, 4, 7, and 10 is the natural logarithm of Apple Mobility's walking index for city i at date t. The dependent variable in columns 2, 5, 8, and 11 is the natural logarithm of Apple Mobility's driving index for city i at date t. The dependent variable in columns 3, 6, 9, and 12 is the natural logarithm of Apple Mobility's transit index for city i at date t. $Lockdown_{ct}$ is an indicator variable for the entire post-period following a lockdown in country c (or state/province g for the US, Brazil, and Canada), and $Lifting_{ct}$ is an indicator variable for the period following the first date which marks the lifting of restrictions in country c (or state/province g for the US, Brazil, and Canada). $Voluntary_{ct}$ is an indicator variable for the period between (and including) the first death and the first day of a lockdown in country c (or state/province g for the US, Brazil, and Canada). $Stay\text{-}at\text{-}home_{ct}$ is an indicator variable, from the Oxford COVID-19 Government Response Tracker, for whether a stay-at-home order is in place in country c (or state/province g for the US, Brazil, and Canada) at date t. $Altruism_g$ is the average value for the measure of altruism in region g reported by Falk et al. (2018). $Cases\ per\ capita_{ct-1}$ is the 7-day moving average of the number of infection cases per capita in country c at date $t-1$, multiplied by 1,000. $Population\ density_i$ and $Share\ new\ foreigners_g$ are defined as in Table 1. All regressions control for the 7-day moving averages of the number of infection cases and deaths per capita in country c at date $t-1$, and for the natural logarithm of the Google Trends Index for the search term "Coronavirus" in region g at date $t-1$. Robust standard errors (double-clustered at the city and date levels) are in parentheses.

Table 3
Effect of Government Responses on Mobility: The Role of Patience

	Walking	Driving	Transit	Walking	Driving	Transit	Walking	Driving	Transit	Walking	Driving	Transit
Lockdown	-0.67***	-0.53***	-0.77***	-0.80***	-0.60***	-0.87***	-1.05***	-0.82***	-0.84***			
	(0.08)	(0.06)	(0.10)	(0.08)	(0.06)	(0.10)	(0.17)	(0.11)	(0.24)			
Lockdown × Patience	0.45***	0.27***	0.44***	0.43***	0.23***	0.36***	0.75***	0.52***	0.50***			
	(0.09)	(0.05)	(0.09)	(0.09)	(0.05)	(0.10)	(0.14)	(0.07)	(0.16)			
Lifting	0.21***	0.19***	0.29***	0.21***	0.18***	0.28***	0.53***	0.37***	0.41***			
	(0.04)	(0.04)	(0.06)	(0.04)	(0.04)	(0.06)	(0.16)	(0.12)	(0.14)			
Lifting × Patience	-0.11**	-0.10**	-0.20***	-0.10**	-0.10**	-0.19***	-0.39***	-0.34***	-0.33***			
	(0.05)	(0.04)	(0.06)	(0.05)	(0.04)	(0.06)	(0.08)	(0.05)	(0.07)			
Voluntary				-0.14***	-0.05*	-0.06						
				(0.04)	(0.03)	(0.06)						
Voluntary × Patience				-0.00	-0.08*	-0.15**						
				(0.06)	(0.04)	(0.07)						
Lockdown × Cases per capita							0.03*	0.02*	0.01			
							(0.02)	(0.01)	(0.02)			
Lifting × Cases per capita							0.01	0.00	-0.03			
							(0.02)	(0.02)	(0.02)			
Lockdown × Population density							0.03	-0.06	-0.13			
							(0.08)	(0.04)	(0.09)			
Lifting × Population density							0.00	0.05**	0.07			
							(0.04)	(0.03)	(0.06)			
Lockdown × Share new foreigners							0.37	0.35	0.47			
							(0.35)	(0.24)	(0.54)			
Lifting × Share new foreigners							-0.59**	-0.21	0.37			
							(0.27)	(0.24)	(0.38)			
Stay-at-home										-0.38***	-0.29***	-0.44***
										(0.06)	(0.04)	(0.08)
Stay-at-home × Patience										0.30***	0.21***	0.38***
										(0.07)	(0.04)	(0.08)
City FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Date FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Country-month FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
N	38,467	39,075	26,352	38,467	39,075	26,352	19,608	19,608	14,592	38,315	38,923	26,200
Adj. R^2	0.88	0.91	0.90	0.88	0.91	0.90	0.91	0.94	0.92	0.87	0.90	0.89

$Patience_g$ is the average value for the measure of time preference in region g reported by Falk et al. (2018). All remaining variables are defined, and the empirical specifications are the same, as in Table 2.

Table 4
Effect of Government Responses on Mobility: The Role of Negative Reciprocity

	Walking	Driving	Transit	Walking	Driving	Transit	Walking	Driving	Transit	Walking	Driving	Transit
Lockdown	-0.36***	-0.34***	-0.42***	-0.58***	-0.47***	-0.60***	-0.30**	-0.29***	-0.27			
	(0.05)	(0.04)	(0.06)	(0.07)	(0.05)	(0.07)	(0.14)	(0.09)	(0.18)			
Lockdown × Neg. reciprocity	-0.17	-0.20***	-0.25	-0.04	-0.13*	-0.10	-0.48***	-0.46***	-0.32*			
	(0.11)	(0.07)	(0.17)	(0.12)	(0.06)	(0.16)	(0.15)	(0.09)	(0.19)			
Lifting	0.13***	0.12***	0.13***	0.13***	0.11***	0.13***	0.17	0.07	-0.01			
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.12)	(0.08)	(0.12)			
Lifting × Neg. reciprocity	0.31***	0.22***	0.35***	0.31***	0.22***	0.35***	0.39***	0.36***	0.41***			
	(0.07)	(0.05)	(0.11)	(0.07)	(0.05)	(0.10)	(0.09)	(0.08)	(0.13)			
Voluntary				-0.23***	-0.15***	-0.19***						
				(0.05)	(0.03)	(0.05)						
Voluntary × Neg. reciprocity				0.34***	0.24***	0.31***						
				(0.11)	(0.06)	(0.09)						
Lockdown × Cases per capita							0.05***	0.04***	0.02			
							(0.02)	(0.01)	(0.02)			
Lifting × Cases per capita							-0.02	-0.02	-0.04**			
							(0.02)	(0.02)	(0.02)			
Lockdown × Population density							-0.03	-0.10**	-0.14			
							(0.09)	(0.04)	(0.10)			
Lifting × Population density							0.05	0.10***	0.11*			
							(0.04)	(0.03)	(0.06)			
Lockdown × Share new foreigners							-0.38	-0.17	-0.18			
							(0.43)	(0.24)	(0.55)			
Lifting × Share new foreigners							-0.15	0.17	0.96**			
							(0.25)	(0.23)	(0.37)			
Stay-at-home										-0.18***	-0.15***	-0.15***
										(0.03)	(0.02)	(0.03)
Stay-at-home × Neg. reciprocity										-0.09	-0.12**	-0.25*
										(0.09)	(0.05)	(0.15)
City FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Date FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Country-month FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
N	38,467	39,075	26,352	38,467	39,075	26,352	19,608	19,608	14,592	38,315	38,923	26,200
Adj. R^2	0.87	0.90	0.90	0.88	0.90	0.90	0.91	0.94	0.92	0.87	0.89	0.89

Neg. reciprocity$_g$ is the average value for the measure of negative reciprocity in region g reported by Falk et al. (2018). All remaining variables are defined, and the empirical specifications are the same, as in Table 2.

To show that in regions with greater altruism the reduced response to lockdowns, and the lifting thereof, is due to the reduction of mobility beforehand, we split up the pre-lockdown period into two periods. The first is the pre-COVID period, prior to the first known deadly case in a given country, and the second period encompasses the period thereafter up until a lockdown. To capture such voluntary reduction in mobility prior to lockdowns, we define an indicator variable, $Voluntary_{ct}$, which is equal to one for the period from the first death until the last day before the lockdown in country c (or state/province g for the US, Brazil, and Canada). After including $Voluntary_{ct}$ and its interaction with $Altruism_g$ in columns 4 to 6, we find that while there is a general decline in mobility, cities located in more altruistic regions reduce their mobility by more prior to lockdowns, which partially explains the positive coefficient on $Lockdown_{ct} \times Altruism_g$, i.e., the latter coefficient is similar to, and in the case of walking and driving even smaller than, the absolute value of the coefficient on $Voluntary_{ct} \times Altruism_g$.

In columns 7 to 9, we re-run the baseline specification by including interactions of $Lockdown_{ct}$ and $Lifting_{ct}$ with cases per capita at the country level, population density at the city level, and the share of new foreign-born population at the region level g. The data-availability requirement for these variables leads to a drop in sample size, but our estimates are vastly robust.[6] The heterogeneous effects of lockdowns and the lifting thereof are therefore unlikely to be driven by a potential correlation between altruism and measures related to the intensity of the COVID-19 pandemic or local factors that characterize the population.

In the last three columns, we replace $Lockdown_{ct}$ and $Lifting_{ct}$ with $Stay\text{-}at\text{-}home_{ct}$, which is an indicator variable that is equal to one if stay-at-home requirements are currently in place, and zero otherwise. The estimates on the respective coefficient are statistically significant at the 1% level throughout. Importantly, the interaction effect with $Altruism_g$ is positive and significant at the 1% level, which is consistent with our estimates in the first three columns.

6 Results in all remaining columns of Tables 2, 3, and 4 remain robust when using the subsample that fulfills this additional data requirement.

Altruism dampens both the drop in mobility following more stringent mitigation policies and the increase in mobility after lifting any such restrictions.[7]

Table 3 confirms that all of these findings also hold (at least qualitatively) for more patient regions. Cities located in more patient regions experience a drop in mobility ahead of lockdowns. Furthermore, their mobility remains lower compared to cities in less patient regions following the relaxation of mitigation policies, but the effect is now more symmetric across lockdowns and the lifting thereof. This also holds after controlling for additional interactions of the mitigation policies with country-wide cases, city-level population density, and the region-level share of new foreign-born population. Beyond the desire to do good to others, patient individuals are more likely to restrain themselves and internalize health externalities because they do not discount future health risks as much.[8]

Finally, in regions that exhibit more negative reciprocity, we expect less regard for others' health. In line with this, we find that in regions with higher negative reciprocity lockdowns are effective in imposing such behavior, as they are needed more. The coefficient on $\mathit{Lockdown}_{ct}$ $\times$ $\mathit{Neg.\ reciprocity}_g$ is negative for walking, driving, and transit in the first nine columns of Table 4. Analogously, the coefficient on the interaction with $\mathit{Lifting}_{ct}$ is positive (and always statistically significant at the 1% level), exhibiting similar asymmetry as in the case of altruism (see Table 2). The respective results are qualitatively similar (albeit not statistically significant for walking) when using the $\mathit{Stay\text{-}at\text{-}home}_{ct}$ indicator in the last three columns. At least for said indicator, we also find that the interaction effects with positive reciprocity (from the Global Preferences Survey) are fairly close to the negative equivalent of the respective coefficients for negative reciprocity (see Table A.6 in the Online Appendix).[9]

Given the relatively weak correlation of altruism, patience, and negative reciprocity, the effects are potentially additive, in the sense that, for instance, regions with greater altruism

7 In Table A.5 of the Online Appendix, we use the full range of intensity stages. The results indicate that the largest interaction effects with social and time preferences are indeed concentrated on the last two intensity stages, i.e., the stay-at-home requirements.

8 Using the same data, Sunde et al. (2021) show that variation in patience is systematically related to differences in income as well as the accumulation of human capital, physical capital, and the stock of knowledge.

9 In Table A.7 of the Online Appendix, we document similar effects when using Trust_g: regions that exhibit greater trust react less to government mitigation policies, irrespective of how they are measured, and the relaxation thereof.

and patience may exhibit an even more dampened response to lockdowns and the lifting thereof. In Table A.8 of the Online Appendix, we re-run the first three specifications and simultaneously include all interaction terms with our social preferences. The coefficients on the individual interaction terms remain robust, suggesting that the separate effects in Tables 2, 3, and 4 reflect rather conservative estimates of the heterogeneous response to mitigation policies. In addition, we generate two composite measures of social preferences, which we use in Tables A.9 and A.10 of the Online Appendix. The first one is the average of the values for altruism, patience, and negative reciprocity (multiplied by (-1)). We furthermore compute a second, alternative composite measure of social preferences as the average of the values for altruism, negative reciprocity (multiplied by (-1)), and positive reciprocity. The results are strongly consistent with our baseline estimates.

4 Conclusion

There is an ongoing debate worldwide about how to best design health policies. Our study shows that the need and efficacy of certain measures largely depend on citizens' preferences. Individuals that exhibit strong social preferences and that are more patient tend to better internalize health externalities. As a result, outright constraints—such as lockdowns—are less needed and may even give rise to unintended consequences. Instead, providing economic incentives for certain actions, e.g., vaccination uptake (Campos-Mercade et al., 2021a), may be more effective. Our evidence, based on observations across the globe, lends support to the general validity of the role of social preferences in fostering cooperative behavior in a pandemic. We focus on an early episode of the ongoing pandemic during which the world was confronted with a similar degree of uncertainty. Extending our analysis to later waves would constitute an interesting test of external validity, which—alongside the challenges to obtain a similarly clean setting—we leave for future research.

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ONLINE APPENDIX—NOT FOR PUBLICATION

A. Supplementary Tables

Table A.1
List of Countries in Regression Sample

Country	Number of cities in different regions
Australia	5
Austria	2
Brazil	7
Canada	6
England	12
France	13
Germany	17
India	5
Indonesia	2
Italy	10
Japan	25
Mexico	9
Netherlands	5
Poland	4
Portugal	2
Russia	4
South Africa	2
Spain	4
Sweden	3
Switzerland	4
Turkey	4
United States	111
Vietnam	2

This table lists all countries with at least two cities in different regions that can be matched to the Global Preferences Survey (Falk et al., 2018).

Table A.2

Effect of Government Responses on Mobility: The Role of Altruism—Without US, Brazil, and Canada

	Walking	Driving	Transit	Walking	Driving	Transit	Walking	Driving	Transit	Walking	Driving	Transit
Lockdown	-0.81***	-0.75***	-1.15***	-0.94***	-0.81***	-1.25***	-0.76***	-0.63***	-0.67***			
	(0.10)	(0.07)	(0.12)	(0.10)	(0.07)	(0.14)	(0.17)	(0.13)	(0.22)			
Lockdown × Altruism	0.03	-0.06	0.18	-0.02	-0.08	0.27	-0.04	0.03	0.25			
	(0.14)	(0.06)	(0.23)	(0.16)	(0.06)	(0.25)	(0.20)	(0.13)	(0.26)			
Lifting	0.29***	0.29***	0.32***	0.29***	0.29***	0.32***	0.31*	0.07	0.43**			
	(0.05)	(0.04)	(0.05)	(0.05)	(0.04)	(0.05)	(0.18)	(0.14)	(0.16)			
Lifting × Altruism	-0.15	0.01	-0.08	-0.14	0.02	-0.09	-0.36**	-0.19*	-0.38*			
	(0.10)	(0.04)	(0.17)	(0.10)	(0.04)	(0.17)	(0.15)	(0.10)	(0.22)			
Voluntary				-0.13***	-0.07**	-0.10*						
				(0.04)	(0.03)	(0.05)						
Voluntary × Altruism				-0.05	-0.03	0.24						
				(0.19)	(0.09)	(0.19)						
Lockdown × Cases per capita							0.03	0.05**	0.02			
							(0.03)	(0.03)	(0.03)			
Lifting × Cases per capita							0.02	0.06*	0.06			
							(0.04)	(0.03)	(0.04)			
Lockdown × Population density							0.08	-0.02	0.03			
							(0.09)	(0.04)	(0.08)			
Lifting × Population density							0.06	0.05	-0.01			
							(0.06)	(0.05)	(0.07)			
Lockdown × Share new foreigners							-0.06	-0.07	-0.37			
							(0.42)	(0.28)	(0.51)			
Lifting × Share new foreigners							-0.68**	-0.25	-1.45**			
							(0.32)	(0.25)	(0.57)			
Stay-at-home										-0.43***	-0.38***	-0.58***
										(0.05)	(0.05)	(0.09)
Stay-at-home × Altruism										0.18	0.07	0.68***
										(0.14)	(0.07)	(0.19)
City FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Date FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Country-month FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
N	19,619	20,227	11,000	19,619	20,227	11,000	11,400	11,400	6,840	19,619	20,227	11,000
Adj. R^2	0.88	0.91	0.93	0.88	0.91	0.93	0.92	0.95	0.95	0.87	0.89	0.91

The level of observation is the city-date level it, where city i is in region g of country c. The sample is limited to countries c with at least two cities i in different regions g, and excludes the US, Brazil, and Canada. The dependent variable in columns 1, 4, 7, and 10 is the natural logarithm of Apple Mobility's walking index for city i at date t. The dependent variable in columns 2, 5, 8, and 11 is the natural logarithm of Apple Mobility's driving index for city i at date t. The dependent variable in columns 3, 6, 9, and 12 is the natural logarithm of Apple Mobility's transit index for city i at date t. $Lockdown_{ct}$ is an indicator variable for the entire post-period following a lockdown in country c (or state/province g for the US, Brazil, and Canada), and $Lifting_{ct}$ is an indicator variable for the period following the first date which marks the lifting of restrictions in country c (or state/province g for the US, Brazil, and Canada). $Voluntary_{ct}$ is an indicator variable for the period between (and including) the first death and the first day of a lockdown in country c (or state/province g for the US, Brazil, and Canada). $Stay\text{-}at\text{-}home_{ct}$ is an indicator variable, from the Oxford COVID-19 Government Response Tracker, for whether a stay-at-home order is in place in country c (or state/province g for the US, Brazil, and Canada) at date t. $Altruism_g$ is the average value for the measure of altruism in region g reported by Falk et al. (2018). $Cases\ per\ capita_{ct-1}$ is the 7-day moving average of the number of infection cases per capita in country c at date $t-1$, multiplied by 1,000. $Population\ density_i$ and $Share\ new\ foreigners_g$ are defined as in Table 1. All regressions control for the 7-day moving averages of the number of infection cases and deaths per capita in country c at date $t-1$, and for the natural logarithm of the Google Trends Index for the search term "Coronavirus" in region g at date $t-1$. Robust standard errors (double-clustered at the city and date levels) are in parentheses.

Table A.3
Effect of Government Responses on Mobility: The Role of Patience—Without US, Brazil, and Canada

	Walking	Driving	Transit	Walking	Driving	Transit	Walking	Driving	Transit	Walking	Driving	Transit
Lockdown	-0.97***	-0.80***	-1.45***	-1.10***	-0.85***	-1.55***	-1.44***	-1.07***	-1.13***			
	(0.11)	(0.08)	(0.17)	(0.10)	(0.08)	(0.19)	(0.18)	(0.14)	(0.25)			
Lockdown × Patience	0.45***	0.16*	0.68**	0.47***	0.14	0.51*	1.08***	0.72***	0.85***			
	(0.13)	(0.08)	(0.27)	(0.13)	(0.08)	(0.28)	(0.17)	(0.13)	(0.27)			
Lifting	0.35***	0.33***	0.34***	0.35***	0.33***	0.34***	1.20***	0.70***	1.03***			
	(0.06)	(0.04)	(0.09)	(0.06)	(0.04)	(0.09)	(0.21)	(0.16)	(0.15)			
Lifting × Patience	-0.16*	-0.09	-0.05	-0.16*	-0.09	-0.05	-0.93***	-0.65***	-0.80***			
	(0.09)	(0.06)	(0.15)	(0.08)	(0.06)	(0.15)	(0.14)	(0.11)	(0.16)			
Voluntary				-0.15***	-0.04	0.00						
				(0.05)	(0.04)	(0.06)						
Voluntary × Patience				0.06	-0.09	-0.35***						
				(0.07)	(0.06)	(0.11)						
Lockdown × Cases per capita							0.07**	0.08***	0.06**			
							(0.03)	(0.02)	(0.03)			
Lifting × Cases per capita							-0.08**	-0.00	-0.04			
							(0.04)	(0.03)	(0.05)			
Lockdown × Population density							0.06	-0.03	-0.06			
							(0.08)	(0.04)	(0.08)			
Lifting × Population density							0.01	0.03	0.08			
							(0.04)	(0.02)	(0.08)			
Lockdown × Share new foreigners							0.71*	0.42	0.10			
							(0.37)	(0.31)	(0.47)			
Lifting × Share new foreigners							-1.40***	-0.81***	-1.50***			
							(0.35)	(0.28)	(0.54)			
Stay-at-home										-0.56***	-0.44***	-0.92***
										(0.07)	(0.05)	(0.13)
Stay-at-home × Patience										0.35***	0.15**	0.63***
										(0.08)	(0.06)	(0.14)
City FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Date FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Country-month FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
N	19,619	20,227	11,000	19,619	20,227	11,000	11,400	11,400	6,840	19,619	20,227	11,000
Adj. R^2	0.89	0.91	0.93	0.89	0.91	0.93	0.92	0.95	0.95	0.88	0.89	0.91

The level of observation is the city-date level it, where city i is in region g of country c. The sample is limited to countries c with at least two cities i in different regions g, and excludes the US, Brazil, and Canada. The dependent variable in columns 1, 4, 7, and 10 is the natural logarithm of Apple Mobility's walking index for city i at date t. The dependent variable in columns 2, 5, 8, and 11 is the natural logarithm of Apple Mobility's driving index for city i at date t. The dependent variable in columns 3, 6, 9, and 12 is the natural logarithm of Apple Mobility's transit index for city i at date t. $Lockdown_{ct}$ is an indicator variable for the entire post-period following a lockdown in country c (or state/province g for the US, Brazil, and Canada), and $Lifting_{ct}$ is an indicator variable for the period following the first date which marks the lifting of restrictions in country c (or state/province g for the US, Brazil, and Canada). $Voluntary_{ct}$ is an indicator variable for the period between (and including) the first death and the first day of a lockdown in country c (or state/province g for the US, Brazil, and Canada). $Stay\text{-}at\text{-}home_{ct}$ is an indicator variable, from the Oxford COVID-19 Government Response Tracker, for whether a stay-at-home order is in place in country c (or state/province g for the US, Brazil, and Canada) at date t. $Patience_g$ is the average value for the measure of time preference in region g reported by Falk et al. (2018). $Cases\ per\ capita_{ct-1}$ is the 7-day moving average of the number of infection cases per capita in country c at date $t-1$, multiplied by 1,000. $Population\ density_i$ and $Share\ new\ foreigners_g$ are defined as in Table 1. All regressions control for the 7-day moving averages of the number of infection cases and deaths per capita in country c at date $t-1$, and for the natural logarithm of the Google Trends Index for the search term "Coronavirus" in region g at date $t-1$. Robust standard errors (double-clustered at the city and date levels) are in parentheses.

Table A.4
Effect of Government Responses on Mobility: The Role of Negative Reciprocity—Without US, Brazil, and Canada

	Walking	Driving	Transit	Walking	Driving	Transit	Walking	Driving	Transit	Walking	Driving	Transit
Lockdown	-0.81***	-0.72***	-1.07***	-0.96***	-0.80***	-1.23***	-0.71***	-0.56***	-0.45**			
	(0.10)	(0.07)	(0.12)	(0.09)	(0.07)	(0.12)	(0.18)	(0.11)	(0.22)			
Lockdown × Neg. reciprocity	-0.07	-0.15*	-0.56***	0.04	-0.09	-0.45**	-0.59***	-0.58***	-0.51***			
	(0.14)	(0.08)	(0.19)	(0.15)	(0.08)	(0.22)	(0.18)	(0.10)	(0.18)			
Lifting	0.23***	0.26***	0.27***	0.23***	0.27***	0.27***	0.45***	0.18**	0.25*			
	(0.04)	(0.03)	(0.06)	(0.04)	(0.03)	(0.06)	(0.13)	(0.09)	(0.14)			
Lifting × Neg. reciprocity	0.44***	0.23***	0.27**	0.44***	0.23***	0.28***	0.67***	0.49***	0.59***			
	(0.08)	(0.06)	(0.10)	(0.08)	(0.06)	(0.10)	(0.10)	(0.07)	(0.13)			
Voluntary				-0.20***	-0.12***	-0.20***						
				(0.05)	(0.03)	(0.06)						
Voluntary × Neg. reciprocity				0.37**	0.25**	0.28**						
				(0.16)	(0.10)	(0.12)						
Lockdown × Cases per capita							0.08**	0.09***	0.05			
							(0.04)	(0.03)	(0.03)			
Lifting × Cases per capita							-0.10***	-0.02	-0.05			
							(0.03)	(0.03)	(0.04)			
Lockdown × Population density							0.06	-0.03	-0.01			
							(0.09)	(0.04)	(0.08)			
Lifting × Population density							0.05	0.06	0.07			
							(0.04)	(0.04)	(0.06)			
Lockdown × Share new foreigners							0.08	0.01	-0.62			
							(0.43)	(0.27)	(0.48)			
Lifting × Share new foreigners							-0.52	-0.20	-0.24			
							(0.34)	(0.29)	(0.63)			
Stay-at-home										-0.43***	-0.37***	-0.51***
										(0.06)	(0.05)	(0.09)
Stay-at-home × Neg. reciprocity										-0.01	-0.07	-0.51***
										(0.12)	(0.06)	(0.11)
City FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Date FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Country-month FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
N	19,619	20,227	11,000	19,619	20,227	11,000	11,400	11,400	6,840	19,619	20,227	11,000
Adj. R^2	0.89	0.91	0.93	0.89	0.91	0.93	0.92	0.95	0.95	0.87	0.89	0.91

The level of observation is the city-date level it, where city i is in region g of country c. The sample is limited to countries c with at least two cities i in different regions g, and excludes the US, Brazil, and Canada. The dependent variable in columns 1, 4, 7, and 10 is the natural logarithm of Apple Mobility's walking index for city i at date t. The dependent variable in columns 2, 5, 8, and 11 is the natural logarithm of Apple Mobility's driving index for city i at date t. The dependent variable in columns 3, 6, 9, and 12 is the natural logarithm of Apple Mobility's transit index for city i at date t. $Lockdown_{ct}$ is an indicator variable for the entire post-period following a lockdown in country c (or state/province g for the US, Brazil, and Canada), and $Lifting_{ct}$ is an indicator variable for the period following the first date which marks the lifting of restrictions in country c (or state/province g for the US, Brazil, and Canada). $Voluntary_{ct}$ is an indicator variable for the period between (and including) the first death and the first day of a lockdown in country c (or state/province g for the US, Brazil, and Canada). $Stay\text{-}at\text{-}home_{ct}$ is an indicator variable, from the Oxford COVID-19 Government Response Tracker, for whether a stay-at-home order is in place in country c (or state/province g for the US, Brazil, and Canada) at date t. $Neg.\ reciprocity_g$ is the average value for the measure of negative reciprocity in region g reported by Falk et al. (2018). $Cases\ per\ capita_{ct-1}$ is the 7-day moving average of the number of infection cases per capita in country c at date $t-1$, multiplied by 1,000. $Population\ density_i$ and $Share\ new\ foreigners_g$ are defined as in Table 1. All regressions control for the 7-day moving averages of the number of infection cases and deaths per capita in country c at date $t-1$, and for the natural logarithm of the Google Trends Index for the search term "Coronavirus" in region g at date $t-1$. Robust standard errors (double-clustered at the city and date levels) are in parentheses.

Table A.5

Effect of Government Responses on Mobility and the Role of Social Preferences: Separate Intensity Stages

	Walking	Driving	Transit	Walking	Driving	Transit	Walking	Driving	Transit
Intensity 1	-0.12***	-0.10***	-0.23***						
	(0.03)	(0.02)	(0.04)						
Intensity 1 × Altruism	-0.04	-0.07	0.23**						
	(0.08)	(0.05)	(0.10)						
Intensity 2	-0.35***	-0.29***	-0.50***						
	(0.05)	(0.04)	(0.07)						
Intensity 2 × Altruism	0.25**	0.17**	0.65***						
	(0.12)	(0.08)	(0.17)						
Intensity 3	-0.74***	-0.74***							
	(0.09)	(0.09)							
Intensity 3 × Altruism	0.35**	0.39***							
	(0.14)	(0.11)							
Intensity 1				-0.27***	-0.17***	-0.27***			
				(0.05)	(0.04)	(0.05)			
Intensity 1 × Patience				0.27***	0.12***	0.14**			
				(0.07)	(0.04)	(0.06)			
Intensity 2				-0.50***	-0.38***	-0.61***			
				(0.07)	(0.04)	(0.09)			
Intensity 2 × Patience				0.40***	0.24***	0.41***			
				(0.08)	(0.04)	(0.09)			
Intensity 3				-0.85***	-0.76***				
				(0.10)	(0.10)				
Intensity 3 × Patience				0.39***	0.25***				
				(0.10)	(0.07)				
Intensity 1							-0.13***	-0.11***	-0.19***
							(0.03)	(0.02)	(0.04)
Intensity 1 × Neg. reciprocity							0.03	-0.00	-0.05
							(0.09)	(0.05)	(0.10)
Intensity 2							-0.28***	-0.24***	-0.32***
							(0.04)	(0.03)	(0.06)
Intensity 2 × Neg. reciprocity							-0.07	-0.11*	-0.26
							(0.12)	(0.06)	(0.17)
Intensity 3							-0.58***	-0.66***	
							(0.09)	(0.10)	
Intensity 3 × Neg. reciprocity							-0.22*	-0.04	
							(0.12)	(0.11)	
City FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Date FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Country-month FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
N	38,315	38,923	26,200	38,315	38,923	26,200	38,315	38,923	26,200
Adj. R^2	0.87	0.90	0.90	0.88	0.90	0.90	0.87	0.90	0.89

The level of observation is the city-date level it, where city i is in region g of country c. The sample is limited to countries c with at least two cities i in different regions g. The dependent variable in all columns is the natural logarithm of the mean of Apple Mobility's walking, driving, and transit indices for city i at date t. *Intensity* x_{ct} is an indicator variable, from the Oxford COVID-19 Government Response Tracker, for intensity stage $x \in \{1, 2, 3\}$ in country c (or state/province g for the US, Brazil, and Canada) at date t. In columns 3, 6, and 9, intensity stages 2 and 3 are pooled as there is only one city with transit data for which intensity stage 3 is reached in our sample period. $Altruism_g$, $Patience_g$, and $Neg.\ reciprocity_g$ are defined as in Tables 2, 3, and 4. All regressions control for the 7-day moving averages of the number of infection cases and deaths per capita in country c at date $t-1$, and for the natural logarithm of the Google Trends Index for the search term "Coronavirus" in region g at date $t-1$. Robust standard errors (double-clustered at the city and date levels) are in parentheses.

Table A.6
Effect of Government Responses on Mobility: The Role of Positive Reciprocity

	Walking	Driving	Transit	Walking	Driving	Transit	Walking	Driving	Transit	Walking	Driving	Transit
Lockdown	-0.38***	-0.36***	-0.46***	-0.56***	-0.47***	-0.61***	-0.21	-0.27**	-0.31			
	(0.06)	(0.04)	(0.06)	(0.07)	(0.05)	(0.08)	(0.17)	(0.11)	(0.21)			
Lockdown × Pos. reciprocity	0.02	0.05	0.25***	-0.03	0.03	0.25**	-0.45**	-0.16	-0.04			
	(0.11)	(0.04)	(0.09)	(0.12)	(0.05)	(0.10)	(0.21)	(0.10)	(0.22)			
Lifting	0.14***	0.13***	0.14***	0.14***	0.12***	0.14***	0.17	0.04	0.06			
	(0.02)	(0.02)	(0.03)	(0.02)	(0.02)	(0.03)	(0.15)	(0.11)	(0.14)			
Lifting × Pos. reciprocity	-0.01	-0.02	-0.06*	-0.01	-0.02	-0.05*	-0.08	-0.07	-0.04			
	(0.05)	(0.04)	(0.03)	(0.05)	(0.03)	(0.03)	(0.10)	(0.07)	(0.11)			
Voluntary				-0.19***	-0.11***	-0.14***						
				(0.05)	(0.03)	(0.05)						
Voluntary × Pos. reciprocity				-0.08	-0.05	-0.00						
				(0.06)	(0.03)	(0.05)						
Lockdown × Cases per capita							0.05***	0.04***	0.02			
							(0.02)	(0.01)	(0.02)			
Lifting × Cases per capita							-0.01	-0.01	-0.04*			
							(0.02)	(0.02)	(0.02)			
Lockdown × Population density							-0.04	-0.11**	-0.15			
							(0.09)	(0.05)	(0.10)			
Lifting × Population density							0.07	0.11***	0.11*			
							(0.04)	(0.03)	(0.07)			
Lockdown × Share new foreigners							-0.64	-0.30	-0.14			
							(0.45)	(0.27)	(0.60)			
Lifting × Share new foreigners							-0.15	0.21	0.80**			
							(0.27)	(0.23)	(0.39)			
Stay-at-home										-0.18***	-0.16***	-0.17***
										(0.03)	(0.02)	(0.03)
Stay-at-home × Pos. reciprocity										0.08	0.08**	0.24***
										(0.10)	(0.04)	(0.08)
City FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Date FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Country-month FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
N	38,467	39,075	26,352	38,467	39,075	26,352	19,608	19,608	14,592	38,315	38,923	26,200
Adj. R^2	0.87	0.90	0.90	0.87	0.90	0.90	0.91	0.94	0.92	0.87	0.89	0.89

The level of observation is the city-date level it, where city i is in region g of country c. The sample is limited to countries c with at least two cities i in different regions g. The dependent variable in columns 1, 4, 7, and 10 is the natural logarithm of Apple Mobility's walking index for city i at date t. The dependent variable in columns 2, 5, 8, and 11 is the natural logarithm of Apple Mobility's driving index for city i at date t. The dependent variable in columns 3, 6, 9, and 12 is the natural logarithm of Apple Mobility's transit index for city i at date t. $Lockdown_{ct}$ is an indicator variable for the entire post-period following a lockdown in country c (or state/province g for the US, Brazil, and Canada), and $Lifting_{ct}$ is an indicator variable for the period following the first date which marks the lifting of restrictions in country c (or state/province g for the US, Brazil, and Canada). $Voluntary_{ct}$ is an indicator variable for the period between (and including) the first death and the first day of a lockdown in country c (or state/province g for the US, Brazil, and Canada). $Stay\text{-}at\text{-}home_{ct}$ is an indicator variable, from the Oxford COVID-19 Government Response Tracker, for whether a stay-at-home order is in place in country c (or state/province g for the US, Brazil, and Canada) at date t. $Pos.\ reciprocity_g$ is the average value for the measure of positive reciprocity in region g reported by Falk et al. (2018). $Cases\ per\ capita_{ct-1}$ is the 7-day moving average of the number of infection cases per capita in country c at date $t-1$, multiplied by 1,000. $Population\ density_i$ and $Share\ new\ foreigners_g$ are defined as in Table 1. All regressions control for the 7-day moving averages of the number of infection cases and deaths per capita in country c at date $t-1$, and for the natural logarithm of the Google Trends Index for the search term "Coronavirus" in region g at date $t-1$. Robust standard errors (double-clustered at the city and date levels) are in parentheses.

Table A.7
Effect of Government Responses on Mobility: The Role of Trust

	Walking	Driving	Transit	Walking	Driving	Transit	Walking	Driving	Transit	Walking	Driving	Transit
Lockdown	-0.43***	-0.38***	-0.53***	-0.61***	-0.51***	-0.69***	-0.31**	-0.30***	-0.28			
	(0.06)	(0.04)	(0.07)	(0.07)	(0.05)	(0.08)	(0.15)	(0.10)	(0.18)			
Lockdown × Trust	0.42***	0.23***	0.51***	0.35***	0.16**	0.44***	0.45***	0.30***	0.45**			
	(0.11)	(0.06)	(0.13)	(0.12)	(0.06)	(0.14)	(0.17)	(0.09)	(0.21)			
Lifting	0.15***	0.13***	0.15***	0.15***	0.13***	0.15***	0.10	-0.01	0.04			
	(0.02)	(0.02)	(0.03)	(0.02)	(0.02)	(0.03)	(0.14)	(0.10)	(0.13)			
Lifting × Trust	-0.12*	-0.10**	-0.12**	-0.11*	-0.09**	-0.11**	-0.17**	-0.17***	-0.13			
	(0.07)	(0.05)	(0.05)	(0.06)	(0.05)	(0.05)	(0.08)	(0.06)	(0.09)			
Voluntary				-0.18***	-0.11***	-0.15***						
				(0.05)	(0.03)	(0.05)						
Voluntary × Trust				-0.11	-0.16***	-0.13*						
				(0.07)	(0.05)	(0.08)						
Lockdown × Cases per capita							0.04**	0.03**	0.02			
							(0.02)	(0.01)	(0.02)			
Lifting × Cases per capita							0.00	-0.00	-0.04*			
							(0.02)	(0.02)	(0.02)			
Lockdown × Population density							-0.02	-0.10**	-0.13			
							(0.09)	(0.04)	(0.10)			
Lifting × Population density							0.05	0.10***	0.11			
							(0.04)	(0.03)	(0.07)			
Lockdown × Share new foreigners							-0.65	-0.36	-0.47			
							(0.43)	(0.26)	(0.55)			
Lifting × Share new foreigners							-0.02	0.30	0.94**			
							(0.26)	(0.25)	(0.40)			
Stay-at-home										-0.23***	-0.19***	-0.26***
										(0.03)	(0.02)	(0.04)
Stay-at-home × Trust										0.38***	0.21***	0.53***
										(0.10)	(0.05)	(0.11)
City FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Date FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Country-month FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
N	38,467	39,075	26,352	38,467	39,075	26,352	19,608	19,608	14,592	38,315	38,923	26,200
Adj. R^2	0.88	0.90	0.90	0.88	0.90	0.90	0.90	0.94	0.92	0.87	0.90	0.89

The level of observation is the city-date level it, where city i is in region g of country c. The sample is limited to countries c with at least two cities i in different regions g. The dependent variable in columns 1, 4, 7, and 10 is the natural logarithm of Apple Mobility's walking index for city i at date t. The dependent variable in columns 2, 5, 8, and 11 is the natural logarithm of Apple Mobility's driving index for city i at date t. The dependent variable in columns 3, 6, 9, and 12 is the natural logarithm of Apple Mobility's transit index for city i at date t. $Lockdown_{ct}$ is an indicator variable for the entire post-period following a lockdown in country c (or state/province g for the US, Brazil, and Canada), and $Lifting_{ct}$ is an indicator variable for the period following the first date which marks the lifting of restrictions in country c (or state/province g for the US, Brazil, and Canada). $Voluntary_{ct}$ is an indicator variable for the period between (and including) the first death and the first day of a lockdown in country c (or state/province g for the US, Brazil, and Canada). $Stay\text{-}at\text{-}home_{ct}$ is an indicator variable, from the Oxford COVID-19 Government Response Tracker, for whether a stay-at-home order is in place in country c (or state/province g for the US, Brazil, and Canada) at date t. $Trust_g$ is the average value for the measure of trust in region g reported by Falk et al. (2018). $Cases\ per\ capita_{ct-1}$ is the 7-day moving average of the number of infection cases per capita in country c at date $t-1$, multiplied by 1,000. $Population\ density_i$ and $Share\ new\ foreigners_g$ are defined as in Table 1. All regressions control for the 7-day moving averages of the number of infection cases and deaths per capita in country c at date $t-1$, and for the natural logarithm of the Google Trends Index for the search term "Coronavirus" in region g at date $t-1$. Robust standard errors (double-clustered at the city and date levels) are in parentheses.

Table A.8

Effect of Government Responses on Mobility: Joint Test of the Role of Altruism, Patience, and Negative Reciprocity

	Walking	Driving	Transit
Lockdown	-0.69***	-0.53***	-0.92***
	(0.08)	(0.05)	(0.10)
Lockdown × Altruism	0.23**	0.13*	0.57***
	(0.10)	(0.07)	(0.13)
Lockdown × Patience	0.41***	0.25***	0.43***
	(0.08)	(0.05)	(0.10)
Lockdown × Neg. reciprocity	-0.13	-0.25***	-0.28**
	(0.11)	(0.07)	(0.11)
Lifting	0.27***	0.23***	0.32***
	(0.04)	(0.03)	(0.04)
Lifting × Altruism	-0.33***	-0.23***	-0.22***
	(0.05)	(0.05)	(0.06)
Lifting × Patience	-0.08**	-0.08**	-0.16***
	(0.04)	(0.03)	(0.04)
Lifting × Neg .reciprocity	0.27***	0.26***	0.27***
	(0.05)	(0.05)	(0.06)
City FE	Y	Y	Y
Date FE	Y	Y	Y
Country-month FE	Y	Y	Y
N	38,467	39,075	26,352
Adj. R^2	0.88	0.91	0.90

The level of observation is the city-date level it, where city i is in region g of country c. The sample is limited to countries c with at least two cities i in different regions g. The dependent variable in column 1 is the natural logarithm of Apple Mobility's walking index for city i at date t. The dependent variable in column 2 is the natural logarithm of Apple Mobility's driving index for city i at date t. The dependent variable in column 3 is the natural logarithm of Apple Mobility's transit index for city i at date t. $Lockdown_{ct}$ is an indicator variable for the entire post-period following a lockdown in country c (or state/province g for the US, Brazil, and Canada), and $Lifting_{ct}$ is an indicator variable for the period following the first date which marks the lifting of restrictions in country c (or state/province g for the US, Brazil, and Canada). $Altruism_g$ is the average value for the measure of altruism in region g reported by Falk et al. (2018). $Patience_g$ is the average value for the measure of time preference in region g reported by Falk et al. (2018). $Neg.\ reciprocity_g$ is the average value for the measure of negative reciprocity in region g reported by Falk et al. (2018). All regressions control for the 7-day moving averages of the number of infection cases and deaths per capita in country c at date $t-1$, and for the natural logarithm of the Google Trends Index for the search term "Coronavirus" in region g at date $t-1$. Robust standard errors (double-clustered at the city and date levels) are in parentheses.

Table A.9
Effect of Government Responses on Mobility: Social Preferences Index

	Walking	Driving	Transit	Walking	Driving	Transit	Walking	Driving	Transit	Walking	Driving	Transit
Lockdown	-0.63***	-0.53***	-0.87***	-0.77***	-0.61***	-0.99***	-0.92***	-0.78***	-0.85***			
	(0.07)	(0.05)	(0.09)	(0.08)	(0.06)	(0.10)	(0.16)	(0.09)	(0.19)			
Lockdown × Soc. Pref. Index	0.95***	0.66***	1.30***	0.78***	0.48***	1.04***	1.36***	1.06***	1.14***			
	(0.16)	(0.11)	(0.21)	(0.21)	(0.13)	(0.26)	(0.21)	(0.11)	(0.24)			
Lifting	0.29***	0.25***	0.34***	0.28***	0.24***	0.33***	0.42***	0.29***	0.32***			
	(0.04)	(0.03)	(0.05)	(0.04)	(0.04)	(0.05)	(0.13)	(0.08)	(0.12)			
Lifting × Soc. Pref. Index	-0.50***	-0.44***	-0.59***	-0.47***	-0.41***	-0.55***	-0.72***	-0.66***	-0.59***			
	(0.10)	(0.09)	(0.12)	(0.10)	(0.09)	(0.11)	(0.12)	(0.08)	(0.10)			
Voluntary				-0.12***	-0.05*	-0.08*						
				(0.04)	(0.03)	(0.05)						
Voluntary × Soc. Pref. Index				-0.22	-0.29**	-0.37**						
				(0.19)	(0.12)	(0.17)						
Lockdown × Cases per capita							0.02	0.02	0.01			
							(0.02)	(0.01)	(0.02)			
Lifting × Cases per capita							0.02	0.01	-0.03			
							(0.02)	(0.02)	(0.02)			
Lockdown × Population density							0.03	-0.06	-0.08			
							(0.08)	(0.04)	(0.09)			
Lifting × Population density							0.01	0.06*	0.04			
							(0.04)	(0.03)	(0.06)			
Lockdown × Share new foreigners							0.39	0.42*	0.53			
							(0.42)	(0.24)	(0.53)			
Lifting × Share new foreigners							-0.57**	-0.22	0.45			
							(0.26)	(0.23)	(0.36)			
Stay-at-home										-0.38***	-0.32***	-0.54***
										(0.06)	(0.04)	(0.07)
Stay-at-home × Soc. Pref. Index										0.68***	0.54***	1.09***
										(0.13)	(0.09)	(0.16)
City FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Date FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Country-month FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
N	38,467	39,075	26,352	38,467	39,075	26,352	19,608	19,608	14,592	38,315	38,923	26,200
Adj. R^2	0.88	0.91	0.90	0.88	0.91	0.90	0.91	0.94	0.92	0.87	0.90	0.90

The level of observation is the city-date level it, where city i is in region g of country c. The sample is limited to countries c with at least two cities i in different regions g. The dependent variable in columns 1, 4, 7, and 10 is the natural logarithm of Apple Mobility's walking index for city i at date t. The dependent variable in columns 2, 5, 8, and 11 is the natural logarithm of Apple Mobility's driving index for city i at date t. The dependent variable in columns 3, 6, 9, and 12 is the natural logarithm of Apple Mobility's transit index for city i at date t. $Lockdown_{ct}$ is an indicator variable for the entire post-period following a lockdown in country c (or state/province g for the US, Brazil, and Canada), and $Lifting_{ct}$ is an indicator variable for the period following the first date which marks the lifting of restrictions in country c (or state/province g for the US, Brazil, and Canada). $Voluntary_{ct}$ is an indicator variable for the period between (and including) the first death and the first day of a lockdown in country c (or state/province g for the US, Brazil, and Canada). $Stay\text{-}at\text{-}home_{ct}$ is an indicator variable, from the Oxford COVID-19 Government Response Tracker, for whether a stay-at-home order is in place in country c (or state/province g for the US, Brazil, and Canada) at date t. $Cases\ per\ capita_{ct-1}$ is the 7-day moving average of the number of infection cases per capita in country c at date $t-1$, multiplied by 1,000. $Population\ density_i$ and $Share\ new\ foreigners_g$ are defined as in Table 1 of the main paper. $Soc.\ Pref.\ Index_g = \frac{1}{3} Altruism_g + \frac{1}{3} Patience_g - \frac{1}{3} Neg.\ reciprocity_g$, where $Altruism_g$, $Patience_g$, and $Neg.\ reciprocity_g$ are the respective average values in region g reported by Falk et al. (2018). All regressions control for the 7-day moving averages of the number of infection cases and deaths per capita in country c at date $t-1$, and for the natural logarithm of the Google Trends Index for the search term "Coronavirus" in region g at date $t-1$. Robust standard errors (double-clustered at the city and date levels) are in parentheses.

Table A.10

Effect of Government Responses on Mobility: Alternative Social Preferences Index

	Walking	Driving	Transit	Walking	Driving	Transit	Walking	Driving	Transit	Walking	Driving	Transit
Lockdown	-0.40***	-0.37***	-0.55***	-0.61***	-0.50***	-0.72***	-0.39**	-0.41***	-0.47**			
	(0.06)	(0.04)	(0.06)	(0.07)	(0.05)	(0.08)	(0.17)	(0.10)	(0.19)			
Lockdown × Soc. Pref. Index *Alt.*	0.32*	0.28***	1.00***	0.08	0.15	0.84***	0.43	0.54***	0.73***			
	(0.16)	(0.10)	(0.20)	(0.20)	(0.10)	(0.23)	(0.29)	(0.14)	(0.27)			
Lifting	0.19***	0.15***	0.19***	0.19***	0.15***	0.19***	0.16	0.05	0.09			
	(0.03)	(0.02)	(0.03)	(0.03)	(0.02)	(0.03)	(0.12)	(0.09)	(0.12)			
Lifting × Soc. Pref. Index *Alt.*	-0.47***	-0.31***	-0.45***	-0.44***	-0.30***	-0.44***	-0.73***	-0.61***	-0.48***			
	(0.13)	(0.10)	(0.12)	(0.13)	(0.09)	(0.11)	(0.12)	(0.09)	(0.13)			
Voluntary				-0.20***	-0.12***	-0.15***						
				(0.05)	(0.03)	(0.05)						
Voluntary × Soc. Pref. Index *Alt.*				-0.44**	-0.29***	-0.29*						
				(0.18)	(0.10)	(0.15)						
Lockdown × Cases per capita							0.04**	0.02*	0.01			
							(0.02)	(0.01)	(0.02)			
Lifting × Cases per capita							0.03	0.02	-0.02			
							(0.02)	(0.02)	(0.02)			
Lockdown × Population density							-0.02	-0.09*	-0.10			
							(0.09)	(0.05)	(0.09)			
Lifting × Population density							0.06	0.10***	0.07			
							(0.05)	(0.03)	(0.06)			
Lockdown × Share new foreigners							-0.31	-0.04	0.13			
							(0.48)	(0.27)	(0.59)			
Lifting × Share new foreigners							-0.29	0.07	0.71*			
							(0.24)	(0.23)	(0.37)			
Stay-at-home										-0.21***	-0.18***	-0.27***
										(0.03)	(0.02)	(0.04)
Stay-at-home × Soc. Pref. Index *Alt.*										0.32**	0.30***	0.89***
										(0.15)	(0.09)	(0.16)
City FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Date FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Country-month FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
N	38,467	39,075	26,352	38,467	39,075	26,352	19,608	19,608	14,592	38,315	38,923	26,200
Adj. R^2	0.87	0.90	0.90	0.88	0.90	0.90	0.91	0.94	0.92	0.87	0.90	0.89

The level of observation is the city-date level it, where city i is in region g of country c. The sample is limited to countries c with at least two cities i in different regions g. The dependent variable in columns 1, 4, 7, and 10 is the natural logarithm of Apple Mobility's walking index for city i at date t. The dependent variable in columns 2, 5, 8, and 11 is the natural logarithm of Apple Mobility's driving index for city i at date t. The dependent variable in columns 3, 6, 9, and 12 is the natural logarithm of Apple Mobility's transit index for city i at date t. $Lockdown_{ct}$ is an indicator variable for the entire post-period following a lockdown in country c (or state/province g for the US, Brazil, and Canada), and $Lifting_{ct}$ is an indicator variable for the period following the first date which marks the lifting of restrictions in country c (or state/province g for the US, Brazil, and Canada). $Voluntary_{ct}$ is an indicator variable for the period between (and including) the first death and the first day of a lockdown in country c (or state/province g for the US, Brazil, and Canada). $Stay\text{-}at\text{-}home_{ct}$ is an indicator variable, from the Oxford COVID-19 Government Response Tracker, for whether a stay-at-home order is in place in country c (or state/province g for the US, Brazil, and Canada) at date t. $Cases\ per\ capita_{ct-1}$ is the 7-day moving average of the number of infection cases per capita in country c at date $t-1$, multiplied by 1,000. $Population\ density_i$ and $Share\ new\ foreigners_g$ are defined as in Table 1 of the main paper. $Soc.\ Pref.\ Index\ Alt._g = \frac{1}{3} Altruism_g - \frac{1}{3} Neg.\ reciprocity_g + \frac{1}{3} Pos.\ reciprocity_g$, where $Altruism_g$, $Neg.\ reciprocity_g$, and $Pos.\ reciprocity_g$ are the respective average values in region g reported by Falk et al. (2018). All regressions control for the 7-day moving averages of the number of infection cases and deaths per capita in country c at date $t-1$, and for the natural logarithm of the Google Trends Index for the search term "Coronavirus" in region g at date $t-1$. Robust standard errors (double-clustered at the city and date levels) are in parentheses.

B. Literature Review

Our paper contributes to the large and expanding literature that emphasizes the role of social preferences and their importance for social interactions, social capital, and economic outcomes. In our empirical analysis, we employ experimentally validated measures of social preferences from Falk et al. (2018). The related literature scrutinizes both the determinants (Kosse et al., 2020) and outcomes of prosocial behavior, e.g., in the labor market (Dohmen et al., 2009; Kosse and Tincani, 2020). Our paper highlights an equally important but perhaps overlooked aspect, namely the health consequences of social preferences and cooperation.

We use the spread of the COVID-19 pandemic as a salient health risk that gives rise to externalities from mobility. As such, our paper relates not only to the host of papers that assess the economic impact of the pandemic, but especially to those that consider the determinants of mobility during the pandemic (see, among others, Coven and Gupta, 2020; Glaeser et al., 2020; Goolsbee and Syverson, 2021). This strand of literature scrutinizes, in particular, the role of cultural traits or other beliefs about society for the development of mobility around the pandemic (e.g., Bazzi et al., 2021, on "rugged individualism" in the US). More closely related are Durante et al. (2021), who focus on civic capital in Italy, and Campos-Mercade et al. (2021), who show that prosociality matters for health behaviors in a representative sample in Sweden where mitigation policies were widely absent.

In contrast to these studies, we employ novel data for 258 cities in 23 countries in conjunction with experimentally validated survey, rather than observational, measures for a broader range of social preferences. We take advantage of the granular nature of our data to shed light on how a variety of social preferences interact with mitigation policies by affecting mobility ahead of lockdowns, and lasting until even after any such mitigation measures are relaxed. In line with Durante et al. (2021), we find that trust also mutes mobility responses to government interventions. Our range of social preferences, however, capture complexities that extend beyond generalized trust[1] and are, thus, better suited to capture social interactions that are potentially harmful during a pandemic. The global dimension of our analysis is

1 Bohnet and Frey (1999), Ashraf et al. (2006), Dohmen et al. (2012), and Schwerter and Zimmermann (2020), among others, discuss the individual primitives of trust and cooperation.

no less important, as there is growing consensus and a call in the experimental literature for cross-validating results across countries and cultures to guarantee the generality of the conclusions (List, 2020).

C. Data Appendix

Apple Mobility. Mobility is split into three categories: walking, driving, and transit. Given the nature of the data,[2] these variables primarily capture outside activities for which users seek directions. The data are at a daily frequency, and provide the relative volume of direction requests compared to a baseline volume on January 13, 2020.

Apple does not provide information about the coverage and, hence, representativeness, of their data. However, since several studies (see, e.g., Cot et al., 2021) show for a broad set of countries that a reduction in mobility, measured using the Apple Mobility data, is associated with a strong reduction in infection rates after a couple of weeks, this suggests that the data cover a broad share of the population.

Policy responses. First, we generate a dummy variable that is one from the first day of an official country-wide (or state-/province-wide) lockdown onward and zero otherwise, and a second dummy variable that is one from the first day of an official country-wide (or state-/province-wide) lifting of such mitigation policies onward and zero otherwise. For this purpose, we use the country-wide lockdown and lifting dates provided by Wikipedia.[3] Since in the US, Brazil, and Canada policy responses differ across states/provinces, we use state-/province-wide lockdown and lifting dates for a given city in the respective state/province for our city-level regressions. We use Wikipedia for Brazil and Canada, and for the US we obtain these data from the National Academy for State Health Policy.[4] Since in some cases the lifting or re-opening started gradually, it may be difficult to determine a unique starting date. To this end, we cross-validate these dates with a list of re-opening dates provided by the New York Times.[5] In case the start dates of the lifting period differ, we use the earlier date to generate our dummy variable.

Second, we use information on stay-at-home requirements from the Oxford COVID-19 Government Response Tracker (OxCGRT), which is available from January 1, 2020 onward. For most of the countries in our data, the index is at the country-day level. Like our lockdown

2 See https://www.apple.com/covid19/mobility.
3 See https://en.wikipedia.org/wiki/COVID-19 pandemic_lockdowns.
4 See https://www.nashp.org/governors-prioritize-health-for-all.
5 See https://www.nytimes.com/article/coronavirus-timeline.html.

data, for the US, Brazil, and Canada it is available at a more granular (e.g., state/province) level. The index comprises four intensity stages, ranging from no measures taken to a recommendation to stay at home and, ultimately, to requirements to not leave the house with more or less minimal exceptions. We generate an indicator variable that equals one for the last two intensity stages (the stay-at-home requirements) and zero otherwise.[6]

Control variables. First, we obtain daily numbers on infections and deaths due to COVID-19 at the country level from Johns Hopkins University.[7] This time series starts on January 22, 2020, determining the beginning of the time span covered in our empirical analysis. To account for possibly very noisy daily variation in these variables, we include their moving averages of the past seven days in our regressions.

Second, to control for general awareness, or potential fear, of COVID-19, we use the daily number of Google searches for the term "Coronavirus" in each region, provided by Google Trends.[8] For a given time period (in our case, January 22 to June 30), Google Trends assigns to the day with the highest search volume in a given country or region the value 100, and re-scales all other days accordingly. Since this leads to large spikes in the time-series data, we use the natural logarithm of these values for our analysis.

Third, we include additional control variables based on annual data from the OECD database.[9] For each variable, we always use the most granular level and most recent data available. In particular, we use the population density of a city, measured in inhabitants per km^2, and the share of new (less than ten years) foreign-born inhabitants in a region.

Global Preferences Survey. This globally representative dataset includes responses regarding time, risk, and social preferences for a large number (80,000) of individuals for all countries in our sample and more.[10]

The experimentally validated preference measures are standardized, so that each of them has a mean of 0 and a standard deviation of 1. As pointed out by Falk et al. (2018), economic

6 For more information and the current version of a working paper describing the approach, see https://www.bsg.ox.ac.uk/research/research-projects/coronavirus-government-response-tracker.
7 See https://github.com/CSSEGISandData/COVID-19/tree/master/csse_covid_19_data/csse_covid_19_time_series.
8 See https://trends.google.com/trends/?geo=US.
9 See https://stats.oecd.org/index.aspx.
10 For more information on this survey, see https://www.briq-institute.org/global-preferences/home and also Falk et al. (2016, 2018).

preferences tend to vary significantly within countries. Therefore, we use their dataset on individual-level, rather than country-level, survey responses, and compute for each variable the average value at the level of the regions corresponding to the cities in the Apple Mobility data.

D. Variation in Treatment Timing

In our setup, lockdown policies are adopted at different points in time. There is a recent debate in the literature about potential challenges that could arise when using a difference-in-differences (DiD) approach with variation in treatment timing. In particular, Goodman-Bacon (2021) shows that any two-way fixed-effects estimator of a DiD with variation in treatment timing is a weighted average of all possible comparisons between the pre- and post-treatment time periods as well as the treatment and control groups. Specifically, he shows how to decompose the two-way fixed-effects estimator into the single 2x2 estimates and their corresponding weights. The advantage of using such a decomposition is that one can see which comparison drives the results obtained from a two-way fixed-effects model.

In our case, our two-way fixed-effects estimator equals a combination of three different comparisons: the earlier treated versus the later treated as control group (hence, countries that receive a lockdown earlier versus the ones that receive it later), the later treated versus the earlier treated as control group (hence, countries that faced a lockdown earlier serve as control group), and the treated versus the never treated (countries with a lockdown versus countries that never had a lockdown). As shown by Goodman-Bacon (2021), the second comparison, where earlier treated countries serve as the control group, can be problematic and can bias the two-way fixed-effects estimator, especially when treatment effects vary over time. If this is the case, one obtains a negative weight on this comparison.

To address this concern, we decompose the two-way fixed-effects estimator from a basic regression of mobility on $Lockdown_{ct}$ and city and date fixed effects. In line with our estimates in the first row of Tables 2, 3, and 4, the coefficient on $Lockdown_{ct}$ is negative. The separate effects for walking, driving, and transit from the three different comparisons and their corresponding weights can be seen in Table D.1 below. The "unbiased DiD" equals the weighted average of the first and third comparison.

Our two-way fixed-effects estimator does not suffer from a large bias, since the weighted average using all comparisons (labeled as "DiD" in the table) and the weighted average using only the first and the third comparison ("unbiased DiD") are very similar to each other. This is due to two reasons. First, the estimates stemming from the comparison of countries with a later lockdown versus countries with an earlier lockdown do not differ much from the other two. Second, this comparison has a very small weight assigned, so it is unlikely to bias our estimates substantially.

Table D.1
Goodman-Bacon Decomposition

Comparison	Weight	Estimate	
Earlier treated vs. Later control	0.099	-0.541	
Later treated vs. Earlier control	0.156	-0.358	
Treated vs. Never treated	0.746	-0.125	
DiD			-0.203
Unbiased DiD			-0.174

(a) Walking

Comparison	Weight	Estimate	
Earlier treated vs. Later control	0.099	-0.47	
Later treated vs. Earlier control	0.156	-0.409	
Treated vs. Never treated	0.745	-0.123	
DiD			-0.202
Unbiased DiD			-0.164

(b) Driving

Comparison	Weight	Estimate	
Earlier treated vs. Later control	0.063	-0.609	
Later treated vs. Earlier control	0.099	-0.37	
Treated vs. Never treated	0.838	-0.339	
DiD			-0.359
Unbiased DiD			-0.358

(c) Transit

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