Health Externalities and Policy: The Role of Social Preferences*

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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.

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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 also 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 regional variation in social preferences to estimate heterogeneous responses to mitigation policies. 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. The granularity of our data allows us to control for time-varying unobserved heterogeneity at the (typically country) level at which the mitigation policies are implemented. In this manner, we can 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.

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 data set 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 – most importantly, altruism, patience, and negative reciprocity – 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 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

1 While our empirical results hold for all three mobility indices, transit tends to react more than walking or driving. This is reasonable since the congestion of cities' transportation systems increases infection risk, reflecting general geographical aspects related to cities' density.

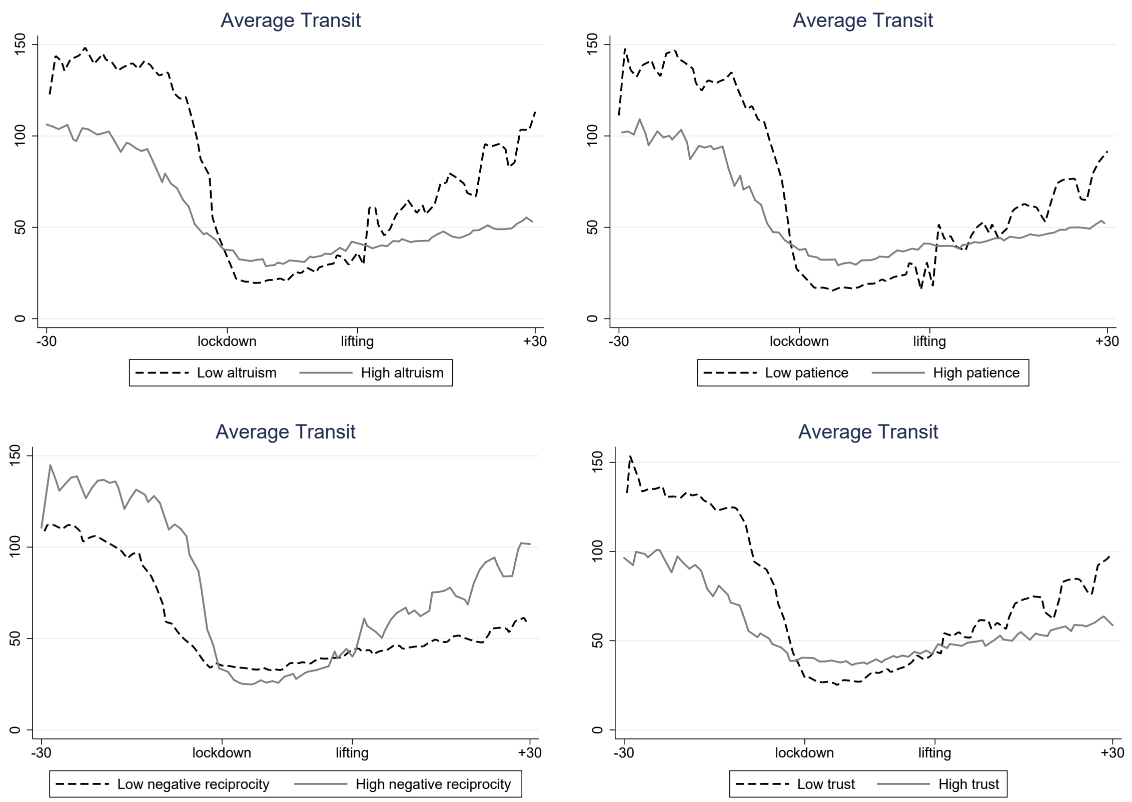

Figure 1
Mobility around Global Lockdown and Lifting Dates
Average city-level values for transit from Apple Mobility data around lockdown and lifting dates for regions in the top and bottom quartile of the distribution of the average value of altruism, patience, negative reciprocity, and trust based 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).

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 any lockdown, and picks up even before any 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 also in non-anonymous interactions, which are potentially most dangerous in a pandemic. Patience favors self-control, hence it increases the efficacy of prosocial incentives. Finally, in social anthropology, negative reciprocity indicates the intent to extract something or pursue personal interests in neglect of others, from which it follows that more of it reduces the incentives to care about others. The main take-away is that external constraints are less needed, or even ineffective, when prosocial incentives are stronger.

Our empirical strategy exploits regional heterogeneity in social preferences while controlling for time-varying unobserved heterogeneity at the country level, which is the level at which mitigation policies are typically implemented. 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 social 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 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, the best proxy for social contacts. 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. Consistent with Durante et al. (2021), we find that trust also mutes mobility responses to government interventions (see Figure 1 and our Online Appendix). Our range of social preferences, however, capture complexities that extend well beyond "generalized" trust[2] and are, thus, better suited to capture social interactions that are potentially harmful during a pandemic.[3] The global dimension of our analysis is 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).

2 Berg et al. (1995), Bohnet and Frey (1999), Costa-Gomes et al. (2014), Bohnet and Zeckhauser (2004), Ashraf et al. (2006), Huck et al. (2012), Dohmen et al. (2012), and Schwerter and Zimmermann (2020) are among the studies, some of which involve trust games conducted in the laboratory and in the field, that uncover the individual primitives of trust and cooperation.

3 In theoretical work (Alfaro et al., 2021), we rationalize our empirical findings through the lens of an SIR-network model where social-activity intensity depends on individual preferences, namely patience and altruism, and on community traits, namely the matching technology's returns to scale (geographical density) and reciprocity among groups.

2. Data and Empirical Strategy

2.1. Data Description

To measure mobility at the city level, we use a data set provided by Apple, which is based on direction requests in Apple Maps.[4] Mobility is split into three categories: walking, driving, and transit. The data are at a daily frequency, and provide the relative volume of direction requests compared to a baseline volume on January 13, 2020. Unfortunately, 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.

To capture policy responses of governments across the globe, we take two approaches. 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.[5] 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.[6] 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.[7] In case the start dates of the lifting period differ, we use the earlier date to generate our dummy variable.

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

Alternatively, 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 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.[8]

Besides including city, date, and country by month fixed effects, we use the following control variables in our regression analysis. First, we obtain daily numbers on infections and deaths due to COVID-19 at the country level from Johns Hopkins University.[9] 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.[10] 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.[11] 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.

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

8 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.
9 See https://github.com/CSSEGISandData/COVID-19/tree/master/csse_covid_19_data/csse_covid_19_time_series.
10 See https://trends.google.com/trends/?geo=US.
11 See https://stats.oecd.org/index.aspx.

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
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	669	390	0.00	385	673	0.00	659	399	0.01
Share new foreigners	36%	31%	0.02	34%	33%	0.68	35%	33%	0.33

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 (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 value for the Oxford COVID-19 Government Response Tracker (during our entire sample period) from 0 to 100, 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) and the average share of new foreign-born population (region level), alongside the p-value from a two-sided difference-in-means test.

Survey.[12] This globally representative data set includes responses regarding time, risk, and social preferences for a large number (80,000) of individuals for all countries in our sample and more. In particular, this data set provides experimentally validated measures of altruism, patience, and negative reciprocity, which we use to test for heterogeneous effects in our empirical analysis.[13]

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

12 For more information on this survey, see https://www.briq-institute.org/global-preferences/home and also Falk et al. (2016, 2018).

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

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. These 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 preferences tend to vary significantly within countries. Therefore, we use their data set 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.

We present summary statistics in Table 1. The top panel 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 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 (Falk et al., 2018), 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 barely correlated 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 (the US, Brazil, and Canada being the only exceptions in our data). 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 $\mathit{Preference}_g$—namely greater altruism, patience, or less negative reciprocity—reduce their mobility by more preceding any government responses, thereby dampening any additional effect of $\mathit{Lockdown}_{ct}$ on mobility. Similarly, we conjecture that such regions increase their mobility less following the lifting of mitigation policies, captured by $\mathit{Lifting}_{ct}$. To test this, we estimate the following regression specification at the city-day level it:

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

where the dependent variable is the natural logarithm of Apple Mobility's walking, driving, or transit index for city i at date t; $\mathit{Lockdown}_{ct}$ is an indicator variable for the entire post-period following a lockdown in country c (or state/region g for the US, Brazil, and Canada), and $\mathit{Lifting}_{ct}$ is an indicator variable for the period following the first date which marks the lifting of restrictions in country c (or state/region 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 $t-1$. $\mathit{Preference}_g$ 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 day 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 day 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.[14] This is because government policies are typically put in place with the entire,

14 In our setup, treatment effects vary across countries and time, which can affect the magnitude of our estimates. In Online Appendix B, 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.

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.[15]

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.

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

15 A crude 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).

actually govern the mobility response to mitigation policies. In the last two rows of 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. To account for the possibility that our estimates for the differential impact of mitigation policies are driven by a potential correlation between social preferences and other factors, we will in a robustness check control for interactions of our mitigation-policy variables with not only population density, but also the share of new foreign-born population and the number of infections.

3. Results

In Tables 2, 3, and 4, we estimate specification (1) and test for heterogeneous effects across regions within a country by including interactions of $Lockdown_{ct}$ and $Lifting_{ct}$ with, respectively, $Altruism_g$, $Patience_g$, and $Neg.\ reciprocity_g$. As dependent variables, we use 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).

We hypothesize that regions in which individuals report to be more altruistic or patient should exhibit a reduced response to lockdowns as they are more likely to refrain from social activities for the sake of internalizing any externalities on other individuals. We also test for analogous effects following the initial lifting of previous lockdown decisions, i.e., whether regions with more altruistic or patient individuals are subsequently less likely to pick up their mobility. Finally, agents that exhibit negative reciprocity are more prone to mimic any acts of mobility out of inequity aversion, so the negative effect of lockdowns and the positive effect of lifting the latter on city-level mobility should be stronger (weaker) for regions in which individuals exhibit greater (less) negative reciprocity.

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/region 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/region 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/region 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/region 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

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/region 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/region 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/region g for the US, Brazil, and Canada). $\textit{Stay-at-home}_{ct}$ 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/region 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). $\textit{Cases per capita}_{ct-1}$ 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. $\textit{Population density}_i$ and $\textit{Share new foreigners}_g$ 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 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

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/region 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/region 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/region 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/region 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.

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. Analogously, any increase in recorded outside activities following the lifting of mitigation policies, such as lockdowns, is dampened in regions with more altruistic individuals. This is in line with our hypothesis. Lockdowns, much like all naïve policies, therefore have only a limited effect on mobility. Analogously, altruistic agents are less likely to increase their mobility following the lifting of mitigation policies.

A one-standard-deviation increase in $Altruism_g$ (= 0.37, see top panel of Table 1) reduces the effectiveness of lockdowns by 24% (= $(0.37 \times 0.29)/0.44$), 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% (= $(0.37 \times 0.37)/0.24$), 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.

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/region 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 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.[16] 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 an indicator variable capturing whether stay-at-home requirements are currently in place, $Stay\text{-}at\text{-}home_{ct}$ (taken from the Oxford COVID-19 Government Response Tracker). The variable increases from 0 to 1 when stay-at-home requirements are implemented, but drops from 1 to 0 when they are lifted. The estimates on the respective coefficient in the last three columns of Table 2 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. Altruism dampens both the drop in mobility following more stringent mitigation policies and the increase in mobility after lifting any such restrictions.

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. More than a desire to do good to others, patience represents a means of self-control. Hence, any intent to internalize potential health externalities is pursued with greater efficacy by more patient individuals.[17]

Finally, in social psychology, reciprocity is a social norm by which a kind act is returned in exchange for another kind act. The definition of negative reciprocity in social anthropology is somewhat more subtle as it reflects the intent to extract something or pursue personal

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

17 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.

interests in neglect of others. It follows that in regions that exhibit more negative reciprocity, we should naturally 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 $Lockdown_{ct} \times$ *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 $Lifting_{ct}$ 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 *Stay-at-home*$_{ct}$ indicator in the last three columns.[18]

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 and patience may exhibit an even more dampened response to lockdowns and the lifting thereof. In Table A.6 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. Note that even though the partially muted response to mitigation policies in regions that exhibit more prosocial behavior, as measured by our social preferences, affects transit more than walking and driving, our estimates hold – across all specifications – when using a single mobility index, defined as the average of the three indices (see Table A.7 of the Online Appendix).

4. Concluding Remarks

As countries and societies become increasingly interconnected and harmful risks can travel the globe quickly – threatening human survival, the fabric of societies, and the sustainability of the economy – cooperation can be an effective tool to improve policy effectiveness. Our analysis

18 In Table A.5 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.

shows that in more cooperative societies there is less of a need for external constraints. This can be seen as another manifestation of the expectations critique, by which policies designed in neglect of the response in human behavior are ineffective at best. As a consequence, most economic policies are incentive-based and, according to our results, so should be epidemiological policies, including preventive ones which may require cooperation across countries.

Methodologically, we concentrate our efforts on constructing the largest possible data set with two goals in mind. First, the extensive and granular variations allow us to refine our empirical identification. Second, following a recent call in experimental studies for cross-validation, our results are not tailored or confined to any specific countries, cultures, or ethnic groups, but are instead derived from observations across the globe. Our evidence lends support to the general validity of the role of social preferences in fostering cooperative behavior, independently of the specific context.

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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/region 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/region 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/region 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/region 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/region 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/region 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/region g for the US, Brazil, and Canada). *Stay-at-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/region 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/region 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/region 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/region 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/region 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: 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/region 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/region 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/region 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/region 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.6
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/region 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/region 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.7
Effect of Government Responses on Mobility and the Role of Social Preferences: One Mobility Index

	Mob. index	Mob. index	Mob. index	Mob. index	Mob. index	Mob. index	Mob. index	Mob. index	Mob. index	Mob. index	Mob. index	Mob. Index
Lockdown	-0.42***	-0.59***	-0.37***	-0.56***	-0.68***	-0.53***	-0.48***	-0.92***	-0.32***			
	(0.05)	(0.07)	(0.05)	(0.06)	(0.07)	(0.05)	(0.13)	(0.14)	(0.11)			
Lockdown × Altruism	0.15*			0.03			0.34***					
	(0.09)			(0.08)			(0.11)					
Lockdown × Patience		0.32***			0.28***			0.59***				
		(0.06)			(0.07)			(0.10)				
Lockdown × Neg. reciprocity			-0.16*			-0.08			-0.47***			
			(0.08)			(0.08)			(0.12)			
Lifting	0.20***	0.19***	0.12***	0.19***	0.19***	0.12***	0.08	0.41***	0.10			
	(0.03)	(0.04)	(0.02)	(0.03)	(0.04)	(0.02)	(0.12)	(0.12)	(0.09)			
Lifting × Altruism	-0.24***			-0.22***			-0.24***					
	(0.07)			(0.07)			(0.08)					
Lifting × Patience		-0.09**			-0.09**			-0.34***				
		(0.04)			(0.04)			(0.06)				
Lifting × Neg. reciprocity			0.24***			0.24***			0.39***			
			(0.06)			(0.06)			(0.08)			
Voluntary				-0.12***	-0.08**	-0.18***						
				(0.04)	(0.03)	(0.04)						
Voluntary × Altruism				-0.25***								
				(0.08)								
Voluntary × Patience					-0.07							
					(0.05)							
Voluntary × Neg. reciprocity						0.28***						
						(0.08)						
Lockdown × Cases per capita							0.01	0.01	0.02			
							(0.02)	(0.02)	(0.02)			
Lifting × Cases per capita							0.02	0.01	-0.02			
							(0.02)	(0.02)	(0.02)			
Lockdown × Population density							-0.06	-0.02	-0.07			
							(0.07)	(0.06)	(0.06)			
Lifting × Population density							0.09**	0.04	0.08***			
							(0.04)	(0.03)	(0.03)			
Lockdown × Share new foreigners							-0.03	0.40	-0.18			
							(0.34)	(0.29)	(0.32)			
Lifting × Share new foreigners							0.01	-0.33	0.05			
							(0.25)	(0.23)	(0.22)			
Stay-at-home										-0.22***	-0.32***	-0.17***
										(0.03)	(0.05)	(0.02)
Stay-at-home × Altruism										0.20**		
										(0.08)		
Stay-at-home × Patience											0.24***	
											(0.05)	
Stay-at-home × Neg. reciprocity												-0.10
												(0.07)
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	39,075	39,075	39,075	39,075	39,075	39,075	19,608	19,608	19,608	38,923	38,923	38,923
Adj. R^2	0.89	0.89	0.89	0.89	0.89	0.89	0.92	0.93	0.93	0.88	0.89	0.88

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. $Lockdown_{ct}$ is an indicator variable for the entire post-period following a lockdown in country c (or state/region 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/region 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/region 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/region g for the US, Brazil, and Canada) at date t. $Altruism_g$, $Patience_g$, and $Neg.\ reciprocity_g$ are defined as in Tables 2, 3, and 4. $Cases\ per\ capita_{ct-1}$ 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.

B. 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 B.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 B.1
Goodman-Bacon Decomposition

Comparison	Weight	Estimate	
Earlier treated vs. Later control	0.099	-0.543	
Later treated vs. Earlier control	0.156	-0.359	
Treated vs. Never treated	0.745	-0.136	
DiD			-0.211
Unbiased DiD			-0.184

(a) Walking

Comparison	Weight	Estimate	
Earlier treated vs. Later control	0.099	-0.472	
Later treated vs. Earlier control	0.157	-0.410	
Treated vs. Never treated	0.744	-0.131	
DiD			-0.209
Unbiased DiD			-0.171

(b) Driving

Comparison	Weight	Estimate	
Earlier treated vs. Later control	0.063	-0.617	
Later treated vs. Earlier control	0.100	-0.373	
Treated vs. Never treated	0.837	-0.360	
DiD			-0.377
Unbiased DiD			-0.378

(c) Transit