

Research



Cite this article: Heroy S, Loaiza I, Pentland A, O'Clery N. 2021 COVID-19 policy analysis: labour structure dictates lockdown mobility behaviour. *J. R. Soc. Interface* **18**: 20201035. <https://doi.org/10.1098/rsif.2020.1035>

Received: 23 December 2020

Accepted: 9 March 2021

Subject Category:

Life Sciences—Mathematics interface

Subject Areas:

environmental science, biocomplexity

Keywords:

COVID-19, mobile device location data, human mobility, labour economics, inequality, policy analysis

Author for correspondence:

Samuel Heroy

e-mail: s.heroy@ucl.ac.uk

Electronic supplementary material is available online at <https://doi.org/10.6084/m9.figshare.c.5354831>.

COVID-19 policy analysis: labour structure dictates lockdown mobility behaviour

Samuel Heroy^{1,2}, Isabella Loaiza^{3,4}, Alex Pentland³ and Neave O'Clery^{1,2}

¹The Bartlett Centre for Advanced Spatial Analysis, University College London, London W1 4TJ, UK

²Mathematical Institute, University of Oxford, Radcliffe Observatory Quarter, Woodstock Road, Oxford OX2 6GG, UK

³MIT Media Laboratory, Massachusetts Institute of Technology, E15-383, 20 Ames Street, Cambridge, MA 02139, USA

⁴ICTEAM Institute - Pôle en ingénierie mathématique, UCLouvain, Louvain-la-Neuve 1348, Belgium

SH, 0000-0003-2936-9437; IL, 0000-0001-8426-510X; AP, 0000-0002-8053-9983; NO'C, 0000-0003-1876-8002

Countries and cities around the world have resorted to unprecedented mobility restrictions to combat COVID-19 transmission. Here we exploit a natural experiment whereby Colombian cities implemented varied lockdown policies based on ID number and gender to analyse the impact of these policies on urban mobility. Using mobile phone data, we find that the restrictiveness of cities' mobility quotas (the share of residents allowed out daily according to policy advice) does not correlate with mobility reduction. Instead, we find that larger, wealthier cities with more formalized and complex industrial structure experienced greater reductions in mobility. Within cities, wealthier residents are more likely to reduce mobility, and commuters are especially more likely to stay at home when their work is located in wealthy or commercially/industrially formalized neighbourhoods. Hence, our results indicate that cities' employment characteristics and work-from-home capabilities are the primary determinants of mobility reduction. This finding underscores the need for mitigations aimed at lower income/informal workers, and sheds light on critical dependencies between socio-economic classes in Latin American cities.

1. Introduction

Across the world, governments and scientists alike have struggled immensely with the question of which policies will most effectively reduce the spread of coronavirus disease 2019 (COVID-19). In a cross-country analysis of case data, Hsiang *et al.* [1] find that in six countries various policies ranging from full lockdown to paid sick leave prevented or delayed an estimated 495 million cases from January to June 2020, but that the effects of specific policies differed from country to country. Evidence from China [2,3] and across Europe [4] demonstrates clearly that full and persistent lockdown is by far the most effective measure in curbing spread. However, it is not yet clear how local economic conditions affect policy success.

Epidemic mitigation policies are not implemented in a vacuum. For instance, a tech hub has many jobs that can be performed remotely with relative ease, while a manufacturing centre does not. Globally, cities with many teleworkable jobs have been better able to reduce work commutes [5,6]. More generally, wealthier cities and wealthier neighbourhoods have been more adept at reducing urban mobility [7–10], and experienced lower COVID-19 death rates at least in the UK and USA [11,12]. However, the relationship between lockdown severity, city wealth and observed mobility reduction remains not well understood. For example, are harsh mobility restrictions as effective in less wealthy cities? Or does the nature of the local economy outweigh policy severity?

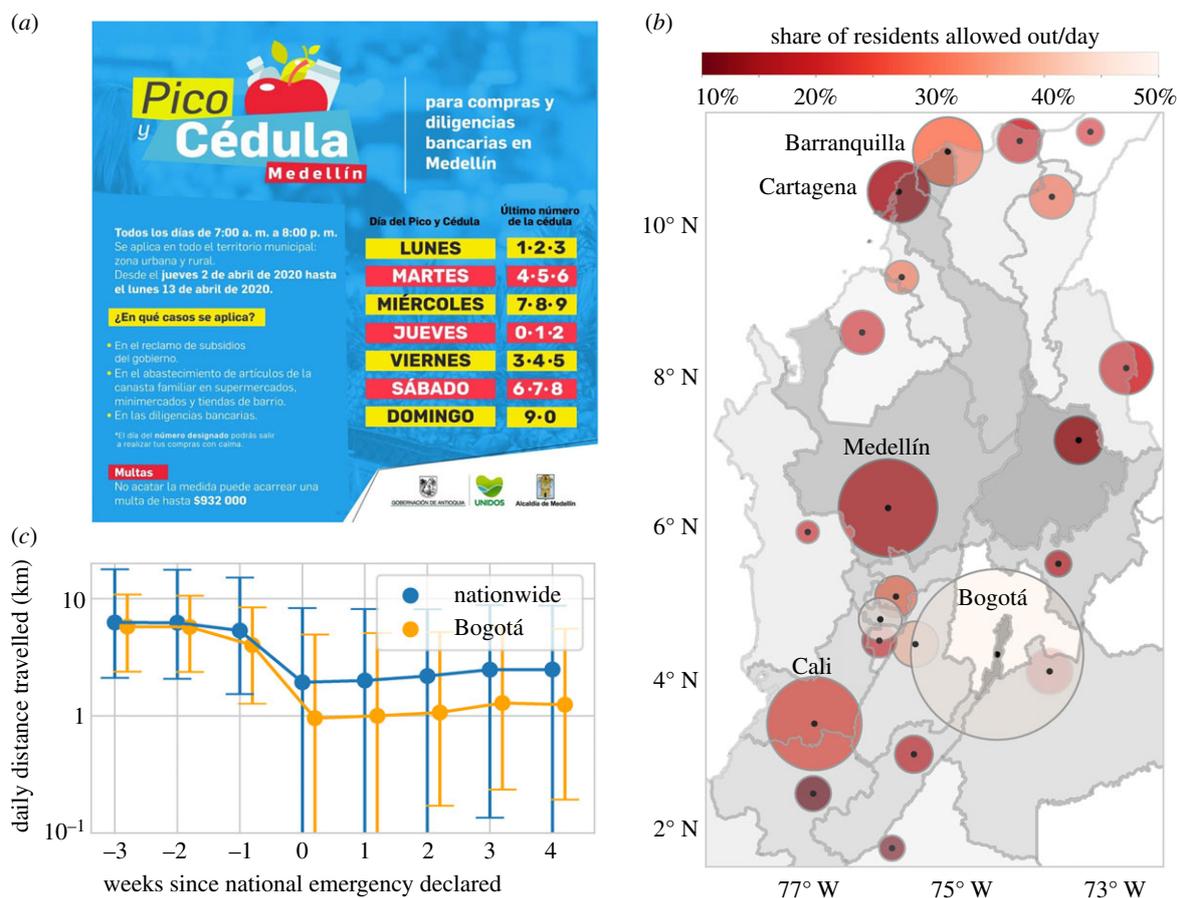


Figure 1. Colombian municipalities administered locally varying policies in which residents were allowed to go out for essential purposes on days corresponding to their national ID/gender. (a) During the first half of the study period, Medellín allowed out three ID numbers daily (30% of residents), though it later tightened the policy to only allow out two ID numbers daily (20% of residents). Image reproduced with permission from the Alcaldía de Medellín. (b) The capital municipalities (points, size proportional to population) of the most populous departments in Colombia, coloured by the average share of residents allowed out per weekday from 13 to 27 April. Departments are shaded by GDP *per capita*. (c) Users nationwide reduced their mobility greatly from 19 March (end of week -1), when the government first announced national lockdown-related policies. From 19 March to 9 April (weeks 0–2), residents nationwide were instructed to stay at home unless absolutely necessary, but localized policies took effect from 6 April (week 2) in all municipalities except Bogotá, which implemented the pico y género policy on 13 April (week 3).

Latin American countries generally had more time to prepare for the in-coming pandemic and develop appropriate policy measures [13]. In Colombia, Ecuador and Panamá, residents were allowed out for essential trips on days of the week corresponding to their national ID number and/or gender [14,15]. We can quantify the restrictiveness of this type of policy via, for example, the share of residents allowed out daily. We specifically focus on Colombian cities which implemented local variations of these policies. For example, in Bogotá residents were allowed out every other day based on their gender, whereas Florencia allowed just 10% of residents out daily (figure 1). Additionally, socio-economic conditions vary significantly between Colombian cities, with the largest cities having much higher composite wealth and industry sophistication [16,17]. These variations in policy and wealth represent a natural experiment in which we examine the relationship between local policy, city wealth and observed mobility reduction.

We use mobile phone data (call records) to characterize changes in city residents' urban mobility in an 11 day period beginning with the introduction of local lockdown measures. Urban mobility metrics from mobile phones have frequently been used to quantify mobility reductions in the wake of COVID-19 as well as other infectious diseases, both to characterize lockdown measures [2,18] and to predict epidemic spread [19–22].

Our key finding is that more severe mobility quotas have no significant impact on local mobility reduction levels. An implication of this finding is that fine-tuned restrictions, which calibrate the share of people allowed out daily, do not lead to a proportional decrease in mobility. On the other hand, city size is strongly correlated with mobility reduction, in terms of both trip frequency and daily distance travelled. Hence, cities with higher labour formality, gross domestic product (GDP) *per capita*, and industrial complexity experience more reduced mobility—irrespective of the quota imposed. Furthermore, within cities, commuters to wealthy and commercial areas are most disrupted. Hence, both high-income and associated service workers are more likely to stay at home. Taken together, these results have important implications for the design of lockdown policies, the success of which depends critically on local economic conditions.

2. Methods

2.1. Data

2.1.1. Municipal policy details

We collected (Spanish language) 'pico y cédula'/'pico y género' [14,15] policy advice from official municipal websites and social media accounts for the municipalities of interest in order to compute mobility quotas. Generally, municipal advice specified days

for which local residents with ID numbers ending in certain digits were allowed out (exceptions were made for key workers). In some cases, gender (or both gender and ID) was used to differentiate residents' allowed days out.

In order to determine the share of residents allowed out daily (mobility quota), we make simple assumptions—that each municipality is equally represented by gender (noting that gender aspects of mobility have been studied using mobile phone data in Chile [23] and in Panamá [24] during the COVID-19 pandemic) and that ID numbers are uniformly distributed (i.e. that residents in each municipality are equally likely to have an ID ending in any digit). With these assumptions, we first calculate the share of residents allowed out every day in late March/early April and then take the weekday average for the study period (13–27 April). We identify this average as the mobility quota allowed_{*m*}.

In some cases, municipal advice included information regarding curfews (toqué de queda) or days segmented into times at which residents were allowed out. Also, some municipalities provided other information—including car-based restrictions (pico y placá) or information regarding where 'pico y cédula' would be implemented (e.g. at grocery stores and/or public transit). Finally, municipalities differed in weekend-based restrictions—in some municipalities, the local government administered a stay-at-home order on the weekend while in others there were either special restrictions for weekends or the same as those during the week. In accord with many other studies of both general mobility patterns [25,26] and social distancing [8,9], we focus our analysis on (more regular and predictable) weekday mobility patterns and therefore weekday restrictions as well.

2.1.2. Mobility data

Call detail record (CDR)-extracted mobility measures correlate well with measures from other data sources [27]. While extended detection and response (XDR)/GPS-based mobile phone data have more spatio-temporal accuracy, we use CDRs in part because of the wide penetration of our dataset throughout Colombia and in part because CDRs are reflective of users of both smartphones and ordinary cell phones. Although every mobility dataset may be subject to some bias [28], XDR/GPS-based data are likely to have more socio-economic bias (without careful control) especially in a middle-income country as such data typically come exclusively from smartphones (in 2019, smartphone penetration in Colombia was only 59% [29]).

Our analysis relies on mapping individuals to spatial units—the granularity of these units is important to the precision of our analysis. Generally, tower density varies according to municipal population, with some pairs of towers in densest cities being very close together. Pinpointing user location to very precise geographic locales (e.g. a single tower) with CDRs is generally difficult for a variety of both behavioural and technical (e.g. load-sharing) reasons, while accuracy may be enhanced by pinpointing to a more aggregate level [30,31]. We perform an agglomerative clustering algorithm [32] to join tower-associated Voronoi polygons with centroids that were within 100 m of one another. Then, we use these clusters to perform a (more aggregate) Voronoi tessellation on tower cluster centres and associate each tower with its enclosing polygon.

2.1.3. Home/work detection and active user selection

Our analysis relies on having accurate estimations of home/work cell location, as well as spatio-temporal resolution of user location. Applying more stringent criteria for home/work cell detection and activity levels (activity refers to the frequency with which users make calls or receive in-network calls), however, reduces the sample size of our data and therefore the

Table 1. List of variable names.

trip frequency _{<i>i</i>}	% of weekdays in which a user makes a trip of \geq 1 km
daily dist _{<i>i</i>}	weekday-average maximum distance from home cell in which user <i>i</i> is observed
disrupted _{<i>i</i>}	indicator of commute disrupted for user <i>i</i> (=1 if their commute is disrupted)
allowed _{<i>m</i>}	% of residents allowed out on average in a day in municipality <i>m</i>
pop _{<i>m</i>}	population of municipality <i>m</i>
strat _{<i>c</i>}	socio-economic stratum of cell <i>c</i>
complex _{<i>m</i>}	industrial complexity of municipality <i>m</i>
formal _{<i>m</i>}	formality rate of municipality <i>m</i>
GDP _{<i>m</i>}	GDP <i>per capita</i> of municipality <i>m</i>
cell size _{<i>c</i>}	area in square km of cell <i>c</i>
formal _{<i>c</i>}	indicator of whether cell <i>c</i> \in Bogotá is formal
commute dist _{<i>i</i>}	distance between home/work cells of commuter <i>i</i>
<i>N</i>	number of individuals in sample
<i>M</i>	number of municipalities in sample
<i>N_m</i>	number of individuals in municipality <i>m</i>

statistical power. Here, we describe the criteria that we use to transform raw CDRs to panel data. First, we expect to more accurately estimate true mobility levels for more active users—hence, we limit our subset to users who are active on a majority of weekdays during the lockdown period and at least six during a 'basal period' (1 January–15 March).

There is considerable work on home cell detection from CDRs [25,30,33,34]—recent work suggests that identification is most robust when regularity of night-time location is used as a criterion and tower clustering is used [30]. Here, we identify a user's home by the cluster cell in which they are most consistently most active during night-time hours (here 0.00–7.00/22.30–24.00). Specifically, we identify a home cell if the user registers this cell as their most weeknight active night-time cell in at least three weeks during the basal period and a plurality of weeks during 16 March–30 April (inclusive of our lockdown study period). While it is commonplace to use night-time location to define home cells (e.g. [25,33]), we focus on the consistency of users' detected night-time location across weeks as our calculations depend on users keeping the same home cell during the basal/lockdown periods. This criterion is especially important here because it has been observed that many people have moved residence before/during lockdown [35]—residential movement during the study period would tend to inflate lockdown mobility.

Additionally, the problem of work cell location is quite commonplace. We identify work cells in an analogous manner to our home detection approach [25]. We identify a user with a work cell if that cell is their most common day-time (8.30–18.00) calling location on a plurality of the weeks in the basal period, and if they are active in the work cell on at least 20% of their active days in this period.

With these identifications, we transform location data from raw CDRs to panel data, in which we have estimated the home location as well as mobility levels before/during lockdown for 15 347 users across 22 municipalities. There are roughly 1 million

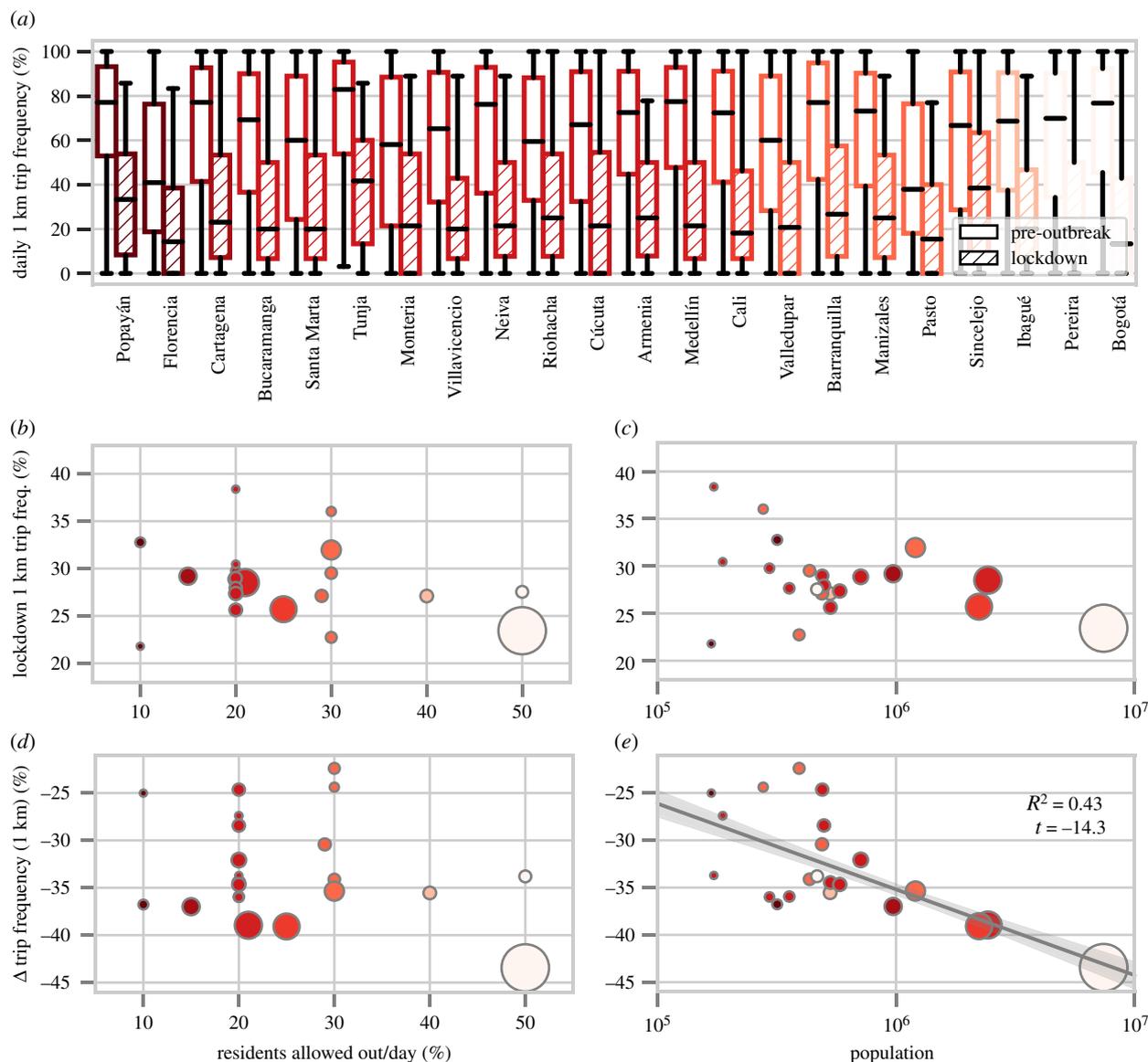


Figure 2. City size, rather than mobility quota severity, is associated with a more pronounced reduction in residents' trip frequency. (a) Empirical distributions of trip frequencies for detected residents in municipalities of interest (ordered by quota). (b,c) Municipality-level mean trip frequency (points, size proportional to population, colour to mobility quota) during lockdown is not related significantly to quota or population. (d,e) Increasing population (but not mobility quota) has a strong reducing effect on the municipality-level median reduction in trip frequency (standard error bars and 95% confidence intervals calculated via bootstrapping).

unique users across 2020 in the raw CDR dataset, but many of these are not sufficiently active (especially during the lockdown period), fail to register a sufficiently consistent home cell and/or are not based in one of the municipalities of interest.¹ For 9069 of the 15 347 users, we also estimate a pre-pandemic work cell that is unique from their home cell (in the other cases, either we do not detect a work cell or the work cell and home cell are the same).

2.1.4. Socio-economic stratum

The national government surveys urban residential dwelling conditions to assign socio-economic strata [36]. These data are provided in the form of survey indices mapped to geographical areas. Stratum tends to be highly spatially correlated owing to socio-economic segregation. We first compute average strata for the second most granular designation—'secciones urbanas' (urban sections), and then we use geographically weighted spatial averaging to assign strata to our tower cluster cells. Finally, we use $k=2$ nearest-neighbour averaging [37] to assign

stratum to clusters that do not intersect urban sections (see electronic supplementary material, figure S2). The distribution of stratum estimations across users is depicted in electronic supplementary material, figure S1B.

2.1.5. Municipality-level demographic/economic variables

In addition to the cell-level socio-economic stratum, we use municipality-level official estimations of (a) population, (b) nominal GDP per capita, (c) labour formality, and (d) economic complexity. Estimates of (a) and (b) are available from DANE [36] at <https://www.dane.gov.co/index.php/estadisticas-por-tema/demografia-y-poblacion> and <https://dane.maps.arcgis.com/apps/MapSeries/index.html?appid=71f231f4e31a40ec8796d559544e9103>. For (c), we use the same very simple methodology as in [17]. That is, we simply associate labour formality with the (2017) count of formal employees in the municipality [38] divided by the working age (15–64) population [36]. This approach of course suffers from a number of limitations—(i) some of these employees will be based outside the municipality; (ii) a share of workers will be

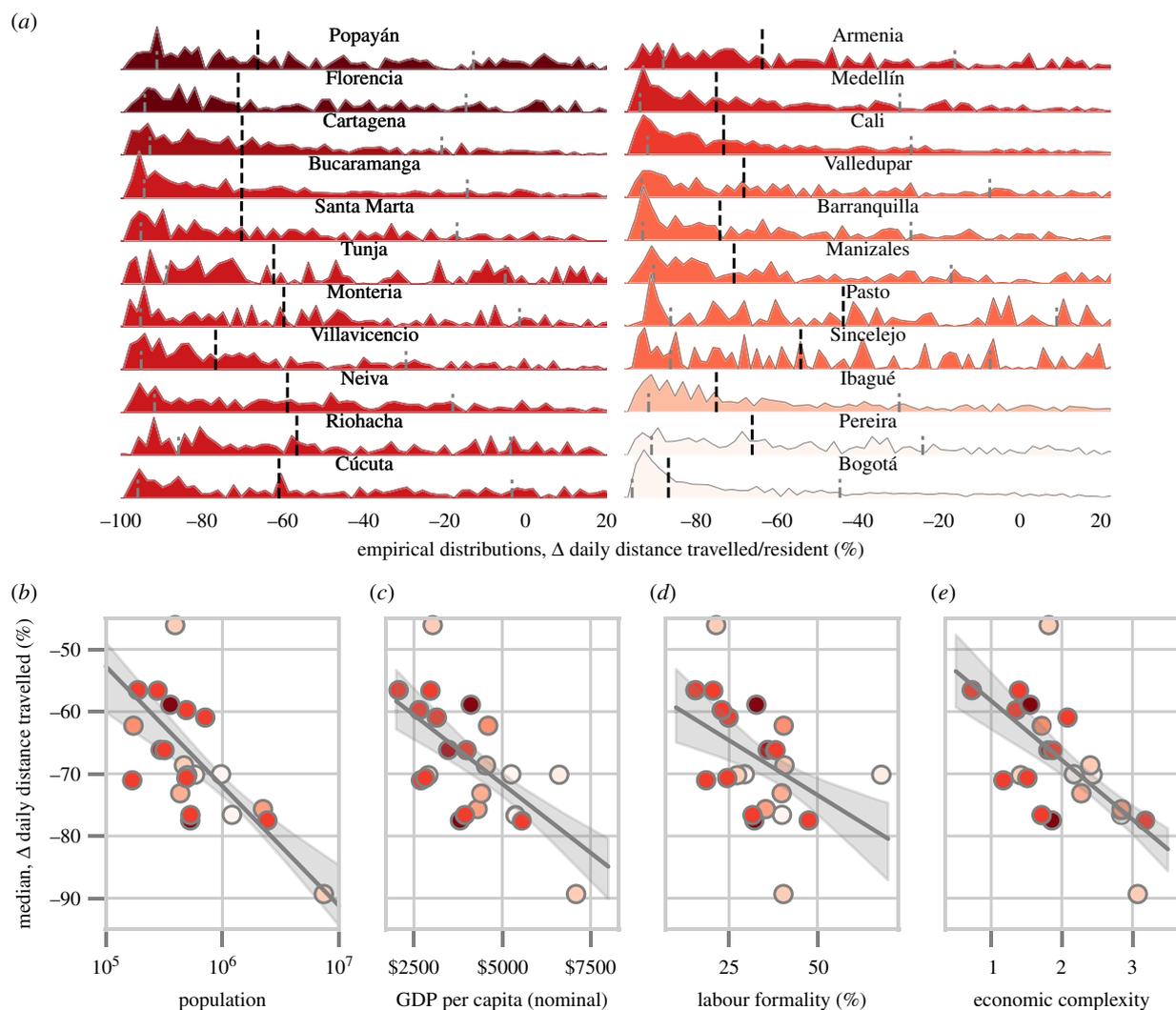


Figure 3. Residents of larger, wealthier municipalities with more formalized labour experienced more pronounced reductions in daily distance travelled during the lockdown period. (a) Empirical (kernel density) municipality-level distributions of relative change in daily distance travelled from the basal period to lockdown. Vertical dashed black (grey) lines represent municipality-level median (quartile) estimates. Municipalities are coloured/ordered by mobility quota (as in figure 2). (b–e) Municipality population, as well as economic complexity, GDP *per capita* and labour formality are associated with more pronounced relative change in daily distance travelled.

outside the working age population; and (iii) not everyone in the working population is in the workforce. Despite these limitations, it is a commonly used methodology to estimate labour formality and we expect that none of these assumptions will overwhelmingly bias our estimations for labour formality in any particular municipality. Finally, for (d) we use municipality-level industrial employment data [38], and then compute economic complexity using the method of Hidalgo *et al.* [17,39,40].

2.2. Mathematical modelling

In general, our mathematical modelling relies on individual-level regression analyses, though we additionally perform certain aggregate analyses as well (results are generally comparable). Where appropriate, we use a weighted approach so that all municipalities in our sample carry equal weight in our regressions. Because our response variables generally obey complex distributions, we generally use a regression bootstrapping scheme to generate confidence intervals, *p*-values and standard errors. A detailed enumeration of our methodology can be found in electronic supplementary material, section S1. Generally, we use the subscript *i* for individuals in our dataset and

the subscript *m(i)* to denote the city to which a resident belongs (for municipality-level variables) as well as *c(i)* to denote the cell to which a resident belongs (for cell-level variables). We use the subscripts *m* and *c* to indicate municipality/cell-level variables (table 1).

3. Results

3.1. ID and gender-based mobility restrictions

During the early stages of COVID-19 exposure, the Colombian government ordered municipal governments to impose local mobility restrictions. Most municipalities (22 departmental capitals) imposed ‘pico y cédula’ restrictions in which residents were allowed out on certain days corresponding to the terminating digit of their national ID numbers. However, the ID numbers allowed out daily varied between municipalities (figure 1a). For example, two of the smallest municipalities only allowed residents out roughly one weekday per every two weeks (10% of residents allowed out daily). The largest city and capital, Bogotá,

Table 2. Individual/municipality-level regression estimates for effects of mobility quota and city size on lockdown behaviour. Statistical significance is indicated by asterisks. Parentheses indicate standard error estimates.

dep. variable: Δ trip frequency _{<i>i</i>}				
ind. variable	(i)	(ii)	(iii)	(iv)
<i>(a) individual-level effects</i>				
allowed _{<i>m(i)</i>}	−0.12*** (0.02)		0.04 (0.03)	0.04 (0.03)
log (pop _{<i>m(i)</i>})		−9.07*** (0.63)	−9.49*** (0.77)	−9.13*** (0.83)
interaction _{<i>m(i)</i>}				−0.25 (0.16)
const	−29.97*** (0.67)	19.25*** (3.79)	20.74*** (4.21)	18.64*** (4.65)
<i>N</i> (individuals)	15 347	15 347	15 347	15 347
<i>R</i> ²	0.002	0.018	0.018	0.018
dep. variable: mean (Δ trip frequency _{<i>i</i> ∈ <i>m</i>})				
ind. variable	(i)	(ii)	(iii)	(iv)
<i>(b) aggregate effects</i>				
allowed _{<i>m</i>}	−0.12*** (0.02)		0.04 (0.03)	0.04 (0.03)
log (pop _{<i>m</i>})		−9.07*** (0.64)	−9.49*** (0.79)	−9.13*** (0.86)
interaction _{<i>m</i>}				−0.25 (0.16)
const	−29.97*** (0.67)	19.25*** (3.84)	20.74*** (4.31)	18.64*** (4.77)
<i>M</i> (municipalities)	22	22	22	22
<i>R</i> ²	0.05	0.43	0.43	0.44
dep. variable: relative Δ daily dist _{<i>i</i>}				
ind. variable	(i)	(ii)	(iii)	(iv)
<i>(c) individual-level effects</i>				
allowed _{<i>m(i)</i>}	−0.3*** (0.0)		−0.1*** (0.0)	−0.1** (0.0)
log (pop _{<i>m(i)</i>})		−17.1*** (0.9)	−15.8*** (0.9)	−14.8*** (1.1)
interaction _{<i>m(i)</i>}				−0.4** (0.2)
const	−60.5*** (1.0)	29.4*** (5.3)	24.2*** (5.0)	18.4*** (6.2)
<i>N</i> (individuals)	15 347	15 347	15 347	15 347
pseudo <i>R</i> ²	0.001	0.002	0.002	0.003
dep. variable: median (relative Δ daily dist _{<i>i</i> ∈ <i>m</i>})				
ind. variable	(i)	(ii)	(iii)	(iv)
<i>(d) aggregate effects</i>				
allowed _{<i>m</i>}	−0.3*** (0.1)		−0.1 (0.1)	−0.0 (0.1)

(Continued.)

Table 2. (Continued.)

dep. variable: median (relative Δ daily dist _{<i>i</i> ∈ <i>m</i>})				
ind. variable	(i)	(ii)	(iii)	(iv)
log (pop _{<i>m</i>})		−17.7*** (2.6)	−17.2*** (3.0)	−15.9*** (3.3)
interaction _{<i>m</i>}				−0.9 (0.6)
const	−59.4*** (2.4)	34.5** (15.6)	32.6* (16.8)	24.8 (19.3)
<i>M</i> (municipalities)	22	22	22	22
<i>R</i> ²	0.12	0.49	0.49	0.51

*** $p < 0.01$, ** $0.01 \leq p < 0.05$, * $0.05 \leq p < 0.1$.

allowed males/females out on alternating days (50% allowed out daily).

In order to quantify the restrictiveness of municipal policies, we collected local policy advice for the principal departmental capitals from government websites and/or social media. Whereas these ID/gender-based measures were advertised widely, and enforced in certain venues (e.g. public transit, access to banks/supermarkets), the extent of policy enforcement/adherence is generally unclear across municipalities, especially in the informal labour sector.

For each departmental capital, we computed the average percentage of residents allowed out daily (or mobility quota) for 11 weekdays (13–27 April) in the pandemic's early stages (figure 1*b*). This corresponds to an initial 'lockdown' period in which all municipalities had recently enacted ID/gender-based restrictions. Interestingly, on average smaller municipalities permitted fewer people out daily (Pearson's $\rho = 0.43$, $p = 0.04$). Hence, with strong adherence, we would expect that residents of smaller municipalities travelled less frequently during lockdown. In the following section, we will investigate whether this is observed in practice.

3.2. Effects of mobility quota and city size on lockdown mobility

In order to evaluate the effects of localized mobility restrictions, we computed mobility indicators derived from CDRs for 22 out of 23 of Colombia's departmental capital municipalities (omitting one on account of low sample size). For each resident, we compute *trip frequency*, which is the percentage of active days (days in which the user makes or receives a call) in which they travel 1 km from their home cell, and *daily distance travelled*, which is the average distance travelled from their home cell on active days. In order to assess changes in mobility relative to pre-lockdown, we also compute these metrics for a baseline period prior to lockdown and compute change measures.

We find that most users across all municipalities reduced their daily distance travelled during lockdown (figure 1*c*). However, the extent of the reduction varied

greatly across municipalities. We display municipality-level distributions of trip frequencies before and after lockdown in figure 2*a*, and relative change (from baseline) in daily distance travelled in figure 3*a*. Most municipalities had a mean lockdown trip frequency of 25–30% (figure 2*b,c*). This represents a reduction in mobility from baseline levels that were 20–45% higher, with the largest reduction in Bogotá (figure 2*d,c*).

To what extent does mobility quota restrictiveness impact *changes* in trip frequency and daily distance travelled relative to baseline levels? We find no evidence for an effect on daily distance travelled and statistically insignificant evidence ($p > 0.1$) for an effect on reduction in trip frequency. If a municipality reduced the amount of residents allowed out daily by 1%, residents on average decreased their trip frequency by only a meagre additional 0.04% (controlling for population; see table 2*a,b* for detailed results).

This finding—that more severe mobility quotas do not result in proportional reductions in mobility—is unexpected and important, especially considering the breadth of findings on the role of mobility restrictions in controlling infection spread [2,4,41]. We hypothesize that urban residents are more influenced by their economic capacity to comply with rules than by the precise measures implemented locally. As a first step, we investigate the role of urbanization (city size) in mobility reduction. An abundance of previous work has shown that city size is associated with economic prosperity—larger cities boast higher wages and GDP *per capita*, and a higher skilled as well as more formalized labour force working in more sophisticated sectors [16,17,42–46]. These factors generally improve residents' capacity to work remotely and reduce their mobility [7,9,10,21,47].

We find that city size has a strong bearing on mobility reduction. Residents of larger municipalities had more pronounced reductions in trip frequency—for every 10-fold increase in municipal population, the average resident reduced their trip frequency by an additional 9.07%. Additionally, a 10-fold increase in population was associated with a 17.1% additional reduction in daily distance travelled relative to the basal period. Moreover, when we aggregate to

Table 3. Effects of standardized economic variables on lockdown behaviour.

dep. variable: mean (Δ trip frequency $_{i \in m}$)				
ind. variable	(i)	(ii)	(iii)	(iv)
(a)				
$\widetilde{\text{GDPpc}}_m$	−4.13*** (0.26)			
$\widetilde{\text{complex}}_m$		−3.94*** (0.26)		
$\widetilde{\log(\text{pop}_m)}$			−3.50*** (0.24)	
$\widetilde{\text{formality}}_m$				−3.46*** (0.29)
const	−32.89*** (0.31)	−32.89*** (0.31)	−32.89*** (0.31)	−32.89*** (0.31)
<i>M</i> (municipalities)	22	22	22	22
R^2	0.60	0.54	0.43	0.42
dep. variable: median (relative Δ daily dist $_{i \in m}$)				
ind. variable	(i)	(ii)	(iii)	(iv)
(b)				
$\widetilde{\log(\text{pop}_m)}$	−6.9*** (1.0)			
$\widetilde{\text{complex}}_m$		−5.9*** (0.9)		
$\widetilde{\text{GDPpc}}_m$			−5.7 (0.9)	
$\widetilde{\text{formality}}_m$				−4.0*** (1.1)
const	−67.5*** (1.2)	−67.5*** (1.2)	−67.5*** (1.2)	−67.5*** (1.2)
<i>M</i> (municipalities)	22	22	22	22
R^2	0.49	0.37	0.33	0.17

Variable is used to indicate that the enclosed variable is standardized across its distribution.

the municipality level, we find that city size explains nearly half of inter-municipality variance in both cases with $R^2 = 0.43$ for change in trip frequency (figure 2e and table 2b) and $R^2 = 0.49$ for relative change in daily distance travelled (figure 3b and table 2d).

Hence, there is something about larger cities that better enables residents to reduce mobility despite less severe mobility quotas. This result may help to explain recent findings that initial COVID-19 growth is slower on a *per capita* basis in larger cities [48]. We also find that aggregate levels of mobility reduction are significantly associated ($p < 0.01$) with municipality-level economic variables including GDP *per capita* and labour formality rate (figure 3d,e and table 3),

defined as the ratio of formal workers to the working age population [17]. We construct a metric of industrial complexity [17,39,40], which is also, as expected, associated with reduction in daily distance travelled. We standardize these variables in order to facilitate comparison, and display coefficient estimates ordered from left to right in table 3 (we also display results for unstandardized versions of these regressions as well as Spearman correlations in electronic supplementary material, section S3.1). We find generally mixed results as to which of these (highly cross-correlated) variables best predict mobility reduction. While population is associated with the highest magnitude standardized coefficient estimate among all predictors for *relative Δ daily dist.*

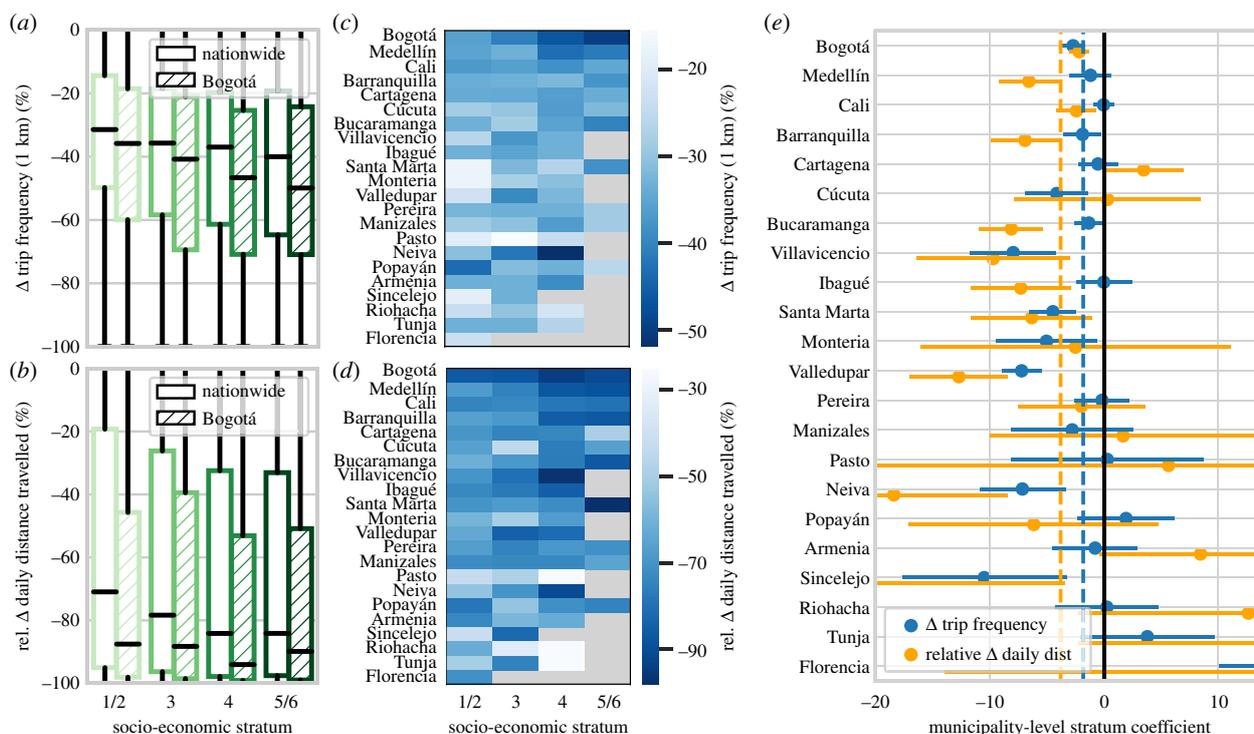


Figure 4. Within municipalities, higher socio-economic status was generally associated with more pronounced mobility reduction. (a,b) Boxplot distributions of residential change in trip frequency and daily distance travelled for varying stratum. (c,d) Municipality-level median estimates of change in trip frequency/daily distance travelled for varying stratum (municipalities ordered by population). (e) Municipality-level coefficient estimates for the effect of stratum on changes in trip frequency and daily distance travelled (error bars represent 95% confidence intervals). Dashed lines represent average effects (under the fixed-effects model) over all municipalities.

travelled, GDP per capita has the highest in the case of Δ trip frequency. However, for both mobility metrics, the confidence intervals for the predictor coefficients are mutually overlapping. More generally, it seems that the economic advantages of larger cities favour mobility reduction and so we next investigate the effects of more granular (neighbourhood-level) socio-economic variables on mobility reduction.

3.3. Intra-city variation by socio-economic status

City size has a clear effect on mobility reduction, but—especially in Latin America—cities themselves are characterized by high internal income inequality [49]. Here we investigate how this drives mobility reduction at an intra-city level. Specifically, we ask if wealthier residents experienced higher levels of mobility reduction.

We use the *stratum* number assigned to each residential block as a proxy for residents' socio-economic status [36]. *Stratum* is a government-assigned designation corresponding to local housing conditions and quality, and has been frequently used to characterize socio-economic status [26,50]. The *stratum* system encompasses six strata of progressively increasing socio-economic status, with one signifying poor quality, often informal housing, and six signifying the richest neighbourhoods (*stratum* 6 is only present in select cities). Most residents countrywide live in medium *stratum* (2/3) housing.

In order to examine the effects of *stratum* on mobility reduction, we calculate changes in trip frequency and relative change in daily distance travelled as a function of *stratum* for each municipality (figure 4a–d). In general, wealthier residents experienced more pronounced reductions in both daily distance travelled and trip frequency—in line with similar

trends observed in cities across Latin America, Europe, the USA and Asia [7–10,21,47]. Pooling across municipalities (and taking into account fixed effects), we find that a 1 s.d. increase in *stratum* was associated with a 1.82% additional decrease in Δ trip frequency (1 km) and a 3.8% additional decrease in *rel. Δ daily distance travelled* ($p < 0.01$ in both cases; estimates are reported in table 4a,b and represented by dashed lines in figure 4e). The importance of *stratum* varies across municipalities—the effect of *stratum* on Δ trip frequency is significant ($p < 0.05$) in 10 out of 22 municipalities, and on *rel. Δ daily distance travelled* is significant in 11 out of 22 municipalities (coefficient estimates displayed in figure 4e, tabulated in electronic supplementary material, §S3.3).

We have observed the effects of socio-economic inequality on mobility reduction at both an inter-city (previous section) and intra-city level. However, we now ask—are inter-city effects explained by differences in socio-economic composition across cities? In other words, is there some effect of city size that is not simply captured by *stratum* variation? In order to disentangle these effects, we split each municipality into low (1/2) and high (4/6) *stratum* subsets and examine the effect of city size on mobility reduction across these subsets. For both groups, we find that increasing city size is associated with a greater reduction in trip frequency and daily distance travelled. The effect is comparably pronounced across low/high *stratum* groups—a 10-fold increase in population is associated ($p < 0.01$) with an additional 7.14% (low)/10.61% (high) reduction in Δ trip frequency (table 5a,b) and an additional 14.3/23.5% reduction in *rel. Δ daily distance travelled* (table 5c,d).

Overall, these findings underscore the role of city size in mobility reduction. We find that this effect is not limited to

Table 4. Pooled/fixed effects of stratum on lockdown behaviour.

dep. variable: mean (Δ trip frequency _{<i>i</i> ∈ <i>m</i>})				
ind. variable	(i)	(ii)	(iii)	(iv)
<i>(a)</i>				
strat _{<i>c(i)</i>}	−4.00*** (0.29)		−2.38*** (0.31)	
$\widetilde{\text{strat}}_{c(i)}$		−1.82*** (0.31)		−1.82*** (0.31)
FE	none	none	muni.	muni.
const	−22.92*** (0.84)	−32.89*** (0.31)		
<i>N</i> (individuals)	15 347	15 347	15 347	15 347
<i>R</i> ²	0.023	0.005	0.047	0.046
dep. variable: relative Δ daily dist _{<i>i</i>}				
ind. variable	(i)	(ii)	(iii)	(iv)
<i>(b)</i>				
strat _{<i>c(i)</i>}	−6.1*** (0.3)		−4.5*** (0.4)	
$\widetilde{\text{strat}}_{c(i)}$		−4.2** (0.4)		−3.8*** (0.3)
FE	none	none	muni.	muni.
const	−53.7*** (1.0)	−69.4*** (0.4)		
<i>N</i> (individuals)	15 347	15 347	15 347	15 347
pseudo <i>R</i> ²	0.002	0.001	0.005	0.005

any socio-economic class in particular, but is instead consistent across strata. In other words, both the city in which a person resides and the socio-economic status of their own neighbourhood influence their level of mobility reduction.

3.4. Disruptions to work commutes

Building on previous findings that show wealthier cities have more jobs that can be performed remotely [6,51,52], we investigate how city size and socio-economic stratum are linked to work commute disruptions. We examine whether (i) city size is linked to more commute disruptions; and (ii) whether residents' home/work stratum is linked to their tendency to forego their commutes.

As is standard practice, we identify home–work commutes via persistent origin–destination flows [25]. We define the commute disruption rate as the percentage of flows that cease during lockdown (see electronic supplementary material, §S2.1 for results corresponding to other definitions). As with trip frequency and distance travelled, we find, as expected, that more commute flows are disrupted in larger cities (figure 5*a* and table 6). For every 10-fold increase in population, the municipality-level commute disruption

rate rises 17.8% ($p < 0.01$), while policy severity has no significant effect.

Using a similar approach to that of the previous section, we examine whether higher stratum residents have more disrupted commute patterns (figure 5*b,c* and table 7*a*). In the largest four municipalities, we find at least marginal evidence ($p < 0.07$) that increasing stratum is associated with higher commute disruption probability. However, we find significance at this level in only one other municipality, suggesting that the home stratum may play a less significant role in commute disruptions than in overall mobility reduction, particularly in smaller municipalities (the pooled average marginal effect under the fixed-effects model is 1.6%, $p < 0.01$). In these cases, other factors such as the type or location of work may also drive commute disruption.

While our data do not reveal the industry or occupation of commuters, we can distinguish workers according to where they work. Broadly, commuters to wealthier areas fall into two groups: they might either work at more formalized, sophisticated firms or provide services to wealthier employers or residents. In the latter case, evidence from the USA points to faster and more pronounced drops in spending among wealthier classes during the pandemic [53],

Table 5. Individual-level regression estimates for effects of mobility quota and city size on stratum-subset lockdown behaviour.

dep. variable: Δ trip frequency _i				
ind. variable	(i)	(ii)	(iii)	(iv)
<i>(a) low-stratum subset</i>				
allowed _{m(i)}	−0.04 (0.03)		0.09** (0.04)	0.10** (0.04)
log(pop _{m(i)})		−7.14*** (0.93)	−8.20*** (1.11)	−7.70*** (1.22)
interaction _{m(i)}				−0.36 (0.24)
const	−30.85*** (1.01)	9.17 (5.53)	12.99** (6.02)	10.01 (6.78)
<i>N</i> (individuals)	6593	6593	6593	6593
<i>R</i> ²	0.000	0.011	0.012	0.013
dep. variable: Δ trip frequency _i				
ind. variable	(i)	(ii)	(iii)	(iv)
<i>(b) high-stratum subset</i>				
allowed _{m(i)}	−0.05 (0.06)		0.12** (0.06)	0.13* (0.07)
log (pop _{m(i)})		−10.61*** (2.15)	−11.96*** (2.24)	−11.70*** (2.90)
interaction _{m(i)}				−0.16 (0.52)
const	−34.86*** (2.11)	25.20** (13.05)	29.86** (13.20)	28.28* (17.38)
<i>N</i> (individuals)	3551	3551	3551	3551
<i>R</i> ²	0.000	0.022	0.024	0.024
dep. variable: relative Δ daily dist _i				
ind. variable	(i)	(ii)	(iii)	(iv)
<i>(c) low-stratum subset</i>				
allowed _{m(i)}	−0.2*** (0.0)		0.0 (0.0)	0.1** (0.0)
log (pop _{m(i)})		−14.3*** (1.1)	−14.4*** (1.2)	−10.0*** (1.4)
interaction _{m(i)}				−1.8*** (0.3)
const	−63.1*** (1.1)	16.1** (6.3)	16.2** (6.7)	−10.4 (8.3)
<i>N</i> (individuals)	6593	6593	6593	6593
pseudo <i>R</i> ²	0.000	0.002	0.002	0.002
dep. variable: relative Δ daily dist _i				
ind. variable	(i)	(ii)	(iii)	(iv)
<i>(d) high-stratum subset</i>				
allowed _{m(i)}	−0.3*** (0.0)		0.3*** (0.0)	0.2*** (0.0)

(Continued.)

Table 5. (Continued.)

dep. variable: relative Δ daily dist.				
ind. variable	(i)	(ii)	(iii)	(iv)
log (pop _{m(i)})		−23.5*** (0.5)	−27.8*** (0.9)	−31.2*** (0.8)
interaction _{m(i)}				1.1*** (0.2)
const	−65.6*** (1.0)	65.2*** (3.4)	81.7*** (4.6)	104.2*** (4.8)
<i>N</i> (individuals)	3551	3551	3551	3551
pseudo <i>R</i> ²	0.001	0.009	0.009	0.010

corresponding to reduced demand for services in these areas. Here, we examine whether the stratum of a commuter's destination is linked to the likelihood that they disrupt their commute. Specifically, we ask whether low-stratum commuters experienced more commute disruptions when working in high-stratum or commercial/industrial areas.

As expected, we find that the likelihood that a commute is disrupted depends considerably on the destination stratum (figure 6). We find a significant ($p < 0.05$) effect of destination stratum on the probability a commute is disrupted in 11 out of 22 municipalities, including six of the largest seven municipalities. These results hold across the general population as well as for the subset of low-stratum (less than or equal to 2) commuters (coefficient estimates are displayed in figure 6*a* and reported in table 7*a,b*)—pooled average marginal effects (under the fixed-effects model) are quite similar for both cases (5.2% for all commuters, 6.1% for low-stratum residents, $p < 0.01$ in both cases). We see this effect most clearly in Bogotá, where commutes terminating in stratum 5/6 are twice as likely to be disrupted as commutes to stratum 5/6 (figure 6*c*). These results demonstrate that both low- and high-income workers that commuted to high-income areas were much more likely to experience disrupted commutes.

Digging deeper into the characteristics of the commute destination, we use administrative formal employment data to identify commercial/industrial centres in Bogotá (figure 6*c*). These correspond to zones with at least 20 000 formal jobs/km² [54]. Generally, these centres include a range of socio-economic strata, and include the central business district (Chico-Lago) and the government (La Candelaria). Controlling for commute distance, we find that commutes to these centres were on average 14.3% ($p < 0.01$) more likely to be disrupted while a one-stratum increase was associated with a 10.2% ($p < 0.01$) increase in the probability a commute was disrupted (point estimates in figure 6*d*, results are reported in table 8*a,b*). As above, we find comparable effects when limiting our commuter sample to low-stratum residents.

Hence, we find that higher income workers—with more teleworkable occupations—were more likely to discontinue their commutes. However, we also observe a sharp lockdown effect for work in higher income and more commercial

locations. While we would certainly expect high-income commuters to stay at home, the evidence points towards a tendency for lower income workers who work in more commercial locations (presumably in service-oriented occupations) to also stay at home. Therefore, we observe a lockdown 'trickle-down' effect—cities with higher income and more formalized firms have more commute disruptions not only for high-income workers, but also for low-income workers. This effect culminates in larger cities having higher levels of both commute and mobility disruption, trends that are consistent throughout our findings.

4. Discussion

Previous work has shown that lockdown policies are successful at reducing mobility and disease caseloads, using data from Europe [4] and China [2,3]. Here we consider whether the restrictiveness of the policy in terms of the share of people allowed out per day is correlated with the size of the reduction in mobility. We found, in accordance with the previous literature, that all cities experienced reductions in urban mobility—but there is no statistical relationship between the severity of local mobility quotas and the degree of mobility reduction. Larger, wealthier cities reduced mobility the most, even though they generally imposed less severe mobility quotas. Smaller cities, with more informal employment, did not experience a comparable reduction.

While the signal linking city size and variables capturing local economic structure to mobility reduction is strong, there are a number of other factors which are likely to have played a role. These include the degree of enforcement of the policy, the availability of economic aid to workers and firms, population density and the number of infections in the city. For example, on a national level, the government provided cash transfers to informal workers and families before and during the study period [55], in addition to a host of economic relief measures [56,57]. Future work might investigate further the role and distribution of aid in policies aimed at mobility restriction. Additionally, residents of cities with larger caseloads early in the pandemic are likely to have been more willing to lock down [58]. Although

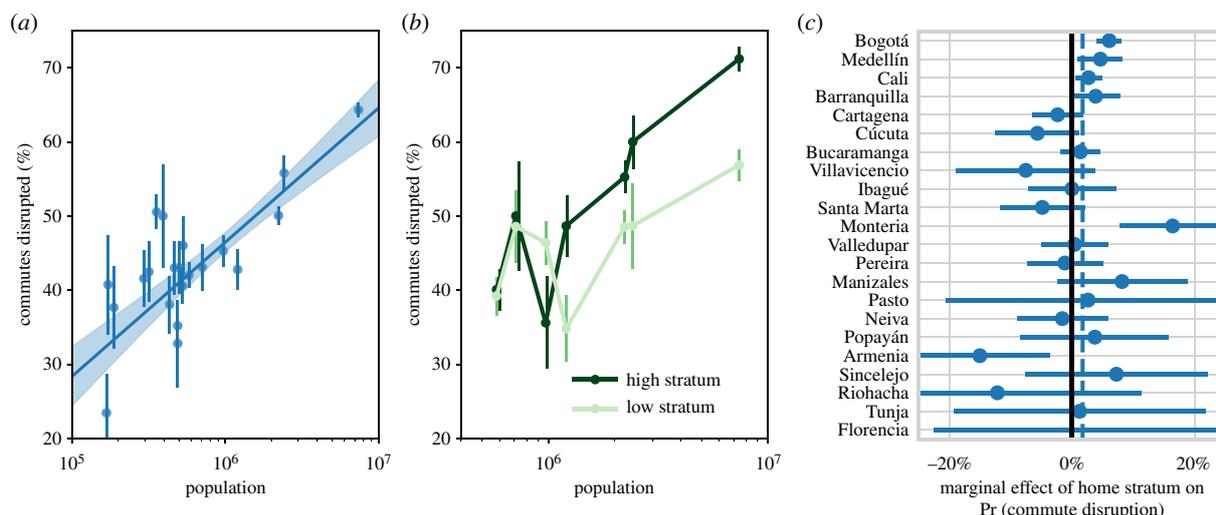


Figure 5. Effects of city size and socio-economic stratum on commute disruption rate. (a) Effect of $\log(\text{population})$ on estimated *commute disruption rate* (error bars represent standard errors, 95% confidence intervals for the ordinary least squares best-fit line are calculated via bootstrapping). (b) Point estimates of low-/high-stratum subsample estimates of *commute disruption rate* for the seven largest municipalities. (c) Municipality-level average marginal effects of *home stratum* on the likelihood a user has their commute disrupted, with point estimates/95% confidence intervals estimated via logistic regression. Dashed vertical lines represent average effects across all municipalities, which are ordered by population.

Table 6. Effects of mobility quota and city size on commute disruption likelihood.

dep. variable: $\log\left(\frac{\Pr(\text{disrupt}=1)}{1-\Pr(\text{disrupt}_i=1)}\right)$				
ind. variable	(i)	(ii)	(iii)	(iv)
allowed _{m(i)}	0.010*** (0.002)		-0.002 (0.02)	-0.000 (0.003)
log (pop _{m(i)})		0.745*** (0.056)	0.767*** (0.062)	0.767*** (0.062)
interaction _{m(i)}			0.031	(0.027)
const	-0.586*** (0.055)	-4.617*** (0.323)	-4.694*** (0.336)	-4.764*** (0.342)
average marginal effects				
allowed _{m(i)}	0.2		-0.0	-0.0
log (pop _{m(i)})		17.8	18.3	18.3
interaction _{m(i)}				0.7
N	9069	9069	9069	9069
LL	-6153	-6075	-6074	-6074

further investigation is needed, we expect to find that (as with GDP *per capita*, formality rate and industrial complexity) these factors correlate with city size and are thus consistent with our findings.

Our findings highlight the role of labour structure in cities' abilities to reduce mobility. Less wealthy, often informal firms have less financial capacity to close operations. Workers at these firms are thus incentivized to continue working despite mobility restrictions. The example of Bogotá depicts this clearly—residents commuting to high-income/formalized work areas were as much as twice as likely to disrupt their commutes (compared with commutes

to low-income areas). This result is borne out even for workers from low-income residential areas, suggesting that firm closures in these higher income/formalized areas affect both low- and high-income workers alike.

Our findings underscore the need for future policy measures to increase aid-based measures alongside or even in place of mobility restrictions. A large share of workers particularly in smaller cities—often informally employed and rarely in teleworkable occupations—cannot work from home (potentially leading to more rapid case growth in smaller cities [48]), and require substantial and sustained support, potentially leading to faster spread. While many countries

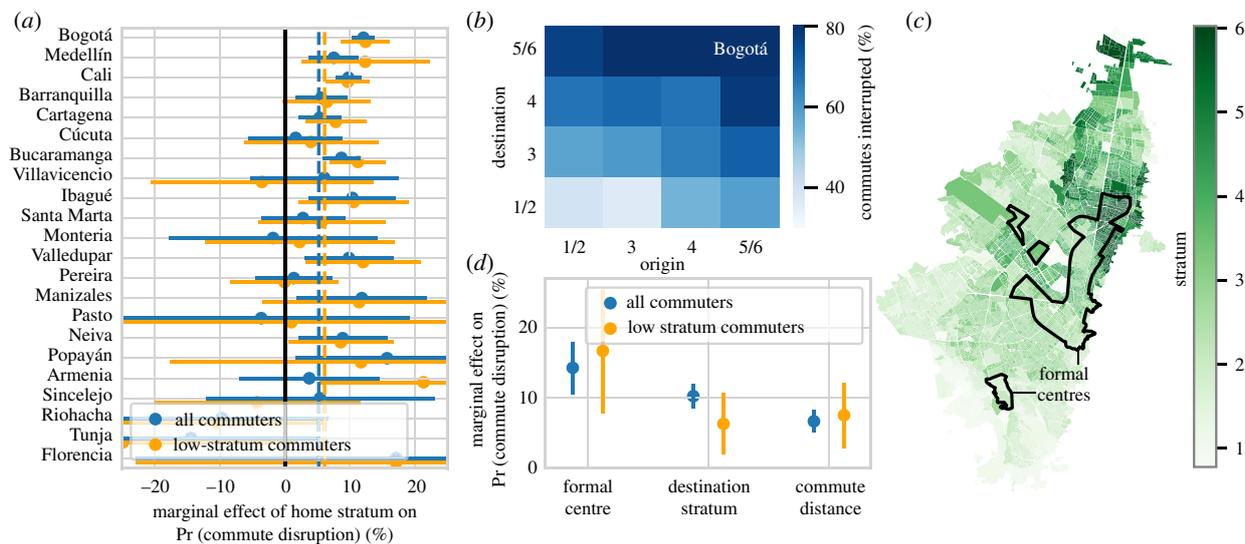


Figure 6. Commutes terminating in wealthier areas and formal labour centres were more likely to be disrupted. (a) Marginal effects of destination stratum on the likelihood a user has their commute disrupted across all detected commuters/in low-stratum commuter subsamples of each municipality, ordered by population (point estimates/95% confidence intervals estimated via logistic regression). (b) Estimates of commute disruption rate in Bogotá for varying home/work stratum. (c) Census-block characterizations of socio-economic stratum in Bogotá, with the outlined regions representing formal employment centres—zones with at least 20 000 formal employees/km². (d) Average marginal effects of commute destination characteristics on the likelihood a commute is disrupted in Bogotá.

Table 7. Logistic regression estimates for effect of home/work stratum on commute disruptions.

dep. variable: $\log\left(\frac{\Pr(\text{disrupt}_i=1)}{1-\Pr(\text{disrupt}_i=1)}\right)$								
ind. variable	(i)	(ii)	(iii)	(iv)	(v)	(vi)	(vii)	(viii)
<i>(a) all commuters</i>								
$\text{strat}_{c(i,\text{home})}$	0.187*** (0.021)		0.079*** (0.023)	0.092*** (0.023)	0.068*** (0.025)		0.031 (0.025)	0.046* (0.026)
$\text{strat}_{c(i,\text{work})}$		0.311*** (0.021)	0.282*** (0.023)	0.289*** (0.023)		0.227*** (0.025)	0.222*** (0.025)	0.232*** (0.026)
$\text{strat}_{c(i,\text{home})} \times \text{strat}_{c(i,\text{work})}$				-0.060*** (0.018)				-0.043** (0.022)
const	-0.817*** (0.059)	-1.209*** (0.064)	-1.332*** (0.074)	-1.365*** (.075)				
FE	none	none	none	none	muni.	muni.	muni.	muni.
average marginal effects								
$\text{strat}_{c(i,\text{home})}$	4.5		1.9	2.2	1.6		0.7	1.1
$\text{strat}_{c(i,\text{work})}$		7.4	6.7	6.8		5.2	5.1	5.3
$\text{strat}_{c(i,\text{home})} \times \text{strat}_{c(i,\text{work})}$				-1.4				-1.0
N	9069	9069	9069	9069	9069	9069	9069	9069
LL	-6126	-6054	-6048	-6042	-5953	-5915	-5914	-5912
dep. variable: $\log\left(\frac{\Pr(\text{disrupt}_i=1)}{1-\Pr(\text{disrupt}_i=1)}\right)$								
ind. variable	(i)	(ii)						
<i>(b) low-stratum commuters</i>								
$\text{strat}_{c(i,\text{work})}$				0.326*** (0.036)				0.271*** (0.042)
FE				none				muni.
const				-1.255** (0.106)				
average marginal effects								
$\text{strat}_{c(i,\text{work})}$				7.7				6.1
N				3360				3360
LL				-2232				-2153

Table 8. Effects of work stratum along with geographical labour formalization on commute disruption likelihood in Bogotá.

dep. variable: $\log \left(\frac{\Pr(\text{disrupt}_i=1 i \in \text{Bogotá})}{1 - \Pr(\text{disrupt}_i=1 i \in \text{Bogotá})} \right)$				
ind. variable	(i)	(ii)	(iii)	(iv)
<i>(a) all commuters</i>				
strat _{c(i,work)}	0.562*** (0.047)			0.505*** (0.048)
formal _{c(i,work)}		0.973*** (0.093)		0.705*** (0.098)
log (commute distance _i)			0.375*** (0.041)	0.327*** (0.043)
const	-1.338*** (0.161)	0.248*** (0.052)	-2.526*** (0.041)	-4.108*** (0.395)
average marginal effects				
strat _{c(i,work)}	12.5			10.2
formal _{c(i,work)}		21.3		14.3
log (commute distance _i)			8.3	6.6
N	2441	2441	2441	2441
LL	-1507	-1533	-1548	-1442
dep. variable: $\log \left(\frac{\Pr(\text{disrupt}_i=1 i \in \text{Bogotá})}{1 - \Pr(\text{disrupt}_i=1 i \in \text{Bogotá})} \right)$				
ind. variable	(i)	(ii)	(iii)	(iv)
<i>(b) low-stratum commuters</i>				
strat _{c(i,work)}	0.541*** (0.095)			0.293*** (0.106)
formal _{c(i,work)}		1.196*** (0.203)		0.779*** (0.220)
log (commute distance _i)			0.638*** (0.098)	0.351*** (0.115)
const	-1.411*** (0.303)	-0.097 (0.107)	-5.244*** (0.851)	-3.914*** (0.887)
average marginal effects				
strat _{c(i,work)}	12.4			6.2
formal _{c(i,work)}		27.3		16.7
log (commute distance _i)			14.3	7.5
N	531	531	531	531
LL	-344	-344	-340	-328

encompassing middle- and high-income economies alike have developed historically unprecedented wage support schemes, the ability of low- and middle-income countries to sustain such schemes in the long term is a topic of central interest. This question's importance is underscored by the current situation in which lower-/middle-income countries will see their vaccine stockpiles grow more slowly. As countries wrestle with how to balance reopening the economy with persistent reduction of viral spread, policymakers must consider the capacity of the non-teleworking, often informal population to adhere to lockdown measures.

Ethics. This article derives from research which was granted approval by the UCL Research Ethics Committee (application 17083.002).

Data accessibility. On account of privacy and ethical concerns, we do not share the individual-level data used to generate these findings. However, we include a repository of municipality-level aggregates as well as code used to generate aggregate findings at <https://github.com/ils246/covid-19/>.

Authors' contributions. S.H. was involved in the conceptualization, methodology, visualization and writing of the original draft. I.L. was involved in the data collection, curation, visualization and writing of the original draft. A.P. and N.O.C. were involved in the conceptualization and writing of the original draft.

Competing interests. We declare we have no competing interests.

Funding. S.H. and N.O.C. acknowledge support from the PEAK Urban programme, funded by UKRI's Global Challenge Research Fund, grant no. ES/P011055/1. I.L. and A.P. are funded by the MIT Connection Science research alliance.

Acknowledgements. The authors would like to thank in no particular order YY Ahn (Northwestern University), Mohsen Bahrami (MIT

Media Lab), Morgan Frank (University of Pittsburgh), Eduardo Lora (Harvard University), Juan Camilo Chaparro (Universidad EAFIT), Julian Cristia (Inter-American Development Bank), Jaime Alfredo Bonet-Morón (Banco de la República Colombia) and Carlos Alberto Medina-Durango (Banco de la República Colombia) for helpful discussion.

References

- Hsiang S *et al.* 2020 The effect of large-scale anti-contagion policies on the COVID-19 pandemic. *Nature* **584**, 262–267. (doi:10.1038/s41586-020-2404-8)
- Fang H, Wang L, Yang Y. 2020 Human mobility restrictions and the spread of the novel coronavirus (2019-ncov) in China. *J. Public Econ.* **191**, 104272. (doi:10.1016/j.jpubeco.2020.104272)
- Maier BF, Brockmann D. 2020 Effective containment explains subexponential growth in recent confirmed COVID-19 cases in China. *Science* **368**, 742–746. (doi:10.1126/science.abb4557)
- Flaxman S *et al.* 2020 Estimating the effects of non-pharmaceutical interventions on COVID-19 in Europe. *Nature* **584**, 257–261. (doi:10.1038/s41586-020-2405-7)
- Sostero M, Milasi S, Hurley J, Fernandez-Macias E, Bisello M. 2020 Teleworkability and the COVID-19 crisis: a new digital divide? European Commission: Joint Research Centre (JRC) Working Papers Series on Labour, Education and Technology. See <https://ec.europa.eu/jrc/sites/jrcsh/files/jrc121193.pdf>.
- Brussevich M, Dabla-Norris E, Khalid S. 2020 Who will bear the brunt of lockdown policies? Evidence from tele-workability measures across countries. IMF Working Paper. See <https://www.imf.org/en/Publications/WP/Issues/2020/06/12/Who-will-Bear-the-Brunt-of-Lockdown-Policies-Evidence-from-Tele-workability-Measures-Across-49479>.
- Bonaccorsi G *et al.* 2020 Economic and social consequences of human mobility restrictions under COVID-19. *Proc. Natl Acad. Sci. USA* **117**, 15 530–15 535. (doi:10.1073/pnas.2007658117)
- Fraiberger SP *et al.* 2020 Uncovering socioeconomic gaps in mobility reduction during the COVID-19 pandemic using location data. (<https://arxiv.org/abs/2006.15195>)
- Carvalho VM, Hansen S, Ortiz A, Garcia JR, Rodrigo T, Rodriguez Mora S, Ruiz de Aguirre P. 2020 Tracking the Covid-19 crisis with high-resolution transaction data. BBVA Research Working Paper. See <https://www.bbva.com/en/publicaciones/global-tracking-the-covid-19-crisis-with-high-resolution-transaction-data>.
- Valentino-DeVries J, Dance GJ. 2020 Location data says it all: staying at home during coronavirus is a luxury. *New York Times*. See <https://www.nytimes.com/interactive/2020/04/03/us/coronavirus-stay-home-rich-poor.html>.
- Caul S. 2020 Deaths involving COVID-19 by local area and socioeconomic deprivation: deaths occurring between 1 March and 31 July 2020. UK Office for National Statistics. See <https://www.ons.gov.uk/peoplepopulationandcommunity/birthsdeathsandmarriages/deaths/bulletins/deathsinvolvingcovid19bylocalareasanddeprivation/deathsoccurringbetween1marchand31july2020>.
- Zhang CH, Schwartz GG. 2020 Spatial disparities in coronavirus incidence and mortality in the United States: an ecological analysis as of May 2020. *J. Rural Health* **36**, 433–445. (doi:10.1111/jrh.12476)
- Prado B. 2020 COVID-19 in Brazil: 'So what?' *Lancet* **395**, 31095–3.
- Guerrero M. 2020 'Pico y cédula' en Colombia: ciudades donde aplica la medida. El Tiempo. See <https://www.eltiempo.com/economia/empresas/pico-y-cedula-en-colombia-conozca-en-que-ciudades-aplica-la-medida-480328>.
- Alsema A. 2020 Coronavirus information for foreigners in Colombia. Colombia Reports. See <https://colombiareports.com/coronavirus-information-for-immigrants/>.
- Duranton G. 2016 Agglomeration effects in Colombia. *J. Regional Sci.* **56**, 210–238. (doi:10.1111/jors.12239)
- O'Clery N, Gomez-Lievano A, Lora E. 2016 The path to labor formality: urban agglomeration and the emergence of complex industries. Center for International Development at Harvard University. See https://growthlab.cid.harvard.edu/files/growthlab/files/rfwp_78.pdf.
- Peak CM *et al.* 2018 Population mobility reductions associated with travel restrictions during the Ebola epidemic in Sierra Leone: use of mobile phone data. *Int. J. Epidemiol.* **47**, 1562–1570. (doi:10.1093/ije/dyy095)
- Badr HS, Du H, Marshall M, Dong E, Squire MM, Gardner LM. 2020 Association between mobility patterns and COVID-19 transmission in the USA: a mathematical modelling study. *Lancet Infect. Dis.* **20**, 1247–1254. (doi:10.1016/S1473-3099(20)30553-3)
- Xiong C, Hu S, Yang M, Luo W, Zhang L. 2020 Mobile device data reveal the dynamics in a positive relationship between human mobility and COVID-19 infections. *Proc. Natl Acad. Sci. USA* **117**, 27 087–27 089. (doi:10.1073/pnas.2010836117)
- Gozzi N, Tizzoni M, Chinazzi M, Ferres L, Vespignani A, Perra N. 2020 Estimating the effect of social inequalities in the mitigation of COVID-19 across communities in Santiago de Chile. See <https://www.medrxiv.org/content/early/2020/10/13/2020.10.08.20204750>.
- Glaeser EL, Gorbach CS, Redding SJ. 2020 How much does COVID-19 increase with mobility? Evidence from New York and four other US cities. National Bureau of Economic Research. See <https://www.nber.org/papers/w27519>.
- Gauvin L, Tizzoni M, Piaggini S, Young A, Adler N, Verhulst S, Ferres L, Cattuto C. 2020 Gender gaps in urban mobility. *Human. Soc. Sci. Commun.* **7**, 1–13. (doi:10.1057/s41599-020-0492-6)
- Woskie LR, Wenham C. 2020 Do men and women lockdown differently? An examination of Panama's COVID-19 sex-segregated social distancing policy. (doi:10.1101/2020.06.30.20143388)
- Louail T, Lenormand M, Picornell M, Cantú OG, Herranz R, Frias-Martinez E, Ramasco JJ, Barthelemy M. 2015 Uncovering the spatial structure of mobility networks. *Nat. Commun.* **6**, 1–8. (doi:10.1038/ncomms7007)
- Lotero L, Hurtado RG, Floría LM, Gómez-Gardeñes J. 2016 Rich do not rise early: spatio-temporal patterns in the mobility networks of different socio-economic classes. *R. Soc. open sci.* **3**, 150654. (doi:10.1098/rsos.150654)
- Alexander L, Jiang S, Murga M, González MC. 2015 Origin–destination trips by purpose and time of day inferred from mobile phone data. *Transp. Res. Part C: Emerg. Technol.* **58**, 240–250. (doi:10.1016/j.trc.2015.02.018)
- Wesolowski A, Eagle N, Noor AM, Snow RW, Buckee CO. 2013 The impact of biases in mobile phone ownership on estimates of human mobility. *J. R. Soc. Interface* **10**, 20120986. (doi:10.1098/rsif.2012.0986)
- GSMA. 2020 The mobile economy: Latin America. See https://www.gsma.com/mobileeconomy/wp-content/uploads/2020/12/GSMA_MobileEconomy2020_LATAM_Eng.pdf.
- Pappalardo L, Ferres L, Sacasa M, Cattuto C, Bravo L. 2020 An individual-level ground truth dataset for home location detection. (<https://arxiv.org/abs/2010.08814>).
- Flowminder. 2020 Understanding CDR aggregates: fundamentals. See <https://covid19.flowminder.org/cdr-aggregates/understanding-cdr-aggregates-fundamentals>.
- Pedregosa F *et al.* 2011 Scikit-learn: machine learning in Python. *J. Mach. Learn. Res.* **12**, 2825–2830.
- Ahas R, Silm S, Järvi O, Saluveer E, Tiru M. 2010 Using mobile positioning data to model locations meaningful to users of mobile phones. *J. Urban Technol.* **17**, 3–27. (doi:10.1080/10630731003597306)

34. Vanhoof M, Reis F, Ploetz T, Smoreda Z. 2018 Assessing the quality of home detection from mobile phone data for official statistics. *J. Official Stat.* **34**, 935–960. (<https://sciendo.com/article/10.2478/jos-2018-0046>)
35. Marsh S. 2020 Escape to the country: how Covid is driving an exodus from Britain's cities. *The Guardian*. See <https://www.theguardian.com/world/2020/sep/26/escape-country-covid-exodus-britain-cities-pandemic-urban-green-space>.
36. Departamento Administrativo Nacional de Estadística (DANE). 2020 Censo nacional de población y vivienda. See <https://www.dane.gov.co/index.php/en/estadisticas-por-tema/demografia-y-poblacion/censo-nacional-de-poblacion-y-vivenda-2018>.
37. Virtanen P *et al.* 2020 SciPy 1.0: fundamental algorithms for scientific computing in Python. *Nat. Methods* **17**, 261–272. (doi:10.1038/s41592-019-0686-2)
38. Colombian Atlas of Economic Complexity. 2017 Colombian formal employment and industry/region mapping. The Center for International Development (CID) at Harvard University. See <http://datlascolombia.com/>.
39. Hidalgo CA, Hausmann R. 2009 The building blocks of economic complexity. *Proc. Natl Acad. Sci. USA* **106**, 10 570–10 575. (doi:10.1073/pnas.0900943106)
40. Hidalgo CA, Klinger B, Barabási AL, Hausmann R. 2007 The product space conditions the development of nations. *Science* **317**, 482–487. (doi:10.1126/science.1144581)
41. Kraemer MU *et al.* 2020 The effect of human mobility and control measures on the COVID-19 epidemic in China. *Science* **368**, 493–497. (doi:10.1126/science.abb4218)
42. Bettencourt LM, Lobo J, Helbing D, Kühnert C, West GB. 2007 Growth, innovation, scaling, and the pace of life in cities. *Proc. Natl Acad. Sci. USA* **104**, 7301–7306. (doi:10.1073/pnas.0610172104)
43. Bettencourt LM, Lobo J, Strumsky D, West GB. 2010 Urban scaling and its deviations: revealing the structure of wealth, innovation and crime across cities. *PLoS ONE* **5**, e13541. (doi:10.1371/journal.pone.0013541)
44. Davis DR, Dingel JI. 2020 The comparative advantage of cities. *J. Int. Econ.* **123**, 103291. (doi:10.1016/j.jinteco.2020.103291)
45. Brinkman J. 2014 The supply and demand of skilled workers in cities and the role of industry composition. FRB of Philadelphia Working Paper. See https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2515329.
46. Alves LG, Mendes RS, Lenzi EK, Ribeiro HV. 2015 Scale-adjusted metrics for predicting the evolution of urban indicators and quantifying the performance of cities. *PLoS ONE* **10**, e0134862. (doi:10.1371/journal.pone.0134862)
47. Weill JA, Stigler M, Deschenes O, Springborn MR. 2020 Social distancing responses to COVID-19 emergency declarations strongly differentiated by income. *Proc. Natl Acad. Sci. USA* **117**, 19 658–19 660. (doi:10.1073/pnas.2009412117)
48. Ribeiro HV, Sunahara AS, Sutton J, Perc M, Hanley QS. 2020 City size and the spreading of COVID-19 in Brazil. *PLoS ONE* **15**, e0239699. (doi:10.1371/journal.pone.0239699)
49. Roberts BR. 2005 Globalization and Latin American cities. *Int. J. Urban Reg. Res.* **29**, 110–123. (doi:10.1111/j.1468-2427.2005.00573.x)
50. Medina C, Morales L, Bernal R, Torero M. 2007 Stratification and public utility services in Colombia: subsidies to households or distortion of housing prices?. *Economia* **7**, 41–99. (doi:10.1353/eco.2007.0013)
51. Dingel JI, Neiman B. 2020 How many jobs can be done at home?. National Bureau of Economic Research. See <https://www.nber.org/papers/w26948>.
52. Hatayama M, Viollaz M, Winkler H. 2020 Jobs' amenability to working from home: evidence from skills surveys for 53 countries. World Bank Policy Research Working Paper (9241). See <https://elibrary.worldbank.org/doi/abs/10.1596/1813-9450-9241>.
53. Chetty R *et al.* 2020 How did COVID-19 and stabilization policies affect spending and employment? A new real-time economic tracker based on private sector data. National Bureau of Economic Research. See https://www.nber.org/system/files/working_papers/w27431/w27431.pdf.
54. Guzman LA, Oviedo D, Bocarejo JP. 2017 City profile: the Bogotá metropolitan area that never was. *Cities* **60**, 202–215. (doi:10.1016/j.cities.2016.09.004)
55. Symmes CJ. 2020 Colombia to spend 3.65 bln on coronavirus economic measures. Thomson Reuters Foundation. See <https://uk.reuters.com/article/health-coronavirus-colombia-economy/colombia-to-spend-3-65-bln-on-coronavirus-economic-measures-idUSL1N2BB0VX>.
56. Ravallion M. 2020 Pandemic policies in poor places. Center for Global Development. See <https://www.cgdev.org/publication/pandemic-policies-poor-places>.
57. Cáárdenas M, Martínez Beltrín H. 2020 COVID-19 in Colombia: impact and policy responses. Center for Global Development. See <https://www.cgdev.org/publication/covid-19-colombia-impact-and-policy-responses>.
58. Van Bavel JJ *et al.* 2020 Using social and behavioural science to support COVID-19 pandemic response. *Nat. Hum. Behav.* **4**, 1–12. (doi:10.1038/s41562-020-0818-9)