SUPPLEMENTARY DATA FOR

Highlighting socio-economic constraints on mobility reductions during COVID-19 restrictions in France can inform effective and equitable pandemic response

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SD1 describes mobile phones data used to measure mobility, the mobility metrics used, and the demographic and socio-economic indicators used. SD2 describes the statistical model, and the fit. It also analyzes fit performance, and explores additional choices of mobility metrics and socio-economic indicators. SD3 reports volumes of retail and online retail in France. SD4 reports an ancillary analysis on 2019 data. SD5 reports the posterior spatial correlation of the models used.

SD1. Description of the indicators

Mobility

<u>*Data description*</u>

To reconstruct mobility, we used mobile phone data from the business service Flux Vision by Orange. These comprise daily origin-destination travel flows of anonymized mobile phone users among 1436 geographical areas (patches) of mainland France, defined according to the 2018 EPCI level (Établissements Publics de Coopération Intercommunale[1]). The location of mobile phone users was inferred by the data provider, by processing the signaling data between the mobile phones and the antennas of the mobile network. These data contain records of both active communication events (e.g., calls and SMSs, data session), and passive location exchanges between the mobile phone and the mobile network (e.g., handover, location update). We had access to aggregated, anonymized origin-destination matrices reporting the daily number of user displacements (trips) among patches. The

[1] https://www.collectiviteslocales.gouv.fr/cartographie-des-epci-a-fiscalite-propre. Accessed March 2021.

anonymization procedure was approved by the French data protection authority (Commission Nationale de l'Informatique et des Libertés). A trip was defined as a user movement between two consecutive locations where that user spends at least one hour. The time cutoff of one hour was established by the data provider according to the spatial resolution: excessively short cutoffs would split single trips into sub-trips; excessively long cutoffs would merge together different trips.

Data representativeness

Mobile phone data are being increasingly used as proxies for population-level human mobility. Notwithstanding, potential sources of bias exist. They are mainly linked to potentially unbalanced population representativeness, geographical coverage, and heterogeneity in user activity. Accounting for a broader range of telecomunication events, signaling data partially overcome this, significantly improving homogeneity and accuracy in spatio-temporal coverage compared to more traditional datasets, such as Call Detail Records (CDRs). The data provider also adjusted travel flows to be representative of the general population, using market share data, socioeconomic data and data on mobile ownership from INSEE, and customer socio-demographic information provided by subscribers. In addition, we focused on French SIM card to avoid the potential bias introduced by mobility patterns of nonresidents. In this context, visitors purchasing French SIM cards may represent a source of bias. We expect this, however, to have a minimal impact, as the end to roaming charges within the EU has decreased the needs to buy local SIM cards. Furthermore, the data provider adjusted the data using the EVE tourism survey for foreign visitors, conducted by the DGE (French General Directorate for Enterprise) and the Bank of France[2].

Definition of mobility metrics

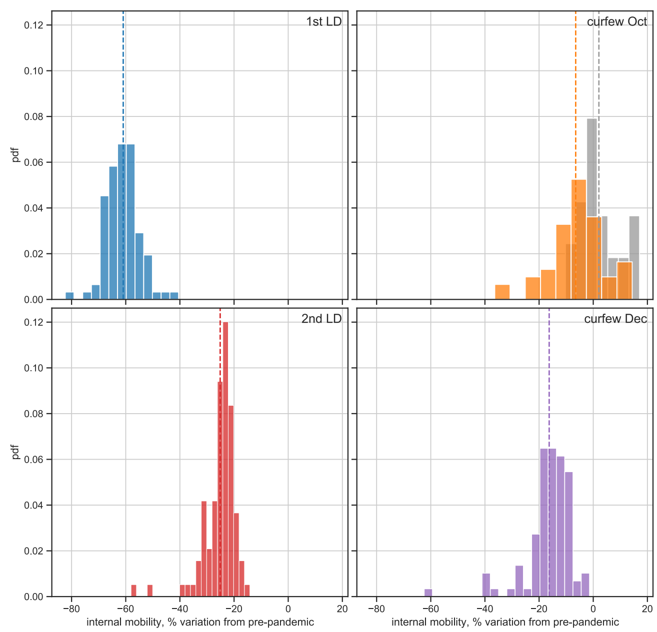
Internal mobility of a department is the number of trips starting and ending within that department. External mobility of a department is the number of trips starting or ending inside that department, but not both. Total mobility of a department is the sum of internal and external mobility. All mobility metrics were computed as relative percentage differences from a pre-pandemic baseline value, obtained as the average value over the period Feb 3-7, 2020. The choice of the baseline is discussed in SD2, and an alternative baseline is also tested.

Internal mobility during restrictions

The average internal mobility (as percentage difference from the baseline) was lowest during the 1st lockdown: -60.9% (the distribution across departments is shown in blue in the figure below, with the dashed line marking the average). During the 2nd lockdown, it was -25.1% (red). During the October curfew the average in departments under curfew was -6.5% (orange); in departments without curfew, it

[2] https://www.entreprises.gouv.fr/files/files/directions_services/etudes-etstatistiques/stats-tourisme/memento/2017/2017-11-MEMENTO-TOURISME-CHAP6-le-tourisme-international-en-france.pdf. Accessed March 2021.

was +2.1% (gray). Finally, during December curfew it was -16.3%. The figure below is a histogram representation of the data in Fig 1F-H of the main text.



Socioeconomic, demographic indicators

- *standard of living – 9th decile* is the 9th decile of the department-level distribution of standard of living. Standard of living of a household is its disposable income divided by the consumption units (1 for the 1st adult, 0.5 for each additional member aged 14 years or older, 0.3 for each child). The 1st, 5th, and 9th deciles are the standard metrics of standard of living adopted by INSEE. We used the 9th decile to focus on differences across income classes. Choosing the 5th decile, however, would have not changed the analysis, as the 5th and 9th are extremely correlated (Pearson correlation coefficient 0.92). The 1st decile is instead weakly correlated to either the 5th or the 9th deciles. We tested its association with mobility, and was nonsignificant in all four periods considered (see SD2), so we discarded it from the study.
- *house crowding* is the fraction of crowded dwellings, according to INSEE's definition (*suroccupation)*, whereby a dwelling is crowded if it lacks at least one of the following characteristics:
    - it has one common room;
    - it has one room per adult;
    - it has one room per 2 children if both younger 7 years old or younger, or both 19 years old or younger and of the same gender.

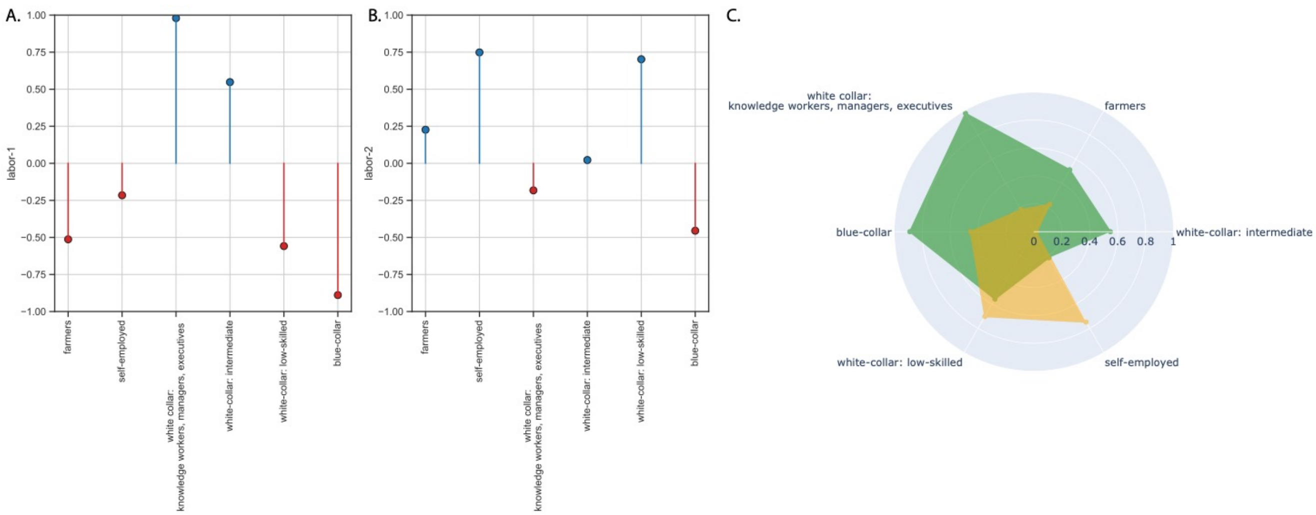
The definition shows that crowding depends not only on density (how many people share a given space), but also on who is sharing the space. As such, the World Health Organization broadly defines it as “a mismatch between the dwelling and the household”, and identifies it as a proxy for social deprivation. Crowding has been associated with adverse health outcomes (involving both communicable and noncommunicable diseases), mental distress, and poor educational achievement[3]. As the CDC pointed out[4], these aspects are all relevant in the contexts of COVID-19-related mobility restrictions: a positive association between crowding and mobility (higher crowding – higher mobility) would be a marker of the inequitable scope and impact of pandemic response.

- *retail stores per 100,000 residents*: we consider to be retail stores four types of what the INSEE (French National Statistical Institute) defines as “commerce de détail à prédominance alimentaire”[5] (retail selling predominantly food). These types are 1) “hypermarché” (supermarket with a surface larger than 2,500 m^2); 2) “supermarché” (supermarket with a surface between 400 and 2500 m^2; 3) “supérette” (convenience store with a surface between 120 and 400 m^2); 4) “épicerie”(convenience store with a surface smaller than 120 m^2). We summed the number of all four types of retail stores in each department, and computed their density as the number every 100,000 units of population. The rationale behind the choice of this indicator is that leaving one’s own home to shop for groceries was allowed during both lockdowns. Also retail stores were kept open during restrictions, to various extents. The availability and reachability of retail could thus be a driver of mobility during restrictions.
- *labor-1* and *labor-2* describe the structure of the job market. They are extracted from data recording the proportion of the active population (age 15-64) working in the following sectors:
    - *farmers (Agriculteurs exploitants) – contains self-employed farmers;*
    - *self-employed (Artisans, commerçants et chefs d’entreprise);*
    - *white collar: knowledge workers*, top-level managers, executives (Cadres et professions intellectueles superieures);
    - *white-collar: intermediate (professions intermediaires) – contains mid/low-level managers, teachers, nurses, technical jobs;*
    - *white-collar: low-skilled (employés) – contains hospitality industry, administrative staff, servers, restaurant and hotel staff, commerce and retail;*
    - *blue-collar (ouvriers).*

  labor-1 and *labor-2* are the two leading components of the Principal Component Analysis (PCA) of this dataset, together explaining 90.1% of its variance. The figure below shows the Pearson

[3] WHO Housing and Health Guidelines. Geneva: World Health Organization; 2018. 3, Household crowding. https://www.ncbi.nlm.nih.gov/books/NBK535289/. Accessed March 2021.
[4] https://www.cdc.gov/coronavirus/2019-ncov/community/health-equity/race-ethnicity.html. Accessed March 2021.
[5] https://www.insee.fr/fr/statistiques/3568602?sommaire=3568656#consulter. Accessed March 2021.

correlation between the original indicators, and the PCA components *labor-1* (panel A) and *labor-2* (panel B). In panel C the absolute value of the correlations is shown as a radar plot for both PCA components.



SD2. Statistical model

Input data

- n number of points (departments);
- n_f number of regressors – this is $n_f = 1$ in the univariate regressions, which estimate the correlation of each indicator (regressor) with mobility independently. It is instead $n_f = 5$ in the multivariate regression, which estimates the adjusted correlations;
- $W \in \mathbb{R}^{n,n}$ contiguity matrix among departments: $W_{ij} = 0$ if i, j do not share a border; $W_{ij} = 1/d_i$ if i, j share a border, with d_i being the number of neighboring departments of i;
- $X \in \mathbb{R}^{n,n_f}$ matrix encoding the values of the regressors in each point (standardized values);
- $y \in \mathbb{R}^n$ mobility in each point (standardized values);

Parameters to estimate

- q intercept [prior $q \sim Normal(0{,}100)$];
- $\beta \in \mathbb{R}^{n_f}$ correlation coefficients [prior $\beta \sim Normal(0{,}10)$];
- σ standard deviation of the error term [prior $\sigma \sim Exponential(0.1)$];
- λ spatial correlation of the error term [prior $\lambda \sim Uniform(-1{,}1)$];

Likelihood

$$y \sim MultiNormal(q + X\beta, \Sigma),$$

with

$$\Sigma = \left[\frac{(1-\lambda W)^T(1-\lambda W)}{\sigma^2}\right]^{-1}.$$

This model is a generalization of an ordinary linear regression, accounting for the fact that the assumption that different data points are independent might not hold. In our case, proximity in geographic space (neighboring departments vs departments further away from each other) might induce a correlation among points, encoded in model parameter λ. It is important to stress that λ is estimated by the fit, not fixed a priori, so our model is free to select the best spatial correlation term given the data (SD5 reports the posterior estimates of λ). To make the relationship between our model and an ordinary linear regression explicit, one can set the spatial correlation term to zero ($\lambda = 0$) in Σ. This would give $\Sigma = \sigma$, diagonalizing the multinormal distribution, and leading to the ordinary linear regression with normal likelihood: $y_i \sim Normal\left(q + \sum_f \beta_f X_{if}, \sigma\right)$.

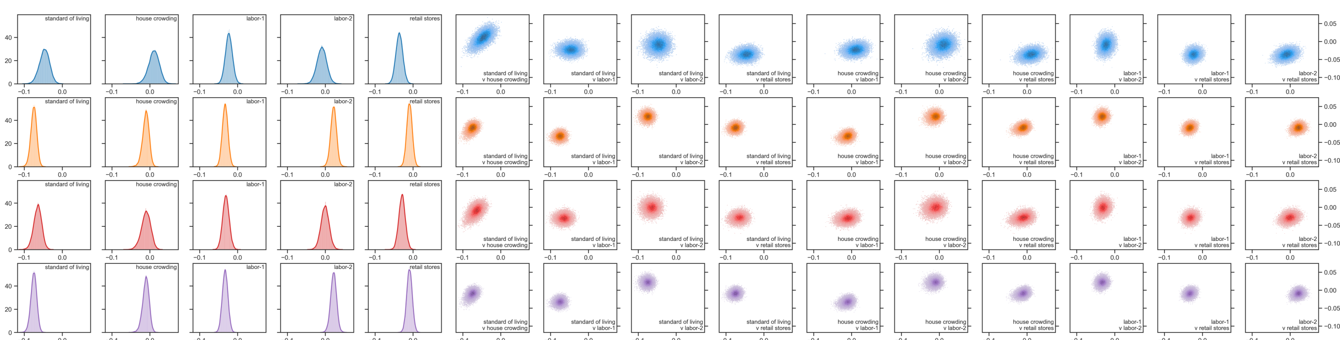
Diagnosis of posterior distributions – multicollinearity diagnostic

Indicator	*VIF (Variance Inflation Factor)*
standard of living – 9^{th} decile	4.9
house crowding	2.2
labor-1	5.4
labor-2	2.1
retail stores per 100,000 residents	2.1

The above table reports variance inflation factors for the considered regressors. The values ~5 for the 1^{st} and the 3^{rd} variable suggest designing and checking our fit against multicollinearity issues. As a standard approach in Bayesian fitting, we decorrelated the input data X using QR decomposition:

1) center the input: $X_{ia}^{center} = X_{ia} - \sum_j X_{ja} / n$;
2) decompose it using QR-decomposition: $X = QR$. The columns of Q are orthogonal, hence independent. The mean of the multinormal distribution becomes $q + X\beta = \tilde{q} + Q\hat{\beta}$, where $\hat{\beta} = R\beta$ and q is shifted by the centering of X.
3) sample the posterior distribution of the new slope parameters $\hat{\beta}$;
4) recover at the end the samples of the original slope parameters: $\beta = R^{-1}\hat{\beta}$

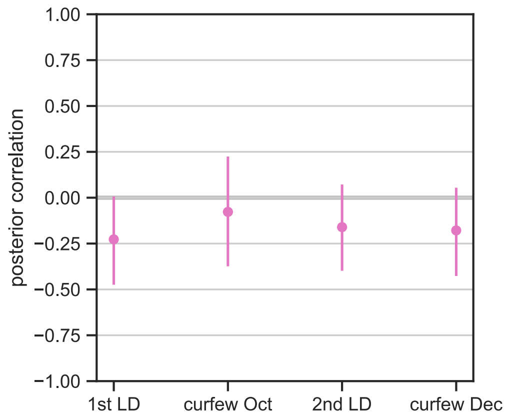
The figure below shows the posterior marginal distribution of the decorrelated slope parameters $\hat{\beta}$ (left plots), and the 2-dimensional pairwise distributions (right plots). 1^{st} lockdown, October curfew, 2^{nd} lockdown, and December curfew are in blue, orange, red, and purple, respectively. The figure shows that all posterior distributions are well-defined, have well-defined maxima, and are correctly reconstructed by MCMC sampling. This proves that correlation among regressors does not impact the performance of our fit, or reliability of our estimates.



Analysis of additional socioeconomic and demographic indicators, and mobility metrics

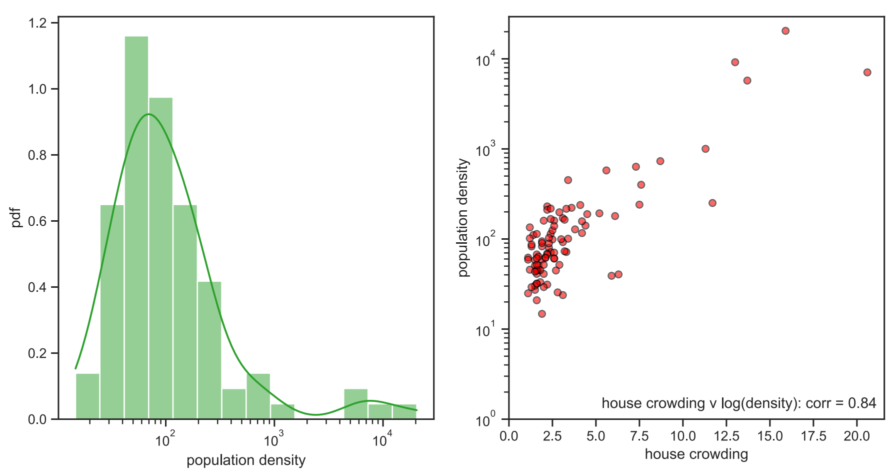
1st decile of standard of living (see SD1)

The (univariate) association of the 1st decile of standard of living and mobility was nonsignificant across all four periods (see figure below), and we discarded from the analysis.

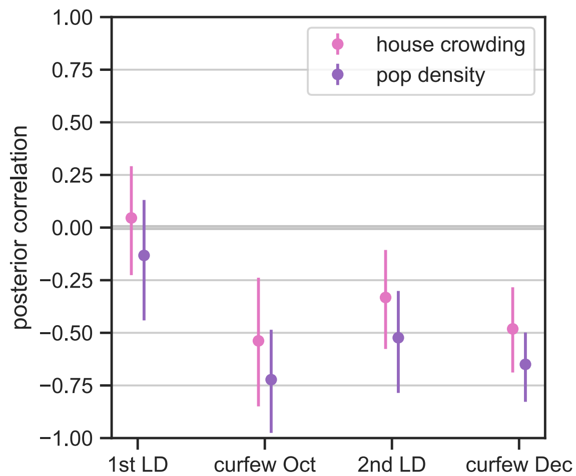


Population density

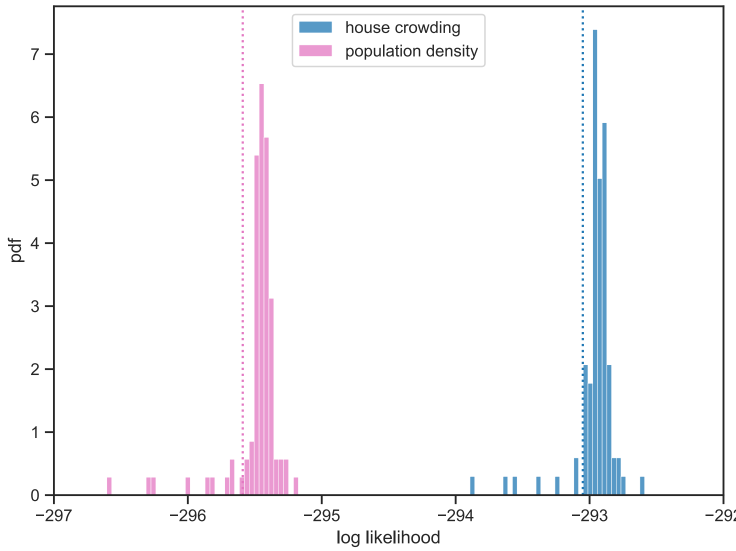
Population density (residents / km^2) across departments spans orders of magnitude, and is very dispersed (mean = 566; 1st decile = 24; 5th decile = 83; 9th dtecile = 6575). The distribution of its logarithm is instead well-behaved (figure below, left panel). It also exhibits high correlation with house crowding (figure below, right panel). This is reasonable, as high population density might be associated to less available, or less affordable, housing space.



Consistently, the (univariate) association of population density (intended as its logarithm henceforth) to mobility follows the same pattern as house crowding (figure below).

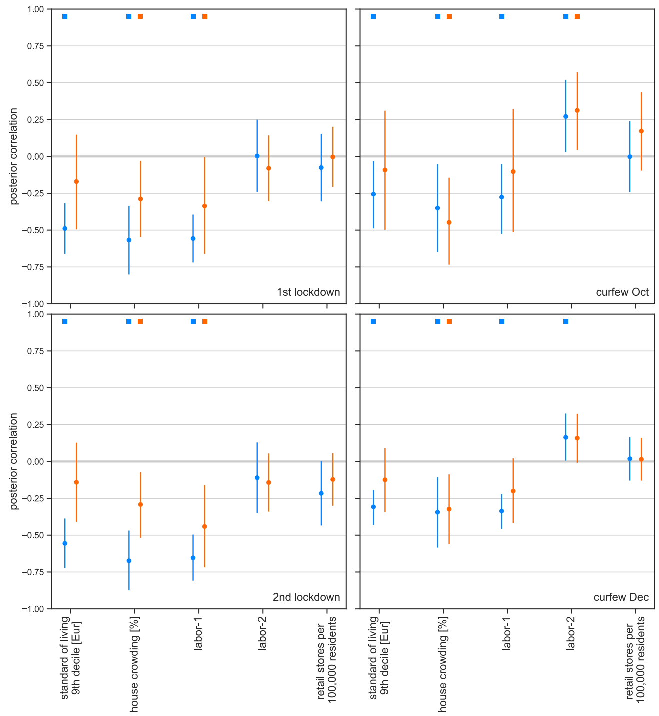


The strong collinearity between these two regressors prevented including both house crowding and population density to the multivariate regression. Density, specifically, had a high variance inflation factor (VIF=9.8). We chose house crowding over population density because it provided a larger improvement to the multivariate fit in terms of explaining mobility differences. To check that, we performed two sets of multivariate regressions: one containing house crowding (and not density), and one containing density (and not house crowding). We applied a leave-one-out cross validation scheme: we left out department *a*, performed the regression on the remaining departments, and then computed the log likelihood L_a of observing the full data (including *a*), given the parameters estimated without *a*. We did that for all departments *a*. High likelihood values mean the regression is correctly fitting the data. The plot below shows the distribution of L_a over all possible departments, for the regression including house crowding (blue), and the regression including density (pink). House crowding consistently gave a higher likelihood, leading to a better fit than population density. This also proved that house crowding is not simply a proxy for the more general metric ‘population density’, but contained additional specific information, consistently with its definition and use (see SD1).



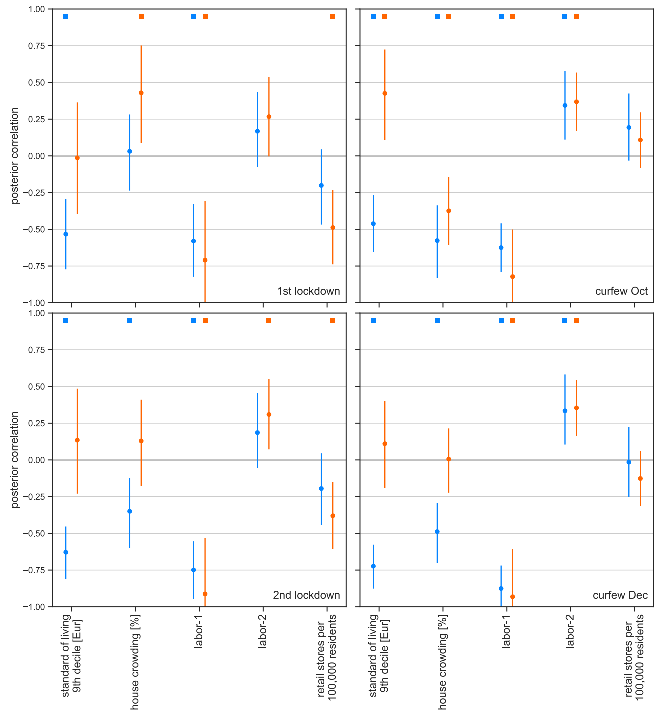
External mobility

External mobility represented, on average, 44% of total mobility during baseline, albeit with considerable differences across departments (IQR=21%). Its reduction was generally more marked than internal mobility during lockdowns (on average 6 and 5 percentage points of additional reduction during 1st and 2nd lockdowns, respectively). The opposite was true during curfews (on average 7 and 4 percentage point less reduced than internal mobility during October and December curfews, respectively). Restrictions impacted internal and external mobility differently: the Pearson correlation between internal and external mobility across departments was lowest during the 1st lockdown (0.36), highest during the October curfew (0.77). As such, the indicators considered might have impacted external mobility differently from internal mobility. The figure above reports the same analysis as the main text, for external mobility. After adjustment, labor-1 was negatively associated with external mobility during lockdowns as it was with internal mobility, but not during curfews. Notably, and differently from internal mobility, house crowding was consistently negatively associated with external mobility. This is possibly linked to the explored relationship between house crowding and density, and reflects the fact that unavoidable mobility for those living in high-density urban areas was restricted to short-range trips. For those living in low-density areas, some of the unavoidable trips had to reach places outside the department of residency. We found no evidence of retail availability impacting external mobility.

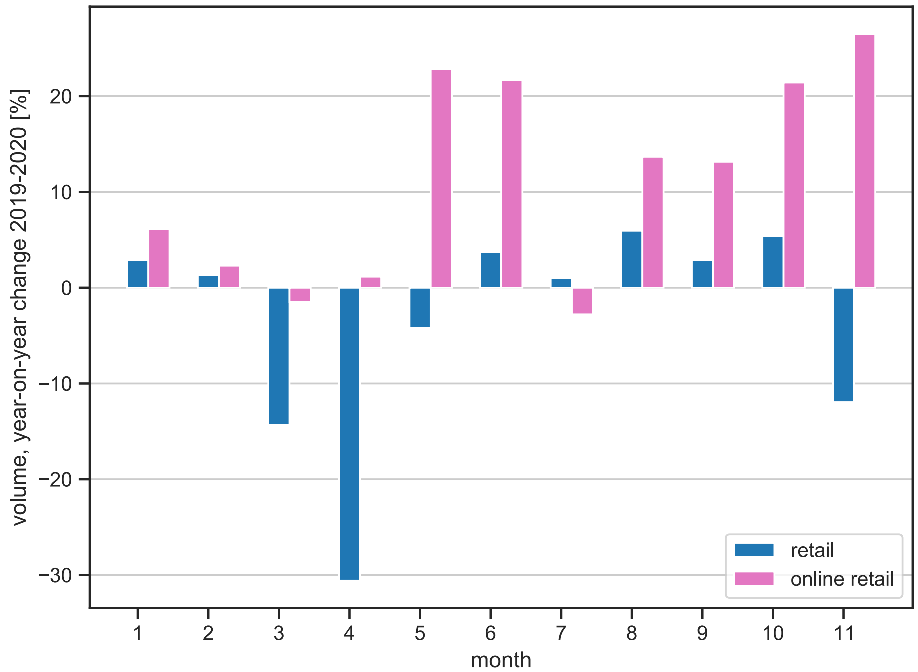


Longer mobility baseline

The available mobility data spanned the whole 2020. Mobility started being affected by the COVID-19 epidemic in March, 2020. Early 2020 in France saw extensive disruptions of public transportation both at local and at national scale, due to a generalized strike of workers in that sector. Also, school holidays – which are known to change mobility patterns in France – affected different regions from Jan 1, to Jan 5, and from Feb 10 until March. Our choice of February 3-7 as the baseline week therefore aimed at avoiding the impact of COVID-19, of transportation disruptions, and of COVID-19. Notwithstanding, the analysis was robust also against the choice of a longer baseline spanning four weeks, starting Jan 13, as the figure below shows.


posterior correlation
1.00
0.75
0.50
0.25
0.00
−0.25
−0.50
−0.75
−1.00
1st lockdown
curfew Oct
2nd lockdown
curfew Dec
standard of living
9th decile [Eur]
house crowding [%]
labor-1
labor-2
retail stores per
100,000 residents

SD3. E-commerce trend for retail



Monthly year-on-year percentage change in volume of retail and online retail during Jan-Nov 2020, in France. Data from Eurostat (https://appsso.eurostat.ec.europa.eu/nui/show.do?dataset=sts_trtu_m&lang=en accessed Feb 9, 2021). Variables used: *Retail trade, except of motor vehicles and motorcycles*; *Retail sale via mail order houses or via Internet*.

SD4. Impact of school holidays on curfew mobility

Two different analyses support the role of school holidays on curfew mobility: *i*) mobility during the same period in 2019 (without restrictions) was also positively associated to *labor-2*; *ii*) mobility during working days right after the end of the 2nd lockdown, and before the start of school holidays, was not associated to *labor-2*.

i. *Mobility during holidays in Fall 2019*

Fall school holidays:

- Oct 18 to Nov 1, 2020,
- Oct 20 to Nov 3, 2019.

Mobility during curfew was measured during Oct 26-29, 2020. The corresponding range in 2019 was Oct 28-31, 2019.

Correlation between labor-2 and mobility during Oct 28-31, 2019 was 0.40 (0.17, 0.62).

ii. *Mobility during December curfew before school holidays*

After the end of the 2nd lockdown, the December curfew was in effect, and school holidays started on Dec 19. Mobility during working days after the end of the lockdown, and before school holidays (Dec 15-18, 2020) was not associated to indicator *labor-2*: adjusted correlation = 0.12 (-0.12, 0.37).

SD5. Spatial correlation

The figure below reports the posterior estimates (median, 95% credible intervals) of the spatial correlation of the error term (λ in **SD2**).