Cross-border Mobility Responses to Covid-19 in Europe: New Evidence from Facebook Data

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Abstract

Background: We use a unique database on Facebook users’ mobility to study the daily evolution of cross-border movements of people during the Covid-19 pandemic. To limit censoring issues, we focus on 45 pairs of European countries, and document the changes in daily traffic during an entire pandemic year. We rely on regression and machine learning models to identify the role of infection threats and containment policies. Permutation techniques allow us to compare the impact and predictive power of these two categories of variables.

Results: In contrast with studies on within-border mobility, our models point to a stronger importance of containment policies in explaining changes in cross-border traffic as compared with international travel bans and fears of being infected. The latter are proxied by the numbers of Covid-19 cases and deaths at destination. Although the ranking among coercive policies varies across modelling techniques, containment measures in the destination country (such as cancelling of events, restrictions on internal movements and public gatherings), and school closures in the origin country (influencing parental leaves) have the strongest impacts on cross-border movements.

Conclusion: While descriptive in nature, our findings have policy-relevant implications. Cross-border movements of people predominantly consist of labor commuting flows and business travels. These economic and essential flows are marginally influenced by the fear of infection and international travel bans. They are mostly governed by the stringency of internal containment policies and the ability to travel.

Keywords: Cross-border mobility; Covid-19; Containment policies; Non-Parmaceutical Interventions
Background

There is strong evidence that within-border (or internal) people’s mobility declined during the Covid-19 crisis. Existing literature relies on big data provided by private cellular phone companies, and documenting spatial movements in real time. [1] uses Vodaphone data for Italy, Portugal and Spain, and finds that women and younger people show the largest drop in mobility. [2] combines telco data with household surveys to highlight a sharp decline in short-distance mobility, as proxied by daily time spent at parks, retail and recreation, grocery, transit locations, and workplaces. Using SafeGraph data, [3] finds that the mobility decline in New York and in four other U.S. cities is mostly driven by the fear of infection, rather than by legal restrictions. Although it also finds a significant impact of non-pharmaceutical interventions (NPIs) such as closing nonessential businesses, sheltering in place, and school closures, the dominant role of infection threats is confirmed by [4], who relies on Google mobility data.

There is, however, scant evidence of the impact of Covid-19 on cross-border (or international) mobility, which is due to the absence of high-frequency data on border crossings.[1] In this paper we aim to fill this research gap by addressing the following research questions: (i) How has the Covid-19 impacted cross-border movements of people? (ii) Are these changes due to coercive measures (such as containment policies or international travel bans) or by the fear of contracting the virus?

Understanding the determinants of cross-border mobility responses to Covid-19 is important for economic and epidemiological reasons. Cross-border movements of people predominantly consists of labor commuting flows and business travels. Economically speaking, labor mobility is a key ingredient for growth and competitiveness in normal times. And in a pandemic context, restrictions placed on how workers move around can slow down economic recovery prospects, by making it more difficult for businesses to hire productive workers. They can also induce severe economic impacts on cross-border workers and their families. Epidemiologically speaking, the role that mobility is playing in the spread of the disease is still unclear. Using SafeGraph data for New York city and for other U.S. cities, [5] find

[1] The recent OECD migration outlook reveals that issuance of new visas and permits in OECD countries plummeted by 46% in the first half of 2020 (by 72% in the second quarter), as compared with the same period in 2019. However, international migrants and refugees account for a tiny proportion, not a say a negligible proportion, of daily cross-border movements of people between European countries. Daily flows predominantly consist of commuting workers and business travels.
that (internal) mobility increased the spread of the disease in the early stage of the pandemic. In the same vein, [6] shows that (internal and international) travel bans enacted during the Chinese Lunar New Year holiday helped reduce the spread of the virus, and [7] argue that an appropriate coordination would considerably improve the likelihood of eliminating community transmission throughout Europe. By contrast, others expressed skepticism about the epidemiological consequences of travel bans, arguing that the impacts of these restrictions are not well understood [8] or poorly effective [9, 10, 11, 12, 13] once patient zero has already spread the virus across regions.

Without taking any position on the fact that cross-border mobility should be limited or encouraged, we use a unique database on daily mobility of European Facebook users to shed light on the evolution of cross-border movements of people during an entire pandemic year, and to compare the effects of coercive policies with those related to the fear of infection. Our results contrast with those obtained for internal mobility. The following sections successively describe our data sources, methods and findings.

**Data**

**Border crossings**

Data on cross-border daily mobility is obtained from Facebook (denoted by FB, henceforth) for the period from the 29th of February 2020 to the 28th of February 2021 [14]. The database documents cross-border flows of FB users with location services enabled, who travel from an origin to a destination country by any means of transportation (car, train, air, etc.) during each 24-hour time period. Only flows with a minimum of 1,000 movers are reported in order to minimize re-identification risk. To limit the impact of censoring, we focus on 45 country pairs (involving 30 contiguous European countries) characterized by at least 25% of uncensored values of daily traffic during the period of observation. This selection limits the ability to generalize of our results but is necessary to limit the impact of censoring, and allow smooth estimation with Machine Learning methods. We use the 7-day centered rolling average of daily flows. Although FB data has high coverage, FB users are not a random sample of the population. This raises concerns about representativeness. Figure A.1 in Appendix mitigates these concerns by showing a strong association
between daily movements of FB users and the (estimated) number of daily border crossings in the pre-Covid-19 period, which are presented in Appendix Table A.1.\footnote{We also find a strong association between the number of FB users and population size at the regional level. Results are available upon request.}

This comforts us that FB data is likely to be representative of the evolution of cross-border mobility during the pandemic.

Let us denote by $M_{i \rightarrow j t}$ the count of FB movers from country $i$ to country $j$ at day $t$. When focusing on contiguous countries (i.e., the pairs of countries that exhibit the largest numbers of daily cross-border movements by far, and that are the least affected by censoring rules), the number of movers from $i$ to $j$ is almost identical to the number of movers from $j$ to $i$ at each day $t$ (i.e., $M_{i \rightarrow j t} \approx M_{j \rightarrow i t}$). The reason is that border crossings predominantly consist of back-and-forth movements of commuting workers and business travelers, who move for short periods and for economic reasons. This is also the case in the summer vacation period when considering a 7-day centered rolling average of daily flows. This means that $M_{i \rightarrow j t}$ and $M_{j \rightarrow i t}$ are reflecting the same reality, and say nothing about the primary direction of the flows. For this reason, we define the level of bilateral traffic of FB users between countries $i$ and $j$ as:

$$T_{ijt}^F \equiv \text{Max} \left[ M_{i \rightarrow j t}^F, M_{j \rightarrow i t}^F \right] ,$$

and see it as a proxy for the scaled sum of the two unobserved unidirectional flows between the two countries, $\phi(M_{i \rightarrow j t} + M_{j \rightarrow i t})$, where the scale factor $\phi$ denotes the fraction of FB users in the actual number of movers (denoted by $M_{i \rightarrow j t}$ and $M_{j \rightarrow i t}$). As $T_{ijt}^F = T_{jit}^F$, we can get rid of the dyadic dimension of the data, treat each country pair as a one-dimensional observation, and divide the size of the sample by two. In the methodological section, however, we explain how priors about the primary direction of the flows can be used to improve the quality of fit of our models.

To avoid dealing with re-scaling issues, we express traffic counts as relative deviations from their initial or pre-Covid-19 levels – in our case, the levels observed at the outset of the pandemic (denoted by day 0). We thus use the relative deviation in bilateral traffic between day 0 and day $t$, $\tau_{ijt} \equiv \frac{T_{ijt} - T_{ij0}}{T_{ij0}}$, as a variable of interest instead of focusing on the level of traffic $T_{ijt}$ itself. Modelling relative
deviations is also helpful to avoid over-fitting large corridors at the expense of small corridors, and mitigates representativeness issues even if the scale factor ($\phi$) varies across country pairs.

Figure 1 portrays these relative deviations in the aggregate level of traffic between all country pairs included in our sample. The curve largely mirrors the three phases of the pandemic, depicting a stark drop in traffic in March 2020, a recovery during the spring and summer periods, and a new contraction in the post-summer period. Between end of February and early April 2020, the aggregate traffic level decreased from 720,000 to 130,000, implying a 82% drop. Aggregate traffic never fully recovered to the February levels in our period of observation. This also holds true during the summer vacation period when international travels were largely liberalized. The pace and strength of these changes vary across the three phases of the pandemic. The drop in March 2020 was strong and sudden, while the summer peak and the post-summer contraction were more gradual.

[Figure 1 about here]

Aggregate fluctuations mask large differences across country pairs. Bilateral traffic returned to its pre-Covid level in a minority of cases. For the majority of corridors, however, the traffic level has not fully recovered. This is illustrated in Figure 2, which depicts the evolution of people’s traffic in corridors involving four open countries, namely Luxembourg, Switzerland, Italy, and Serbia. Luxembourg is the country with the highest share of cross-border workers in Europe. Given the economy’s high reliance on cross-border workers, the Luxembourg government has never implemented international travel restrictions during the pandemic. Luxembourg experienced a significant drop in traffic in March 2020, whatever the partner country. After one month of lockdown, traffic levels recovered pretty quickly until reaching a plateau at about -25% since June 2020. Switzerland is the country with the largest number of cross-border commuters in Europe. This country experienced a larger drop during the first lockdown, and a slower recovery. Furthermore, the variability across corridors is considerably greater than in Luxembourg.

Italy has been severely impacted by the pandemic, and responded with national and international travel bans. We observe similar patterns of contraction and recovery during the first two quarters of 2020, followed by a substantial increase in traffic during the holiday summer period, and a second lockdown-type contraction in the
post-Summer period. Finally, the patterns observed in Serbia are less conclusive as they are more severely affected by censoring rules. Serbia is an important origin and transit country for migrants and refugees entering the EU. Overall these patterns illustrate the need to account for corridor-specific heterogeneity when analyzing the determinants of bilateral traffic. Variations are likely to be influenced by seasonal effects, epidemiological risks, and policy measures implemented in the countries. We now turn to the description of the data sources used to proxy epidemiological conditions and the stringency of national policies.

[Figure 2 about here]

Explanatory features

We link variations in cross-border traffic during the pandemic to daily changes in epidemiological conditions and containment policies in the countries involved. We proxy the severity of the pandemic with the daily numbers of new Covid-19 cases and new Covid-19 related deaths in each country using data from [15]. With regard to containment measures, we use data on daily policy responses from the Oxford Covid-19 Government Response Tracker (OxCGRT) [16]. The latter database consists of 18 ordinal indicators capturing the levels of nonpharmaceutical interventions (NPIs). Based on our priors as to which policies likely affect mobility, we choose to include the eight mobility-related measures that form the "containment and closure policies" block (denoted by C1-C8 in the database) as well as proxies for the intensity of testing and contact tracing (denoted by H2 and H3). We rescale all sets of predictors between 0 and 1, and align them with the definition of the outcome variable using the centered 7-day rolling average at each day.

For all features and days, Figure 3 displays the cross-country mean level of each containment index as a heatmap. Values close to one represent higher Covid-19 cases/deaths or more stringent responses. As containment policies were implemented in most countries during the second half of March 2020, maximum values are observed during this period. Testing and contract tracing were implemented more heterogeneously across countries and peaked in the summer of 2020. Reported number of new Covid-19 related cases/deaths were much greater during the second wave and peaked at the end of the year 2020[^1].

[^1]: Epidemiological conditions are likely to subject to measurement errors. For example, testing and tracing practices played an important role in determining the number of detected cases.
Figure 4 shows the cross-country correlations between each of the explanatory variables and the relative deviations in average traffic (i.e., deviation of the country-specific mean level of traffic with all potential partner countries in the sample). Containment policies are positively correlated with each other, and moderately correlated with epidemiological conditions, which allows us to include both sets of variables jointly in our regression and machine learning models. However, the fact that containment policies are correlated with each other raises concerns of multicollinearity, and motivates the usage of a limited number of synthetic policy indices. These indices are obtained by conducting a Principal Component Analysis (PCA) of all policy measures (C1-C8, and H2-H3) over the entire sample of observations, and by extracting the first two components. The first component mainly represents the C1-C8 measures which are strongly correlated with each other while the second component corresponds to a higher variance for the H2-H3 measures. We will compare the results obtained when using a comprehensive specification, including all (collinear) explanatory variables, with those obtained when using a parsimonious specification, including the two synthetic PCA components as predictors.

Turning to the main correlations of interest (i.e., correlations between the relative deviations in cross-border traffic and each predictor), the figure displays a moderate negative correlation with containment policies, as well as low and positive correlations with testing and tracing policies. The strongest associations are obtained for cancellations of public events, restrictions on public gatherings, requirements to stay at home, and restrictions on internal movements. Two interesting observations arise from these partial correlations. First, the negative correlation between measures of epidemiological intensity (Covid-19 cases and deaths) and changes in total traffic are rather low. This might suggest that, in contrast with studies on within-border mobility, the fear of being infected might play a less important role in explaining changes in cross-border movements. Second, among containment policies, the implementation of international travel bans is far from being the most strongly correlated covariate. This suggests that travel bans might be effective in limiting non-essential travels, but less effective to limit labor commuting flows and business travels, which represent the overwhelming majority of daily border crossings between European
countries (see Table A.1 in Appendix). By contrast, cancellations of events and constraints on internal movements and gatherings are highly correlated with traffic variations, possibly because such constraints better proxy changes in economic activity and incentives to move. In the following section, we describe the regression and machine learning methods used to test these hypotheses using bilateral traffic growth as a dependent variable.

Methods

Mobility patterns identified in the previous section might result from various factors such as travel bans, sanitary measures influencing economic costs and incentives to move for work and business (e.g. sectoral lockdown, work-from-home practices) or for leisure (e.g. shops, restaurant and bar closings), or the fear of the virus itself. Our goal here is to identify the determinants of the relative deviation in daily traffic of people between country $i$ and country $j$ ($\tau_{ijt}$), considering all NPIs and epidemiological daily indicators ($x_{it}$ and $x_{jt}$) during the Covid-19 crisis. Our models are also used to predict the effects of epidemiological restrictions, NPIs and mobility restrictions on traffic counts.

We combine two analytical methods, Econometric Modelling (EM) and Machine Learning (ML). EM and ML techniques are generally used for different purposes. In EM, gravity models are used to explain human mobility flows between two countries. EM models require imposing one analytical specification for the response function, which governs the derivatives of the dependent with respect covariates. EM models are used to test whether explanatory variables are significant predictors for $\tau_{ijt}$. To ensure that the effect of explanatory variables is not driven by spurious correlations (i.e. the joint effect of an unobserved variable on both dependent and explanatory variables), EM models can be saturated with day and corridor dummies (called day- and corridor-specific fixed effects), which capture the incidence of time and corridor-specific unobserved characteristics. A strong association is identified if a statistically significant effect persists after controlling for this large set of dummies. Although forecasting accuracy is also a goal in itself, the focus of EM studies is usually put on causation and robustness of the estimates. ML techniques are at the other extreme of the bias-variance tradeoff. They do not require strong analytical assumptions and allow, by design, to explore a larger set of regression functions including linear
or polynomial combinations of the covariates. This increase of the so-called model capacity comes with two drawbacks. First, the models are more complex and are usually not easy to interpret. Contrary to EM, ML techniques might computationally suffer from the inclusion of large sets of control dummies/fixed effects. Second, there is always a risk of overfitting the training data and the identification of causation links is usually not an objective per se.

We use four models exploring a broad range of learning techniques: (i) A gravity model based on the linear regression method [17]; (ii) A K-nearest neighbors method (KNN), which predicts the dependent variable by interpolation of its nearest observation neighbors in the training set [18]; (iii) A Gradient Boosting method (GBoost), whose predictions are based on a set of decision tree models [19]; (iv) A Multi-layer Perceptron (MLP), which is a classic neural network approach [20, 21]. The last three models rely on different ML regressors, each based on a distinct type of technique. We assess the predictive performance of each model using the very same (and standard) cross-validation ML methodology. The goal of the study is not to design a forecasting model, but rather to identify the main determinants of mobility, and to investigate whether these different approaches generate converging findings. Therefore, instead of validating our model on a particular sub-period (as is usually done to evaluate a time-series model), the observations composing the cross-validation folds are randomly chosen within the full sample. All models are implemented in Python via the Skicit-learn library [22].

Approaches with or without directional priors

Ideally, mobility models aim to characterize the evolution of the unidirectional flow of people \( (M_{i \rightarrow j}) \) from an origin country \( i \) to a destination country \( j \) at day \( t \), or of their relative deviation from the initial reference period \( \mu_{i \rightarrow j t} = \frac{M_{i \rightarrow j t} - M_{i \rightarrow j 0}}{M_{i \rightarrow j 0}} \), based on a set of features available for the same time period. Without loss of generality, the general functional form \( f_M \) of such a model can be written as:

\[
\mu_{i \rightarrow j t} = f_M(x_{it}, x_{jt}, d_{ij}, d_t) + \eta_{i \rightarrow j t} \tag{2}
\]

where \( x_{it} \) represents the set of origin-specific determinant, \( x_{jt} \) is a set of destination-specific determinants, \( d_{ij} \) is a set of bilateral dummies capturing time-invariant
bilateral resistance (including initial $M_{i\rightarrow j0}$, distance, language proximity, cultural proximity, etc.), $d_t$ a set of day dummies capturing weekdays and seasonal trends (e.g. holiday season, general feeling of risk when traveling, etc.), and $\eta_{i\rightarrow jt}$ an error term. In our case, the vectors of explanatory variables $x_{it}$ and $x_{jt}$ capture the set of NPIs and epidemiological variables, and should also be interpreted as variations from period 0 since $x_{i0}$ and $x_{j0}$ are equal to zero in the pre-Covid-19 period.

With FB data, the primary direction of the cross-border flows is unknown, which implies that $M_{i\rightarrow jt}$ and $M_{j\rightarrow it}$ cannot be distinguished a priori. Instead, we observe the relative deviation in bilateral traffic, $\tau_{ijt}$, and we have to estimate the function $f_T$ linking bilateral traffic to the set of explanatory features without being able to distinguish between origin- and destination-specific determinants. A learning approach without directional priors writes as:

$$ \tau_{ijt} = f_T(x_{it}, x_{jt}, d_{ij}, d_t) + \eta_{ijt} \quad (3) $$

It is possible, however, to discipline the model with priors about the direction of the flows. As bilateral traffic is a proxy for the sum of unidirectional flows ($T_{ijt} \simeq \phi(M_{i\rightarrow jt} + M_{j\rightarrow it})$), relative deviations in $T_{ijt}$ can be expressed as a weighted sum of the relative deviations in unidirectional flows: $\tau_{ijt} = \omega_{i\rightarrow j,0} \times \mu_{i\rightarrow jt} + \omega_{j\rightarrow i,0} \times \mu_{j\rightarrow it}$, where $\omega_{i\rightarrow j,0} = 1 - \omega_{j\rightarrow i,0}$ is the pre-Covid-19 share of unidirectional cross-border flows from country $i$ to country $j$ in total traffic between the two countries. Estimates for $\omega_{i\rightarrow j,0}$ are constructed using pre-Covid-19 data on commuters, air travels and international migration, and then used as priors to discipline the model (these shares are depicted in Figure A.2 in Appendix).

We can thus create two sets of weighted features, namely $X_{ijt}^o$ for origin-specific effects, and $X_{ijt}^d$ for destination-specific effects, defined as follows:

$$ X_{ijt}^o = \omega_{i\rightarrow j0} x_{it} + \omega_{j\rightarrow i0} x_{jt} $$
$$ X_{ijt}^d = \omega_{i\rightarrow j0} x_{jt} + \omega_{j\rightarrow i0} x_{it}. $$
The model with directional priors is obtained after replacing \((x_{jt}, x_{jt})\) in Eq. (3) by \((X_{ijt}^o, X_{ijt}^d)\). It writes as:

\[
\tau_{ijt} = f_T(X_{ijt}^o, X_{ijt}^d, d_{ij}, d_t) + \eta_{ijt}^{od}.
\]  (4)

If the true model for unidirectional flow \((f_M(.))\) was linear, plugging weighted covariates in the estimated model for bilateral traffic \((f_T(.))\) would allow retrieving the true origin- and destination-specific coefficients of interest accurately. Although this is not the case when \(f_M(.)\) is nonlinear, using weighted covariates might improve the quality of fit or facilitate the interpretation of the results. The rationale is that the effect of policies depends on where they are implemented and on the primary direction of the flows. Suppose \(\omega_{i\rightarrow j0} \simeq 1\) (i.e., flows mostly go from \(i\) to \(j\)), then an increase in restrictions/stringency at destination (resp. at origin) makes \(X_{ijt}^d\) positive (resp. \(X_{ijt}^o\) positive) and is more (resp. less) likely to reduce the flow of cross-border movements. Using directional priors allows approximating origin- and destination-specific effects without observing the direction of the flows during the pandemic year.

**Permutation Feature Importance**

To identify the main causes of daily mobility variations, the importance of each feature is computed for the different regression approaches with *permutation feature importance* [23]. It has the advantage of working similarly for all regression models considering them as a black-box models [24]. It is defined to be the decrease in the regression score when a single feature value is randomly shuffled across observations.

More exactly, for a given model \(f\), it first calculates a baseline score \(S_f\) provided by \(f\) when it is fitted, and then evaluated with a certain metric on the whole sample. Then for each possible feature \(x\) the modified score \(S_{f,x}^*\) is computed by evaluating \(f\) on the transformed data set where the values of feature \(x\) are randomly permuted across all observations. The mean importance of the feature \(x\) for the model \(f\) is computed as:

\[
I_{f,x} = \frac{1}{K} \sum_{k=1}^{K} \frac{S_f - S_{f,x,k}^*}{S_f}
\]  (5)
where \( K \) is the number of random permutations realized for each feature, and \( S^*_{f,x,k} \) is the \( S^*_{f,x} \) score for the \( k^{th} \) permutation.

In order to compare the importance values of the different models in an equivalent manner, the values \( I_{f,x} \) are scaled between 0% and 100% separately for each model \( f \). The mean features importance \( I_{f,x} \) are computed over 10 permutations using the negative mean absolute error (MAE) and the Root Mean Squared Error (RMSE). This means that the bigger \( I_{f,x} \), the more permutations of the feature \( x \) degrades the quality of predictions for the model \( f \) and the feature is considered as more importantly associated with the target variable.

**Results**

We present our results in two steps. First, we assess the predictive power of the various models. This implies comparing learning methods with or without directional priors and with or without day/corridor control dummies. We compare their predictive performance by using out-of-sample predictions and computing the MAE and RMSE. Second, we use the estimated models to rank the importance of different features relying on permutation techniques. Using multiple models allows assessing the robustness of our findings.

**Validation of models**

We first investigate whether adding priors about the direction of the flows and/or adding a full bunch of day and corridor dummies improves the performance of our learning models. Models without directional priors are described in Eq. (3), while models with priors use weighted regressors, as described in Eq. (4). A 10-fold cross-validation over the whole data set (from the 29th February 2020 until the 28th February 2021) is realized for each model to assess its performance. Table 1 reports the MAE, RMSE and their standard error across cross-validation folds obtained with different learning methods.

It shows that directional priors (\( \omega_{i\rightarrow j,0} \) and \( \omega_{j\rightarrow i,0} \)) do not bring significant additional predictive power under most learning approaches when day and corridor dummies are not factored in (see Panels A and B). The only exception is the G-Boost method. On the contrary, when day and corridor dummies are included (Panels C and D), adding directional priors slightly improve the quality of fit with virtually all learning techniques (except with KNN). In addition, we show below that
distinguishing between origin- and destination-specific effects as in Eq. (4) makes
the interpretation of the results much easier. Therefore, the model with directional
priors will be prioritized in the rest of the analysis.

[Table 1 about here]

Second, we investigate whether the inclusion of day-specific effects – i.e., 366 time
dummies, \(d_t\), that are common to all corridors and capture unobserved variations
such as seasonal changes, synchronized fears of infection, etc. – and corridor-specific
effects – i.e., 45 corridor dummies, \(d_{ij}\), that are time invariant and capture unob-
served variations such as the skill level of the cross-border workforce, linguistic and
cultural proximity between countries, etc. – improves the predictive power of our
models. Again, we perform another 10-fold cross-validation on different versions of
each model. Panels C and D in Table 1 includes both sets of dummies jointly, with
or without directional priors. In the absence of directional priors, the inclusion of
day and corridor dummies reduces the MAE and RMSE by 20 to 30\% whatever
the learning technique used. When directional priors are factored in, the dummies
improve the performance of the linear and MLP models, whereas they deteriorate
the quality of fit under the KNN and G-Boost models. This is because adding day
and corridors dummies drastically increases the number of parameters to be esti-
mated, and some ML approaches (like KNN) are known to suffer from the curse of
dimensionality.

To further explore this issue, Table A.2 in Appendix considers the model with
directional priors and adds one set of dummies at a time. The inclusion of 45
corridor-specific dummies always improves the quality of fit. On the contrary, the
inclusion of 366 day-specific dummies deteriorates the performance of KNN and
G-Boost methods. This confirms that the gains from adding information about
unobserved common time trends, which might already be captured by the relatively
well synchronized trends in observed epidemiological conditions and containment
measures, is outbalanced by the costs linked to the inflated dimensionality of the
computation problem.

Third, ML techniques always outperform the linear EM model. This result was
also expected given that ML is based on more complex prediction methods that
allow for non-linear relationships between variables, and account for non-stationary
variations contained in the matrices of \(X_{ijt}^o\) and \(X_{ijt}^d\). The KNN always produces
the best quality of fit. The error of this approach is minimal when the number of neighbors $k$ used to estimate the relative deviations in traffic is low (say, 2 or 3). Its impressive performance in 10-fold cross-validation can be explained by the fact that the model finds a small number of observations for which the relative deviations in traffic are similar to those that must be predicted. In general, the closest neighbors are observations of the days preceding or following the daily level of traffic observed in the same corridor.

**Main sources of variations in cross-border mobility in Covid times**

In order to identify the government policy indicators having the greatest impact on relative deviations in traffic, the importance of each feature is computed for the different approaches involving directional priors and dummies. Directional priors allow us to distinguish the effects of origin-specific features from those of destination-specific features. Table 2 presents the results from this exercise. Features are ranked by decreasing order on the basis of the average predictive power across the four learning techniques. The column 'Avg.' gives the mean value of error metric averaged over the four models. Panel A provides the results obtained with the saturated models including the large set of corridor and day dummies, which is the first-best model when using linear and MLP learning techniques. Panel B gives the results obtained with corridor dummies only, which is the first-best model when using the KNN and G-Boost techniques. Results of Panel B will be discussed in the next section. In the top part of the table, the models use all individual features depicted in Figure 3, despite the high level of correlation between some of them. In the bottom part of the table, the models use synthetic containment features derived from a PCA analysis.

When considering all individual features, the ranking based on their predictive power varies across models. We identify, however, several common and interesting findings. *First*, school closures in the origin country has the largest average impact on the variation in daily traffic. Remember that cross-border traffic predominantly consists of labor commuting flows and business travels. School closures at origin imply that many parent workers are forced to take parental leave and cannot commute to work. In the same vein, school closures in the destination country are also
paralyzing economic activity in the destination country and reduce incentives to move. Second, variations in traffic are mostly impacted by containment measures. Based on the average predictive power (col. ‘Avg.’), ten out of the twelve most predictive features involve C-type containment measures implemented in the origin or destination countries. Third, the fear of being infected in the destination country, as proxied by the destination-specific number of Covid-19 deaths and cases (appearing in bold characters in Table 2) are among the least predictive features. Fourth, international travel bans in origin and destination countries (appearing in italics in Table 2) also have a low predictive power. We thus conclude that cross-border daily flows are marginally influenced by the fear of infection and international travel bans. They are mostly governed by the stringency of internal containment policies and by family constraints. It is worth noticing that models without directional priors deliver very similar results, as illustrated in Table A.3 in the Appendix.

In addition to school closures, the top panel of of Table 2 suggests that the most important containment measures are the cancellation of public events, restrictions on gatherings, restrictions on internal movements and stay-home requirements. In addition, the twelve most predictive features include 5 destination-specific and 7 origin-specific measures. However, as illustrated in Figure 4, these measures are highly correlated at the national level. Hence, instead of feeding the model with correlated features, the bottom part of the table uses synthetic indices of containment and sanitary measures. We use a PCA analysis to reduce the dimensionality of the origin- and destination-specific containment measures and we extract the first two components of the PCA.

Remember that the first PCA component can be interpreted as an average index of stringency of containment measures (i.e. C1-C8 indices); the second component captures testing and tracing policies (i.e. H2 and H3). The results clearly reveal that the stringency of containment measures in the destination country has, by far, the greatest predictive power. The average stringency of containment measures at origin is the second most predictive power, with an average importance equal to 40% of that of the destination country. This comforts the idea that cross-border daily flows of people mostly involve economic/essential movements which can only be influenced by changes in incentives to move or coercive mobility constraints. In
line with the top part of the Table, variables influencing the fear of infection have negligible impacts on border crossings.

**Discussion**

The EM and ML techniques used in this paper allow highlighting a strong association between the evolution of bilateral traffic between contiguous countries and containment policies in the destination country as well as school closures in the origin country. Association does not imply causation. It could be argued that this statistical association is governed by the influence of unobserved characteristics affecting both policy changes and mobility simultaneously, or that a reverse causation mechanism operates (i.e. cross-border mobility influences policy reforms). The fact that our results are robust to the inclusion of a large set of day and corridor dummies capturing unobserved time- and corridor-specific characteristics strongly mitigates the first misspecification concern.

With regard to reverse causation, concerns are mitigated by the use of high-frequency data. We cannot reject the possibility of a mobility-driven propagation of the virus requiring new containment measures. However, such a mechanism takes time to operate. Mobility shocks at day $t$ do not generate immediate and visible epidemiological consequences, and policy responses are also implemented with a certain delay. By contrast, our estimates suggest that containment policies are contemporaneously associated with changes in cross-border mobility. This prudently supports the existence of a causation effect of containment measures on mobility.

An opposite argument that goes against the reverse causation issue is that it also takes time for information about epidemiological conditions to be assimilated by potential movers. Hence, the fear of infection could be better proxied by the lagged numbers of Covid-19 cases and deaths. Our results are preserved and even reinforced when using lagged proxies for the fear of infection. More precisely, traffic at day $t$ is very badly predicted by the number Covid-19 cases and deaths observed one or two weeks before the date (see Table A.4 in the Appendix). Hence, we can reasonably rule out that the low impact of infection fears at destination is driven by a misspecification problem.

In the same vein, it could be argued that fears are strongly synchronized across countries and captured by the day dummies. These concerns are mitigated by the
fact that removing the 366 day-specific dummies does not alter our conclusions. In Panel B of Table 2, day dummies are excluded. The only significant change is that the number of Covid cases in the origin country has a greater predictive power, possibly implying that people in sick leave self-isolate and stop moving. However, the predictive power of international travel bans (in italics) and fears to be infected at destination (epidemiological conditions at destination are in bold characters) remain low when using both individual and synthetic features. Again, the stringency of containment measures in the destination country has the greatest predictive power by far.

**Conclusion**

Existing literature shows that people within-border mobility has drastically declined in times of Covid-19, primarily because of the fear to be infected in parts of the population. To the best of our knowledge, our study is the first to analyze the effect of Covid-19 and related containment measures on people’s cross-border movements. In line with the findings above, we also document a sharp decline in cross-border mobility in general, especially during the first lockdown and in the second and third waves of the pandemic. However, these variations in cross-border mobility are mostly induced by local containment policies in the destination country, and school closures in both countries. The fear of infection and international travel bans have little influence on cross-border movements.

The likely reason is that cross-border daily flows of people are predominantly made of commuting workers and business travelers who move for economic/essential reasons. These economic flows are observed between contiguous countries, and account for 99% of international movements of people when compared with the flows of migrants and refugees. Their magnitude varies with the economic costs and incentives of moving, which depend on lockdown measures and on the stringency of internal containment policies. In addition, international travel bans do not apply to commuters and businessmen. Although there is no consensus on the fact that these flows contribute to the propagation of the virus, policy-makers must be aware that economic movers hardly adapt their mobility decisions to epidemiological threats. Border crossings can only be controlled with internal coercive policies.
Declarations

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Abbreviations
EM: Econometric Modelling
EU: European Union
FB: Facebook Inc.
G-Boost: Gradient Boosting
KNN: K-nearest neighbors method
MAE: Mean Absolute Error
ML: Machine Learning
MLP: Multi-layer Perceptron
NPIs: non-pharmaceutical interventions
OxCGRT: Oxford Covid-19 Response Tracker
PCA: Principal Component Analysis
RSME: Root Mean Squared Error

Availability of data and materials
The datasets supporting the conclusions of this article are available in the Zenodo repository Cross-border-Mobility-Responses-to-Covid-19-in-Europe, https://doi.org/10.5281/zenodo.4719559

Ethics approval and consent to participate
No ethics approval or consent required.

Competing interests
The authors declare that they have no competing interests.

Consent for publication
Not applicable.

Authors’ contributions
F.D. and P.S. conceived the presented idea. F.D., N.G., P.S. and F.S. contributed to the design and implementation of the research, to the analysis of the results and to the writing of the manuscript. F.D., F.S. and P.S. collected the data. F.S. cleaned the data and produced descriptive graphs. N.G. and F.S. implemented the EM and ML modelling. All authors discussed the results, drafted and critically revised the article.

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**Figures**

**Figure 1** Aggregate Traffic Deviations from Pre-Covid Levels

![Aggregate Traffic Deviations from Pre-Covid Levels](image)

Source: Facebook data on daily border crossings. Notes: Y-axis represents the average of $\tau_{ijt}$, the percentage change (times 100) in the 7-day moving average traffic compared to $t = 0$ over all destinations. The weights are the traffic levels observed in pre-Covid-19 period (i.e., $t = 0$).

**Tables**

|                  | Panel A: No dummies - No prior | Panel B: No dummies - Priors | Panel C: Dummies - No prior | Panel D: Dummies - Priors |
|------------------|-------------------------------|-------------------------------|----------------------------|----------------------------|
|                  | Linear | KNN  | G-Boost | MLP  | Linear | KNN  | G-Boost | MLP  | Linear | KNN  | G-Boost | MLP  | Linear | KNN  | G-Boost | MLP  |
| **avg MAE**      | 0.194  | 0.018| 0.073   | 0.051| 0.201  | 0.019| 0.042   | 0.057| 0.135  | 0.020| 0.050   | 0.041| 0.134  | 0.020| 0.049   | 0.038|
| **std MAE**      | (0.009)| (0.001)| (0.001)| (0.005)| (0.005)| (0.001)| (0.001)| (0.003)| (0.005)| (0.001)| (0.002)| (0.003)|
| **avg RMSE**     | 0.285  | 0.042| 0.106   | 0.083| 0.287  | 0.043| 0.064   | 0.089| 0.210  | 0.045| 0.081   | 0.068| 0.203  | 0.047| 0.077   | 0.064|
| **std RMSE**     | (0.017)| (0.009)| (0.003)| (0.011)| (0.009)| (0.005)| (0.002)| (0.008)| (0.010)| (0.006)| (0.006)| (0.006)| (0.009)| (0.005)| (0.002)| (0.005)|

Note: The table compares the performances of the 4 different approaches (Linear, KNN, G-Boost and MLP) with and without directional priors ($\omega_{i\rightarrow j,0}$), and with or without day/corridor dummies ($d_i$ and $d_{ij}$). Errors are computed from a 10-fold cross-validation on the whole sample.
Figure 2  Traffic Deviations from Pre-Covid Levels for Selected Corridors

Source: Facebook data on daily border crossings. Notes: Y-axis represents $\Delta T_{ij,t}$, i.e. percentage change (times 100) in corridor 7-day moving average traffic compared to $t = 0$ in corridor $ij$.

Figure 3  Average value of government policy measures over the time

Source: Oxford Covid-19 Government Response Tracker (OxCGRT). Note: The values of each government policy indicator is scaled between 0 and 1 and the average is calculated among the 30 countries included in our sample.
Figure 4  Correlation Matrix of the different variables

|                  | C1 School closing | C2 Workplace closing | C3 Cancel events | C4 Restrict gatherings | C5 Close publ transport | C6 Stay at home | C7 Internal movement | C8 Int travel controls | H2 Testing policy | H3 Contact tracing | New cases smoothed | New deaths smoothed | Unilateral traffic growth |
|------------------|-------------------|----------------------|------------------|-----------------------|-------------------------|------------------|----------------------|----------------------|---------------------|--------------------|---------------------|-----------------------|------------------------|
| C1 School closing | 1.00              |                      |                  |                       |                         |                  |                      |                      |                     |                    |                     |                       |                       |
| C2 Workplace closing | 0.52          | 1.00                |                  |                       |                         |                  |                      |                      |                     |                    |                     |                       |                       |
| C3 Cancel events | 0.26              | 0.52                | 1.00             |                       |                         |                  |                      |                      |                     |                    |                     |                       |                       |
| C4 Restrict gatherings | 0.29           | 0.56                | 0.54             | 1.00                 |                         |                  |                      |                      |                     |                    |                     |                       |                       |
| C5 Close publ transport | 0.37           | 0.35                | 0.26             | 0.26                 | 1.00                    |                  |                      |                      |                     |                    |                     |                       |                       |
| C6 Stay at home | 0.42              | 0.51                | 0.46             | 0.45                 | 1.00                    |                  |                      |                      |                     |                    |                     |                       |                       |
| C7 Internal movement | 0.46           | 0.43                | 0.40             | 0.44                 | 0.38                    | 0.50             | 1.00                 |                      |                     |                    |                     |                       |                       |
| C8 Int travel controls | 0.16           | 0.20                | 0.16             | 0.20                 | 0.20                    | 0.17             | 0.15                 | 1.00                 |                     |                    |                     |                       |                       |
| H2 Testing policy | -0.12             | -0.04               | -0.05            | -0.08                | -0.01                   | -0.14            | -0.04                | -0.03                | 1.00                 |                     |                     |                       |                       |
| H3 Contact tracing | -0.15             | -0.07               | -0.10            | -0.08                | -0.01                   | -0.02            | -0.01                | -0.17                | 1.00                 |                     |                     |                       |                       |
| New cases smoothed | 0.25              | 0.39                | 0.27             | 0.40                 | 0.36                    | 0.26             | 0.23                 | 0.05                 | -0.09               | 1.00               |                     |                       |                       |
| New deaths smoothed | 0.06              | 0.24                | 0.17             | 0.19                 | -0.06                   | 0.22             | 0.15                 | -0.02                | 0.20                 | 0.03               | 0.04               | 1.00                 |                       |
| Unilateral traffic growth | -0.26           | -0.35               | -0.44            | -0.47                | -0.27                   | -0.52            | -0.35                | -0.19                | -0.20                | 0.18               | 0.25               | -0.18                | 1.00                  |

Corr

Source: Own computations. Notes: Unilateral traffic growth for each country \(i\) is the relative deviation in aggregate traffic involving country \(i\), \(\sum_{j=1}^{\text{num_countries}} T_{ijt}\), as compared to the pre-Covid-19 period (\(t = 0\)).
### Table 2: Feature ranking by origin and destination

| Features                          | Panel A                  | Panel B                  |
|-----------------------------------|--------------------------|--------------------------|
|                                   | Corridor & Day dummies   | Corr. dum.               |
|                                   | Linear | KNN | G-Boost | MLP | Avg. | Avg. |
| **Indiv. features**               |        |     |        |     |      |      |
| Origin - C1 School closures       | 100    | 69  | 100    | 59  | 82   | 85   |
| Destin - C1 School closures       | 94     | 60  | 36     | 85  | 68   | 68   |
| Origin - C3 Cancel public events  | 19     | 64  | 77     | 68  | 57   | 57   |
| Destin - C3 Cancel public events  | 100    | 50  | 65     | 65  | 52   | 52   |
| Origin - C7 Restr. Internal move  | 0      | 93  | 16     | 100 | 52   | 51   |
| Destin - H2 Testing policy        | 14     | 7   | 87     | 92  | 50   | 43   |
| Origin - C4 Restrictions gatherings | 50    | 51  | 40     | 54  | 49   | 44   |
| Destin - C6 Stay home requirements | 92    | 16  | 12     | 59  | 45   | 21   |
| Origin - C6 Stay home requirements | 17    | 15  | 96     | 54  | 45   | 45   |
| Destin - C4 Restrictions gatherings | 6     | 48  | 70     | 25  | 37   | 42   |
| Destin - C7 Restr. Internal move  | 13     | 66  | 12     | 58  | 37   | 29   |
| Origin - H3 Contact tracing       | 5      | 12  | 27     | 44  | 22   | 22   |
| Origin - C8 International travel bans | 1     | 1   | 45     | 40  | 22   | 18   |
| Origin - New Covid deaths         | 0      | 7   | 73     | 5   | 21   | 46   |
| Destin - New Covid deaths         | 11     | 0   | 21     | 52  | 21   | 75   |
| **Destin - C5 Close public transport** | 6     | 10  | 64     | 0   | 20   | 49   |
| Origin - H3 Close public transport | 34    | 6   | 1      | 39  | 20   | 9    |
| Destin - C5 Close public transport | 31    | 21  | 2      | 14  | 17   | 7    |
| Origin - H3 Contact tracing       | 9      | 33  | 7      | 23  | 17   | 21   |
| Destin - C8 International travel bans | 0     | 12  | 20     | 32  | 16   | 24   |
| **Destin - New Covid cases**      | 12     | 0   | 43     | 6   | 15   | 38   |
| Origin - C5 Close public transport | 18    | 7   | 0      | 31  | 14   | 12   |
| Destin - C2 Workplace closing     | 1      | 23  | 10     | 14  | 12   | 23   |
| Origin - H2 Testing policy        | 9      | 0   | 2      | 10  | 4    | 6    |
| **Synthetic features**            |        |     |        |     |      |      |
| Destin - Component 1              | 100    | 100 | 100    | 100 | 100  | 100  |
| Origin - Component 1              | 13     | 75  | 20     | 49  | 39   | 48   |
| Destin - Component 2              | 1      | 55  | 17     | 19  | 23   | 26   |
| Origin - Component 2              | 9      | 50  | 0      | 0   | 15   | 17   |
| Destin - New Covid cases          | 0      | 0   | 18     | 30  | 12   | 75   |
| Origin - New Covid deaths         | 5      | 14  | 6      | 11  | 9    | 49   |
| Destin - New Covid deaths         | 1      | 13  | 3      | 9   | 6    | 46   |
| Origin - New Covid cases          | 0      | 2   | 1      | 6   | 2    | 38   |

Notes: The different features are ranked following the permutation importance method. For each approach, we provide results obtained with the model including day/corridor dummies (cols. 1-5) and the version including corridors dummies only (col. 6). Directional priors are always used to identify the effects of origin- and destination-specific features. The importance values of each feature is computed over 10 permutations using the negative mean absolute error (MAE). The resulted values are scaled between 0% and 100% separately for each model. The col. ‘Avg.’ averages the results obtained with the four learning techniques. The features are ranked according to the average importance of the models including the day/corridor dummies (Panel A). In Panel B, we only report the ‘Avg.’ score without reporting the model-specific results.