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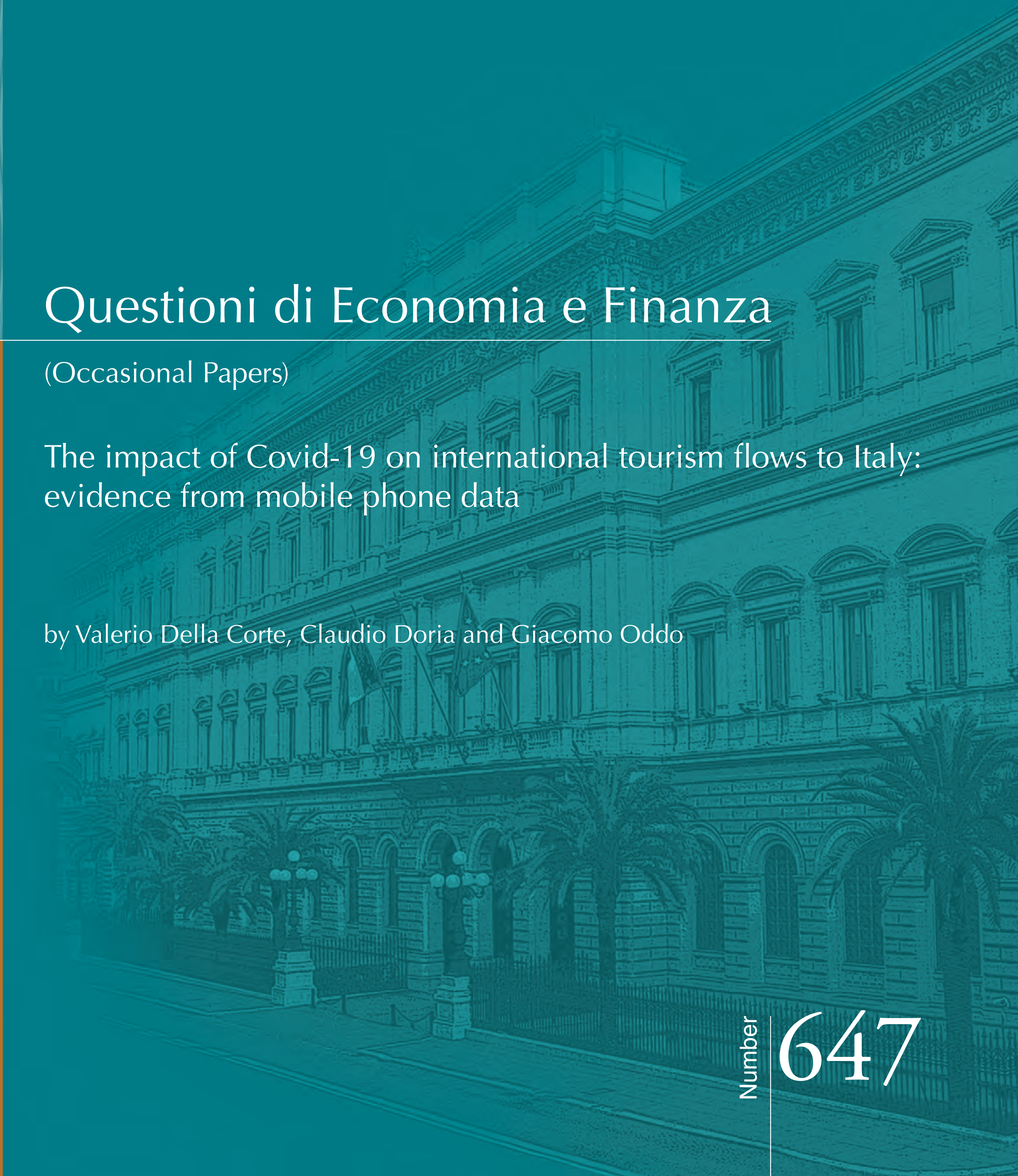

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by Valerio Della Corte, Claudio Doria and Giacomo Oddo

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The series is available online at www.bancaditalia.it .

ISSN 1972-6627 (print)
ISSN 1972-6643 (online)

Printed by the Printing and Publishing Division of the Bank of Italy

THE IMPACT OF COVID-19 ON INTERNATIONAL TOURISM FLOWS TO ITALY: EVIDENCE FROM MOBILE PHONE DATA

by Valerio Della Corte*, Claudio Doria* and Giacomo Oddo*

Abstract

This paper analyses the response to the COVID-19 pandemic of inbound tourism to Italy looking at variation across countries and across provinces. To this end, it uses weekly data on the number of foreign visitors in Italy from January 2019 until February 2021, as provided by a primary mobile phone operator. We document a very robust negative relation at province level between local epidemiological conditions and the inflow of foreign travellers. Moreover, provinces with a historically higher share of art tourism, and those that used to be 'hotel intensive' were hit the most during the pandemic, while provinces with a more prevalent orientation towards business tourism proved to be more resilient. Entry restrictions with varying degrees of strictness played a key role in explaining cross-country patterns. After controlling for these restrictions, we observed that the travellers that could arrive by their own, private, means of transportation decreased proportionally less. Overall, this evidence emphasises that contagion risk considerations played a significant role in shaping international tourism patterns during the pandemic.

JEL Classification: I15, L83, F14.
Keywords: international tourism, travel restrictions, Covid-19.
DOI: 10.32057/0.QEF.2021/0647

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* Bank of Italy, Directorate General for Economics, Statistics and Research.

1 Introduction[1]

The outbreak of the Covid-19 pandemic in the early months of 2020 caused an unprecedented disruption to tourism flows. According to the World Tourism Organisation (UNWTO), in 2020 international arrivals worldwide dropped by 74% (one billion arrivals less than the previous year). Italy was among the first EU countries to be hit: between February and April 2020 positive cases rapidly rose from a few hundreds to over a hundred thousand, with a surge in the number of patients needing intensive care and in the number of deaths.[2]

Fear of contagion and containment measures (including travel bans) resulted in tourism flows dropping to near-zero levels since the end of the first quarter of 2020. During the subsequent quarter of 2020 conditions improved, allowing for the lifting of travel restrictions at EU level in the summer. Italy, among other southern European countries (Spain, Portugal, and Greece), benefited from the recovery of cross-border tourism, although flows remained at around a half of pre-pandemic levels. The second wave of the pandemic that hit Italy after the end of the summer halted again tourism flows since November 2020.

While the overall effect of the pandemic on international tourism was overwhelmingly negative, two main questions deserve closer investigation. The first is to what extent this outcome reflected not only regulatory restrictions and containment measures (travel bans, quarantines, etc.) but also fears of contagion that spontaneously led travellers to stay away from destinations with a locally higher epidemiological risk. Answering this question is highly relevant from a policy perspective: lifting restrictions while the epidemic is still not under control might not be sufficient to revamp tourism flows if travellers' behavior actively responds to the risk of contagion. The second related question is how travel preferences changed in reaction to the pandemic, looking at characteristics that may be indirectly related to contagion risk, such as transport means, type of accommodation and amenities in the destination.

This paper uses a unique combination of weekly mobile phone data and survey data for Italy to provide answers to the above questions, through an overarching analysis of international tourism flows during the pandemic. The high frequency of mobile phone data on the number of foreign visitors by nationality and province allows us to identify precisely the impact of changing patterns in the epidemics and of the adopted policy measures. We estimate reduced-form equations (consistent with a gravity framework) where the number

[1]The views expressed in this study are those of the authors and do not involve the responsibility of the Bank of Italy. While retaining full responsibility for all remaining errors and omissions, the authors wish to thank Silvia Fabiani, Stefano Federico, Fadi Hassan, Alfonso Rosolia, Simonetta Zappa and Alessandro Borin for useful comments on a previous version of this paper.

[2]See Borin et al. (2020).

of foreign travellers in a given location is related to the risk of contagion in the province of stay as well as in the source country, controlling for an extensive set of fixed effects. We also look at how structural characteristics of destinations shaped the dynamics of tourism flows in interaction with the contagion dynamics.

Italy provides an ideal setting for this analysis, being one of the main destination of international travellers worldwide: Italian tourism exports rank sixth in the world, according to UNWTO. The wide variety of destinations and travel purposes (business trip, art visits, beach or mountain holidays etc) as well as the diversified set of travellers' origin countries allows to analyze the interaction between local characteristics of destinations and Covid-19 dynamics both in Italy and abroad.

This paper contributes to the literature on how the outbreak of contagious diseases affects tourism flows. This strand of literature received a first push in the 2000s, after the outbreak of the SARS and the "aviary flu" in Asia (Chou et al., 2004; McKercher and Chon, 2004), followed by studies on MERS (Joo et al., 2019) and the H1N1 influenza (Rassy and Smith (2013); see Cevik (2020) for a comparative analysis of various diseases). As regards Covid-19, existing studies are largely descriptive (Uğur and Akbıyık (2020); Metaxas and Folinas (2020); MacDonald et al. (2020); see Sigala (2020) for a preliminary survey) or focus on a specific segment of the tourism industry, such as short-term rental (Hu and Lee, 2020; Guglielminetti et al., 2021). With this respect, our paper offers a rigorous econometric analysis of the effects of Covid-19 on international tourism in one of the most important destinations worldwide.

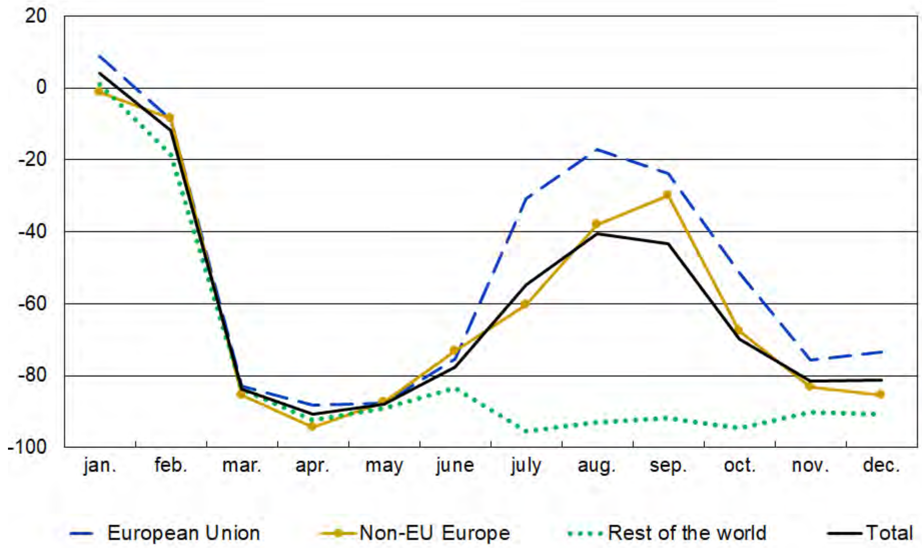
The paper is structured as follows: section 2 provides descriptive evidence on the changes occurred in incoming tourism flows after the pandemic along various dimensions, paving the way for the subsequent econometric analysis. Section 3 presents the database and the empirical model adopted to measure the impact of the pandemic on the incoming tourism flows and its interaction with variables at the province and the country of departure level. In section 4 we present and discuss estimation results, robustness evaluations, and economic interpretation of regression coefficients. Finally, section 5 draws concluding remarks.

2 Aggregate patterns of foreign tourism flows in Italy

This section of the paper presents the main aggregate patterns in foreign tourism to Italy in 2020, highlighting the heterogeneous impact of the pandemic. This evidence guides us in the selection of relevant variables for the empirical model presented in section 3.

The Covid-19 disease started to spread in Italy in the second half of February 2020. The lockdown was applied initially in selected Northern provinces and, since March 9, in the

Figure 1: Changes in the number of foreign arrivals by area of origin



Differences are in percentage term and refer to months in 2020 vis-à-vis the corresponding months in 2019.

entire country. It included a stay-at-home order, the shutdown of all non-essential economic activities and restrictions to both internal and international mobility. In this phase, the outbreak remained concentrated in Northern Italy. These restrictions were lifted during the month of May 2020. The strong containment measures proved to be effective in halting the spread of the disease, and Italy benefited of near-zero rate of new Covid-19 cases throughout the summer. In early June travel restrictions between EU member countries, Schengen Area countries and United Kingdom were lifted, and inbound tourism gradually resumed. New cases rate started picking up again at the end of August, and in the fall a second wave of contagion hit Italy throughout the country, with virtually no province spared from a rise in infections.

According to official statistics, in 2020 foreign visitors in Italy (i.e. including those who did not stay in Italy overnight) were 39 million overall, about 60% less than the previous year.[3] The drop in inbound tourism was sharp from all countries of origin, but particularly severe from farther countries (see table 1 and figure 1): the number of arrivals from Europe (both EU and non-EU) decreased by 56.2% with respect to 2019; those from the Americas and Asia fell by 87% and 81% respectively.

These patterns were likely affected by the travel bans adopted in many countries throughout the world (including Italy), but they may also reflect a preference by foreign tourists

[3] The information derives from the Bank of Italy Survey on International Tourism (BISIT, henceforth), which was established in the mid-'90s to gather data for the compilation of the "travel" item in the current account of the Italian balance of payments. More details on this survey are provided in section A.1 of the appendix.

for destinations closer to home that can be reached by private means of transport. Indeed, the drop of arrivals in regions closer to Italian borders (such as Veneto and Lombardy) was relatively smaller than in the other regions.

Table 1: Changes in the number of foreign travellers in Italy

Area of departure	% Change in arrivals (YoY)
European Union	-54.1
Non-EU Europe	-61.7
Americas	-86.7
Asia	-81.1
Rest of the World	-75.5

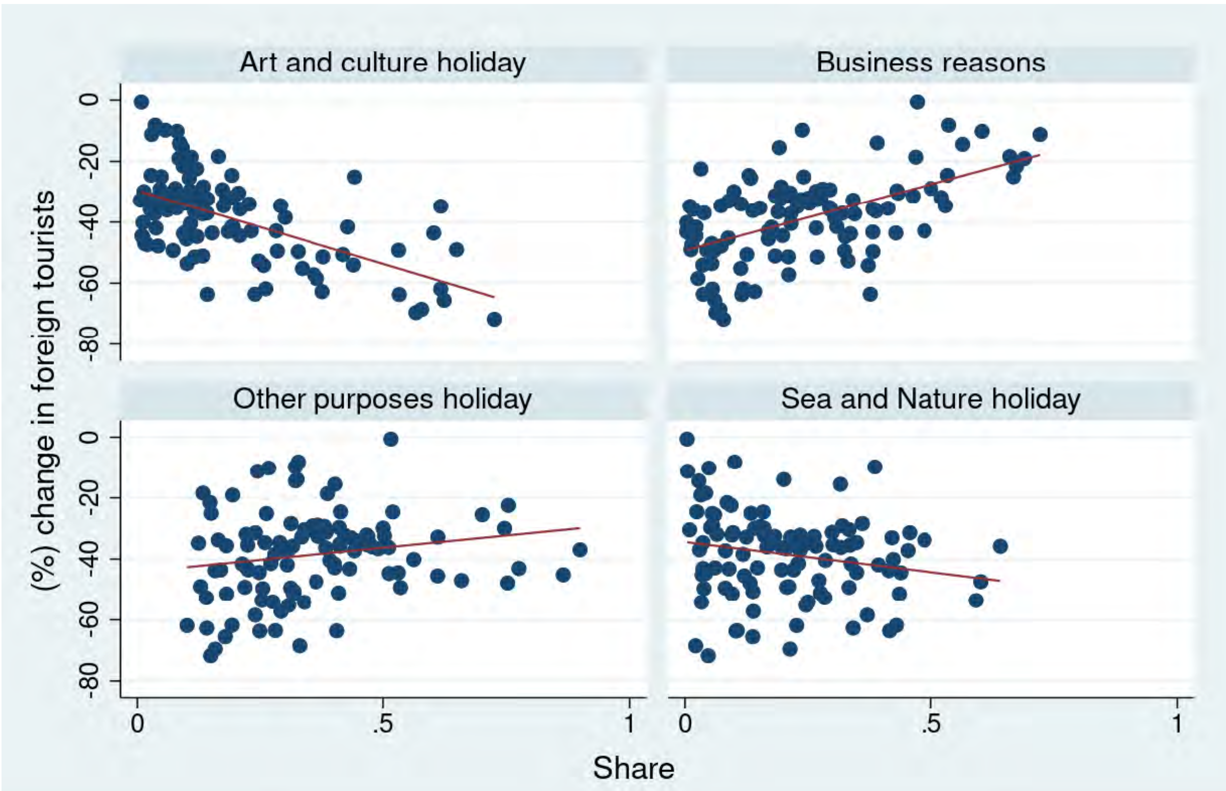
Source: BISIT data. Changes refer to 2020 with respect to 2019.

The pandemic also induced changes along the dimension of the travel's motive, as suggested by the correlation between the ex-ante shares of various travel purposes in each Italian province (which capture their "touristic specialisation") and the change in arrivals between 2019 and 2020 (figure 2).[4] Arrivals dropped systematically more in provinces specialised in cultural tourism purposes, while this correlation is weaker for "sea and nature" holidays. The correlation is instead positive in the case of business tourism, meaning that the provinces that used to have a relatively higher share of tourism related to business reasons suffered much less in terms of decline in foreign arrivals.

Finally, another relevant change was observed along a third dimension of interest: the type of accommodation chosen by visitors during their sojourn in Italy. As shown in table 2, comparing 2020 data with the pre-Covid three-year period (2017–2019), shares of "traditional" accommodations (hotel, B&B, tourist resort) decreased significantly (for over 14 percentage points), mainly to the advantage of independent non-shared accommodations (rented houses or own properties) or other less common accommodations (campers, tents, caravans, etc.). The share of visitors who stayed at home with relatives or friends during their sojourn also grew significantly.

[4]Thanks to the granularity of BISIT data, we could distinguish not only business from leisure tourism, but also holidays aiming at "open air" purposes, such as sojourning by the sea or at the mountains, from more "indoor" purposes, like visiting cities of art and historical landmarks. Further details on the questionnaire are reported in the appendix (section A.1).

Figure 2: Correlation between change in arrivals and travel purpose shares at province level



Each dot represents an Italian province. In all graphs, vertical axis reports the drop in arrivals between 2019 and 2020 in % terms, while horizontal axis reports the share of travellers that used to visit the province before 2020 for the specified travel purpose.

3 The heterogeneous impact of Covid-19 on tourism: data and empirical model

3.1 Data sources and variable definitions

We combine various sources of information about tourism, epidemiological patterns and policy measures in order to build a comprehensive and detailed dataset for our empirical exercise. The dataset covers the time span from January 2019 to February 2021.

Two main sources are used for tourism data, to quantify the number of foreign tourists and to gather information on tourism characteristics. The first source of data comes from a large Italian mobile phone operator. It provides the total number of foreign phone SIM cards detected on the Italian territory, by province and by issuer country. We use the former as information about the province of destination and the latter as a proxy for the country of origin of the traveller. Mobile phone data are available at daily frequency (we aggregate

Table 2: Accommodation choices pre and post Covid-19

Accommodation type	2017–2019	2020
Hotel, resort, and B&B	57.6	43.5
Hosted by friends or relatives	15.6	20.6
Rented house or own house	10.1	13.1
Other accommodations n.i.e.	16.7	22.9
Total	100	100

Source: BISIT data. All values are shares. Values for 2017–2019 are averages. "Other accommodations" includes also camping, caravans, and farmhouses.

them into weekly data). This high frequency enables us to identify precisely the impact of changing patterns in the epidemics and of the policy measures adopted. One limitation is that the number of foreign tourists derived from mobile phone data may be distorted by the presence of communities of foreign residents in Italy. To avoid this potential bias, in our analysis we considered the first forty countries, in terms of number of tourists in 2017-2019, excluding those that have large communities in Italy. The selected countries account for about 92 per cent of the total inbound tourism flows to Italy (over the period 2017-2019); half of them belong to the European Union.[5]

The second source of tourism data is the Bank of Italy Survey on International Tourism (BISIT). The survey questionnaire asks the interviewed traveller to provide information about the kind of transportation used to reach the destination, the purpose of the trip, and the type of accommodation used during the trip (if any). We use data for the period 2017–2019 to construct indicators before the pandemic outbreak: for each province and origin, we quantify the shares of travellers by travel purpose, accommodation type and means of transport.

The epidemiological data regarding the spread of the contagion in Italy are sourced from the Italian Civil Protection Department.[6] At province level, the only available information is the cumulative number of positive Covid-19 cases, at a daily frequency. From this, we compute the number of *new* cases of Covid-19 (gross of recovered patients) over a period of 14 days, per 1000 inhabitants. The resident population in the province at the end of 2019 is retrieved from ISTAT, the Italian national statistical institute.

The corresponding information on the evolution of Covid-19 in the foreign countries of origin was obtained from the European Center for Disease Prevention and Control (ECDC),

[5]Section A.1 of the appendix provide further details on this data source along with the full list of included countries and additional statistics related to their weight in terms of total inbound tourism to Italy.

[6]*Dipartimento di Protezione Civile* is the national body in Italy that deals with the prediction, prevention and management of emergency events. Data on Covid-19 can be retrieved at https://github.com/pcm-dpc/Covid-19.

which provides harmonised and comparable data on the rate of contagion in all European countries and in all other non-European countries considered in our analysis.

As for the containment measures adopted by foreign countries, we used the Oxford Stringency Index (Hale et al., 2021), which reflects restrictions to different aspects of economic and social life, such as mandatory closure of schools and offices to remote functioning, shops and restaurants closures, restrictions on public transportation, and international travel bans. To control for the different intensity of the restrictions by Italian regions enforced since November 2020 we relied on the index developed for Italy by Conteduca (2021).[7]

We also constructed a set of dummies related to the intensity of bilateral travel restrictions enforced by the Italian Government. This information was collected from the legislation acts adopted throughout the period, also relying on the website "reopen.europa.eu", and on the website of Italy's Foreign affairs Ministry "www.viaggiaresicuri.it".

Finally, variables on bilateral distance were retrieved from the CEPII data warehouse (see Mayer and Zignago, 2011).

3.2 The empirical strategy

Our empirical exercise aims at explaining the heterogeneous impact of Covid-19 on international tourism to Italy disentangling the contribution of various factors at the province and the country of origin level. In practice, the empirical strategy relies on two mirror-like reduced-form models for inbound tourism to Italy that are in line with a gravity framework. We estimate those models using the Poisson pseudo maximum likelihood estimator on weekly data from January 2019 to February 2021.[8]

Our first model estimates the effect of the contagion at the province level and of destination's characteristics (as revealed by past travellers' choices on foreign tourism), while controlling for time-varying characteristics of countries of origin with fixed effects (equation 1).

$$\begin{aligned} \text{Tourists}_{opt} = exp\Big(&\alpha_{ot} + \alpha_{opw} + \beta_0 \text{cases}_{\text{pt}-1} + d_{\text{Covid19}} * \big(\boldsymbol{\beta}_1' \text{Purpose}_{\text{op}} + \\ &+ \boldsymbol{\beta}_2' \text{Accommodation}_{op} + \boldsymbol{\beta}_3' \text{Transport}_{op}\big)\Big) + \epsilon_{opt} \end{aligned} \tag{1}$$

The dependent variable, Tourists_{opt}, is the total number of days spent by tourists from

[7]We thank Paolo Conteduca for kindly sharing the data with us.

[8]Morley et al. (2014) show that a gravity equation for tourism can be derived from individual utility theory, after modeling the destination choice problem faced by the tourist. Usage of gravity models for empirical applications in tourism literature is standard; see for instance Cevik (2020).

country o in province p at time t, where temporal unit t denotes a combination of year-week.

The identification strategy exploits the granularity of the dataset to include an extensive set of fixed effects. Country-Province-Week factors (α_{opw}) control for the preference of travellers from a specific country for a specific province p in a week w.[9] Such preferences may be motivated by the availability of convenient flight connections, by business links, and of course by the characteristics of the touristic offer of the destination compared to the domestic market (for example, German tourists may favour beach destinations in Italy in summer weeks relatively more than French, because France offers attractive seaside destinations available for domestic tourism). The inclusion of fixed effects α_{opw} makes our approach conceptually akin to "difference-in-difference".

We also include time-varying factors related to country of departure α_{ot}, which control for all developments occurred in t in the country of departure, in Italy, or in third countries, that could affect the number of arrivals (for instance in terms of the epidemic or in containment measures).[10]

Our main explanatory variable in equation 1 is $\text{cases}_{\textit{pt-1}}$, which is the number of new Covid-19 cases on 1,000 inhabitants recorded in the province during the previous two weeks, a commonly used metric to measure epidemic developments. This variable allows us to verify whether tourists were concerned about the level of contagion risk not only at country level (which is captured by our fixed effects), but also at the local level. Indeed, information on local developments of Covid-19 epidemic are widely and easily available on the web. Therefore such information may be consulted by travellers before travelling to a given country, in order to avoid destinations where the epidemic is spreading faster.

To elicit the effect of the pandemic outbreak on tourists' choices, we interact the variables Purpose_{op}, $\text{Accommodation}_{op}$, and Transport_{op} with a dichotomic variable that marks the Covid-19 period, and takes value one from last week of February 2020 onward. These variables are vectors of shares extracted from BISIT data for the years 2017-2019, as explained in section 3.1. Purpose_{op} reports the shares of various purposes of the trips, as declared by foreign travellers from country o when they visited province p before the pandemic: "art and culture holiday", "sea holiday", "nature holiday", "other purposes trip", and "business reasons" (the latter being the base category). In the same fashion, Purpose_{op} reports the shares of various accommodation choices made by travellers: "hotels and hostels", "camping,

[9] Notice that subscript w refers to the ordering of the week in a generic year in our sample, while the t subscript indicates a specific week in a specific year and thus uniquely identifies our observational unit (a pair country-province).

[10] Since we only have data on inbound tourism to Italy, we cannot identify the response of international tourism to developments in Italy separately from developments in Italy's competitors. Doing so would require a cross-country comparison, i.e. tourism flows toward Italy *and* other foreign destinations.

farmhouses, and caravans", "day-trip" (which is associated with no accommodation at all) and the base category "own house, or hosted by relatives/friends, or at a rented house/flat". Finally, Transport_{op} indicates the shares of transports typologies chosen by travellers from country o to reach their destination p before the pandemic. We classified them into two categories: (i) collective and/or mass transports (airplanes, ships, and trains) and (ii) individual/private transports (cars, caravans, bikes, and motorcycles), our base category.

We estimate the model by Pseudo Poisson Maximum Likelihood regression - PPML, in line with the literature on gravity models of trade (Santos Silva and Tenreyro, 2006).[11] PPML allows the inclusion of null observations, namely bilateral country-province corridors where tourists from country o that stayed in province p in week w in 2019 did not visit the same province in 2020. In our case, these are potentially meaningful observations as they refer to flows that were hit the hardest by the pandemic. Moreover, PPML is a consistent estimator in presence of heteroskedasticity (even if the dependent variable does not follow a Poisson distribution), and lends itself well to model count variables, as our dependent variable. In our inference, we assume double-clustering by country of departure–time and by province–time.

In a second step, we drop the Country-Time fixed effects α_{ot} from the model and introduce variables related to the evolution of the epidemic, the containment measures, the bilateral entry restrictions imposed by Italy, and distance, to explain the cross-country variation in international tourism inflows (equation 2):

$$\begin{aligned} \text{Tourists}_{opt} = exp\Big(&\alpha_{pt} + \alpha_{opw} + d_{\text{Covid19}} * \big(\boldsymbol{\beta_1'}\text{Purpose}_{\text{op}} + \boldsymbol{\beta_2'}\text{Accommodation}_{op} \\ &+ \boldsymbol{\beta_3'}\text{Transport}_{op}\big) + \gamma_1 \text{cases}_{\text{ot}-1} + \boldsymbol{\gamma_2'}\text{Entry restrictions}_{\text{ot}} + \boldsymbol{\gamma_3'}\text{Stringency}_{ot} + \\ &+ d_{\text{Covid19}} * \boldsymbol{\gamma_4'}\text{distance vars}_{\text{op}}\Big) + u_{opt} \end{aligned} \tag{2}$$

We now include fixed effects α_{pt} to control for any factor at play at time t in province p (including Covid-19) that can have an impact on inbound tourism in that province from any destination. This specification is thus designed to estimate the effects of variables indexed by ot (country-of-origin and time), exploiting variation across countries at time t, while controlling for time-varying province specific pt factors.

We consider the following additional explanatory variables: $\text{cases}_{\text{ot}-1}$ is the number of new Covid-19 cases over 1000 inhabitants over a period of 14 days ending in week *t-1* in the country of departure o (see section 3.1). Entry $\text{restrictions}_{\text{ot}}$ is a set of dummies indicating the bilateral travel restrictions (if any) imposed by Italy vis-à-vis other countries.

[11] In practice, we rely on the Stata routine developed by Correia et al. (2019).

We distinguished between (i) the travel restrictions that allow entry from a country only for urgent and/or essential reasons, like health motives or repatriations (Necessity only$_{ot,IT}$), (ii) restrictions that allow entry only for work reasons and/or upon a quarantine period (Quarantine$_{\mathrm{ot,IT}}$), (iii) restrictions that allow entry upon a negative result of swab test (either at arrival or before departure) ($Swab_{ot,IT}$). Stringency$_{ot}$ is the Oxford Stringency index (which takes values in the 0–100 interval, depending on the intensity of containment measures adopted by the country o at time t).[12]

We further interact the indicator variable for the Covid-19 period with two variables measuring distance, to check whether foreign tourists from closer countries reduced their presence in Italy relatively less than tourists from more distant countries, in addition to what is already captured by the variable Transport$_{op}$, which varies by province of destination p and country of departure o. These two variables are the logarithm of bilateral population-weighted distance between Italy and country o, and an indicator variable which is equal to one if the country has a common border with Italy.[13]

4 Results and discussion

4.1 Analysis by local destination

Table 3 shows the results from the estimation of model in equation 1. Column (1) includes only the local contagion variable and the full set of fixed effects: the coefficient of the new cases variable is negative and statistically significant. Given our specification of fixed effects, this implies that if a province records 100 new positive cases per 100,000 inhabitants *more* than other provinces over two weeks, it experiences on average a reduction in the number of foreign tourists about 6 percentage points larger than other provinces during the subsequent week, *ceteris paribus*. The contagion variable remains highly significant, with a slightly more negative coefficient (column 2), when we include controls for the interaction between province–country structural characteristics and a dichotomous variable signalling the start

[12] We also consider separately two indicators related to internal mobility restrictions in the country of departure, which we derived from some categorical variables that constitute the Stringency index. These are: $d_{\mathrm{stayathome}}$, which is equal to one if citizen are given a general stay-at-home order and can move only for work related reasons and/or other essential activities (e.g. grocery shopping), and $d_{\mathrm{noreg.movement}}$ which is equal to one if mobility across regions in the country of departure is restricted. We include these variables on the hypothesis that tourists are more likely to choose travelling abroad (i.e. to Italy) if they face more stringent limitations at home.

[13] The population-weighted distance measures the geographical distance between the largest cities of Italy and country o, where inter-city distances are weighted by the city's population share over country's population. See Mayer and Zignago (2011) for further methodological details.

of the pandemic.[14] The remaining columns of table 3 report the results for the different phases of the epidemic in Italy. We consider three main periods: the first phase goes from 25 February to 2 June 2020 and covers the lockdown period (column 3). The second phase covers the summer period until September 15, when inbound tourism gradually resumed and the rate of new Covid-19 cases was almost negligible (column 4). The third phase covers the second wave of contagion, between mid-September 2020 and February 2021 (column 5). The results show that the negative relation between the number of foreign visitors and new Covid-19 cases is concentrated in the third phase: the second wave of contagion arguably provides in our view a better context to study the impact of new cases on inbound tourism, given the looser travel restrictions than the first wave, combined with the greater awareness from foreign visitors of the contagion risk and more information available to tourists about the local evolution of the epidemic.[15] As regards the summer period (column 4), given the extremely low number of new cases in most provinces at the time, we could not include the *cases* variable for contagion, as it delivered non-significant and/or non-robust results.

Since early November, new restrictive measures differentiated on the basis of an assessment of epidemiological risk at regional level were introduced. After this innovation, epidemiological risk *per se* may not be anymore the key explanatory factor for the decrease in inbound tourism, as internal mobility restrictions too may contribute to it, reducing the attractiveness of a province. We thus include in column 6 a one-week lag of the regional restriction index (RR-Index) constructed by Conteduca (2021).[16] As expected, we find the coefficient of the RR-Index to be negative and statistically significant, meaning that tourists avoided provinces where more stringent restrictions were in place. Nevertheless, the coefficient of our contagion variable remains significant and almost unaffected in size, meaning that even after controlling for internal mobility restrictions, foreign tourists decreased more in provinces where contagion risk was higher.

As a further robustness check, we replace the restriction index with Region–Time fixed effects (column 7). This structure of fixed effects is able to control for the new system of region-based restrictions while also capturing the correlation of the epidemic within provinces of the same region. Yet, the contagion variable remains negative and significant, and only marginally lower, further corroborating the robustness of our results about the adverse effect

[14]We run a number of robustness checks on our contagion variable, finding its magnitude and statistical significance always confirmed (see table A.2 in the appendix)

[15]For instance, Wikipedia has included a clickable map of Italy displaying the number of cases by province since the end of July 2020 at the entry "Covid-19 pandemic in Italy".

[16]We lag this variable to ensure that the level of regional restrictions was in the information set of the tourist *before* departure. However, the coefficient on our contagion remains unchanged if we use the current values.

of contagion on foreign arrivals.[17] Overall, this result suggests that tourists paid attention not only to national dynamics of the epidemic (which is captured by our Country–Time fixed effects α_{ot}), but also to *local* developments of the epidemic, with noteworthy policy implications: even at local level, there is a trade-off implied by loosening restrictions: on one hand it may attract more tourists in the short term; on the other hand, if more arrivals are associated with an increase in the number of cases, it may discourage inbound tourism later in time.

Results on the interaction between province–country structural characteristics and the Covid-19 period are also interesting. The coefficients of these variables can be interpreted as the average differential impact of the outbreak of the pandemic across our observational units (country-province-week). Column (2) shows that provinces that were more "specialised" in art and culture tourism were hit the hardest: a coefficient of -1.1 for art tourism means that an increase in 10% in the proportion of tourists that used to visit the province for that purpose is associated to a 7% larger drop in inbound tourism. The drop would be only about 4% for provinces visited for beach or nature holidays, with tourism for personal reasons purposes (like vacation) hit generally harder than business tourism (our base level). A possible driving factor underlying this result is related to the fact that trips motivated by work reasons were generally exempted by travel restrictions, hence visitors travelling for work reasons could come to Italy even when tourists visiting for holiday reasons could not (for instance, this was the case during the first lockdown for visitors arriving from countries outside Europe). This may have favoured provinces receiving historically higher shares of business travellers, even in a period when conferences and big events were moved on virtual platforms or cancelled.

Results also show that provinces in which tourists used to stay in "hotel-like" accommodations were hit harder than provinces characterised by a larger share of private housing and/or rental houses (our base level). The latter type of accommodation may indeed be perceived as relatively safer by tourists, as it implies less social interactions with other people. Provinces with a higher share of tourists staying in "green" accommodations, like camping and farmhouses, also appear to have been more resilient on average.

Finally, the third feature of interest accounted for by this class of variables is the means of transport; in line with our expectations, provinces that used to have a larger share of visitors arriving by plane (or other shared means of transports, like train or ship) were hit harder, reflecting the perception of a higher risk of infection compared to private non-mass transport means, like cars or caravans. Using an extreme case as an illustrative example,

[17] As a further robustness check, we limited our sample to the weeks before the introduction of the zone-system, obtaining an even larger negative coefficient. Results are available upon request

the number of visitors in a province from a country in which all tourists come by collective means of transport recorded a 30% larger drop than a province in which tourists from the same country arrive by car.

The behaviour of these variables in the various sub-samples is overall consistent to what described for the whole sample. In the summer, interestingly, the relative loss by hotel-intensive provinces appears to be only a half than what estimated for the overall period, suggesting that during this period tourists may have been less concerned with contagion risk, consistently with the near-zero cases in most provinces.

In table A.2 we report our robustness tests of the result on the variable measuring contagion at the province level using different metrics and specifications, finding robust and statistically significant coefficients with a comparable size. First, we consider a longer temporal lag (4 weeks, rather than 1 week) to compute the number of new cases, to account for the fact that tourists may make their travel plans sufficiently in advance. We obtain a coefficient almost identical (column 2).[18] We further check against the effects of few big outliers by winsorising the variable $cases_{p,t-1}$ at the 1$^{\text{st}}$ and 99$^{\text{th}}$ percentiles. Doing so delivers an even higher coefficient (column 3). In column 4 we include a quadratic term , which we find to be significant, suggesting a non linearity in the impact of this variable on arrivals: in other words, tourists seem to refrain more from travelling to Italy when the notification rate of new positive cases at destination gets very high. We then include the *cumulative* number of positive cases at the province level (column 5).This metric takes into account the hypothesis that tourists may be sensitive to the past dynamics of positive cases in the destination province, rather than only to the current situation (although the two variables are to some extent correlated). We find that the notification rate of new positive cases remains highly significant and of similar magnitude. As an additional robustness check, we estimate the baseline model 1 in log-linear formulation by OLS (column 6). The coefficient on our contagion variable again remains negative and statistically significant, and only marginally lower. Finally, we consider two sub-samples: first, we limit the analysis to the first 40 provinces in terms of inbound tourism in previous years (column 7), obtaining similar results. Second we exclude the first two months of 2021 from our sample, to rule out the possibility that our results are distorted by a change occurred in the way new positive cases were recorded before and after 15 January 2021 (before the date, new positive cases were counted based only on the results of PCR molecular tests, while after that date, positive cases detected through rapid antigenic tests were included in the counter for the number of cases). Our results remains substantially unchanged.[19]

[18] Robustness checks with different lags produce similar results, also given the inertia in the spread of the contagion.

[19] A PCR (Polymerase Chain Reaction) molecular test for Covid-19 is a test used to diagnosis people who

Finally tables A.3 shows the estimates of our model in equation 1 in which the analysis only includes EU countries, Schengen members and the United Kingdom. Travellers from these countries were allowed to enter Italy for tourism after June 3rd without quarantine requirements (unlike other countries), and they accounted for most of inbound tourism to Italy in our sample period. We obtain almost identical results.

are currently infected with SARS-CoV-2 and it is considered the most reliable test for diagnosing Covid-19.

Table 3: **Analysis by province: all countries**

dep. var: $Tourists_{opt}$	All sample		1^{st} wave	Summer	2^{nd} wave		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$cases_{pt-1}$	-0.0550***	-0.0694***	0.0370		-0.0664***	-0.0606***	-0.0396***
	(0.00914)	(0.00881)	(0.0225)		(0.00754)	(0.00688)	(0.00349)
d_{Cov19} X purpose$_{\text{op}}$:							
nature and beach		-0.515***	-1.144***	-0.435***	-0.414***	-0.412***	-0.492***
		(0.0342)	(0.120)	(0.0445)	(0.0460)	(0.0452)	(0.0415)
art and culture		-1.091***	-1.540***	-0.945***	-1.079***	-1.090***	-1.127***
		(0.0358)	(0.105)	(0.0500)	(0.0515)	(0.0515)	(0.0422)
other pers. reasons		-0.368***	-0.214***	-0.305***	-0.443***	-0.444***	-0.310***
		(0.0253)	(0.0667)	(0.0362)	(0.0339)	(0.0339)	(0.0257)
d_{Cov19} X accomm.$_{op}$:							
hotels/hostels		-0.668***	-0.985***	-0.401***	-0.967***	-0.973***	-0.499***
		(0.0294)	(0.0781)	(0.0385)	(0.0368)	(0.0365)	(0.0237)
camping/farmhouse		-0.225***	-0.732***	-0.488***	0.406***	0.400***	0.224***
		(0.0484)	(0.135)	(0.0522)	(0.0688)	(0.0680)	(0.0476)
others		-0.499***	-0.631***	-0.288***	-0.713***	-0.721***	-0.491***
d_{Cov19} X airplane$_{op}$		-0.359***	-0.434***	-0.401***	-0.263***	-0.263***	-0.513***
		(0.0263)	(0.0684)	(0.0380)	(0.0362)	(0.0363)	(0.0224)
RR index						-0.00955***	
						(0.00345)	
FE country#prov#week	Yes	Yes	Yes	Yes	Yes	Yes	Yes
FE country#time	Yes	Yes	Yes	Yes	Yes	Yes	Yes
FE reg.#time	No	No	No	No	No	No	Yes
Pseudo R^2	0.99	0.99	0.99	0.99	0.98	0.98	0.99
Observations	340496	311082	75956	84300	127660	127660	127660

The table presents results of the model 1 estimated on the period January 2019 – February 20201, for different specifications of the variable measuring contagion at local level. Standard errors, in parenthesis, are clustered by province–time and country of departure–time. Stars(***, **, and *) indicate statistical significance at 1, 5, and 10 per cent, respectively. Fixed effects by country of departure - province - week (α_{opw}) and country of departure - time (α_{ot}) are always included.

4.2 Analysis by country of departure

In this section we shift our focus to the variation of incoming tourism flows by country of departure of the tourists. In order to do so, as explained in section 3.2, we drop our Country–Time fixed effects and we augment our model with the variables described in 3 (equation 2). We estimate the model over two sets of countries: the entire sample of 40 countries (table 4) and the sub-sample of "passport free" countries of origin (EU and Schengen Area member countries, and United Kingdom, whose citizens were allowed to enter Italy for touristic reasons from 3 June onward, almost always without quarantine requirements). This sub-sample includes those countries which accounted for most of the inbound tourism in our period of analysis and faced very similar restrictions, which makes them more comparable.[20]

Column 1 in table 4 indicates that, unsurprisingly, the most important variables in explaining cross-country variation in foreign tourists' presence are related to the intensity of the bilateral travel restrictions imposed by Italy. The coefficient of the dummy variable $\text{Quarantine}_{ot,IT}$ (which takes value 1 if there is either a compulsory quarantine period in place for tourists coming from that country, or if entry for leisure tourism is forbidden), implies a reduction in tourist presence by about 60 percent *larger* than what recorded by countries not subject to this requirement. The relative drop in international tourism is even more dramatic when entry was allowed only for urgent/essential reasons. On the contrary, screening measures at entry (e.g. swab tests) cause substantially milder reduction in entry flows: the coefficient of the dummy for swab test requirement indicates a 20 percent decrease in tourism flows). The coefficient of the swab test requirement is even not statistically different from zero when we limit the analysis to EU and Schengen countries (and United Kingdom) (table 5), suggesting that this type of screening could contrast the international spread of contagion without significantly hampering inbound tourism flows.

A second result is related to the impact of distance. Our model includes the interaction between a dummy for the Covid-19 period and the share of visitors that used to arrive at the local destination by plane, which displayed a negative and statistically significant coefficient, pointing to a renewed importance of distance during the pandemic. Here we further include a variable measuring bilateral distance between Italy and the country of departure and a dummy for a border in common. We find that distance also had an additional negative effect on the number of foreign travellers when we consider European countries, in particular during the summer months.

While we had clear priors about the coefficients of the above-mentioned variables, we had ambiguous expectations about the effect of contagion and stringency measures in the

[20]Indeed, we can only include the swab test variable, as the dummies on the other travel restrictions would not be identified.

Table 4: **Analysis by country of departure: All countries**

	All (1)	All (2)	1^{st} wave (3)	Summer (4)	2^{nd} wave (5)
$Cases_{ot-1}$	0.0139	0.00798	0.365***	0.354***	0.00539
	(0.00935)	(0.00893)	(0.0790)	(0.0453)	(0.00840)
d_{Cov19} X $\ln(\text{dist})_o$	-0.00779	-0.0131	0.284***	-0.536***	-0.100**
	(0.0451)	(0.0430)	(0.0451)	(0.0785)	(0.0494)
d_{Cov19} X $d_{\text{border}o}$	0.0313	0.0288	-0.221***	0.0165	0.0888*
	(0.0291)	(0.0302)	(0.0703)	(0.0392)	(0.0462)
$\text{Quarantine}_{ot,IT}$	-0.856***	-0.842***	-0.707***	-0.900***	-0.429***
	(0.0862)	(0.0876)	(0.238)	(0.155)	(0.0905)
$\text{Necessityonly}_{ot,IT}$	-1.006***	-1.068***		-1.800***	-0.607***
	(0.204)	(0.210)		(0.193)	(0.207)
$\text{Swab}_{ot,IT}$	-0.270***	-0.307***		-0.825***	-0.151***
	(0.0477)	(0.0463)		(0.0876)	(0.0505)
$Stringency_{ot}$	0.00873***	0.00401***	0.00986***	0.0170***	-0.00232
	(0.00123)	(0.00156)	(0.00322)	(0.00274)	(0.00221)
$d_{stayathome}$		0.203***	-0.0113	-0.124*	0.338***
		(0.0404)	(0.0917)	(0.0705)	(0.0557)
$d_{noreg.movement}$		0.141***	0.143*	0.196***	0.123***
		(0.0344)	(0.0797)	(0.0496)	(0.0425)
Travel restr in o (1)		-0.253***			
		(0.0454)			
Travel restr in o (2)		-0.183***			
		(0.0686)			
Travel restr in o (3)		-0.264***			
		(0.0621)			
Travel restr in o (4)		-0.655***			
		(0.0808)			
X_{op} (controls)	...	...	...	...	...
FE country#prov#week	Yes	Yes	Yes	Yes	Yes
FE prov#time	Yes	Yes	Yes	Yes	Yes
Pseudo R^2	0.98	0.98	0.98	0.99	0.98
Observations	309852	309852	75500	84044	127824

The table presents estimates of the model 2 estimated over different periods for the first 40 countries in terms of tourism receipts to Italy. The 1^{st} wave period (column 1) includes the weeks from 25 February to 2 June 2020). The Summer period (column 2) goes from 3 June to 15 September 2020. The 2^{nd} wave, columns (5), goes from 16 September 2020 onward. Variable $Cases_{ot-1}$ was winsorised at the 1-99% percent level to mitigate possible measurement errors and outliers (there are cases in the original dataset where the number of new cases is negative). The model includes the variables X_{op} (coefficients not shown), namely $d_{\text{Covid19}} * \left(\boldsymbol{\beta}_1'\text{Purpose}_{\text{op}} + \boldsymbol{\beta}_2'\text{Accommodation}_{op} + \boldsymbol{\beta}_3'\text{Transport}_{op}\right)$. Standard errors, in parenthesis, are clustered by province–time and country of departure–time. ***, **, and * indicate statistical significance at 1, 5, and 10 per cent, respectively. Fixed effects by country of departure - province - week (α_{opw}) and province - time (α_{ot}) are always included.

Table 5: **Analysis by country of departure: EU, Schengen members, and UK**

	All (1)	All (2)	1^{st} wave (3)	Summer (4)	2^{nd} wave (5)
$Cases_{ot-1}$	-0.00630	-0.0362***	0.144	0.284***	-0.0389***
	(0.00849)	(0.0125)	(0.0883)	(0.0498)	(0.0114)
d_{Cov19} X $\ln(\text{dist})_o$	-0.222***	-0.345***	0.650***	-0.876***	-0.106
	(0.0529)	(0.0574)	(0.117)	(0.0872)	(0.0792)
d_{Cov19} X $d_{\text{border}o}$	0.00645	0.00768	-0.149*	-0.0564	0.0952**
	(0.0292)	(0.0312)	(0.0768)	(0.0388)	(0.0461)
$\text{Swab}_{ot,IT}$	-0.0366	-0.0274		-0.755***	0.169***
	(0.0376)	(0.0471)		(0.0762)	(0.0461)
$Stringency_{ot}$	0.0113***	0.0153***	0.0148***	0.0213***	0.00726***
	(0.00139)	(0.00184)	(0.00380)	(0.00278)	(0.00274)
$d_{stayathome}$		0.106**	-0.0391	-0.111*	0.194***
		(0.0413)	(0.0935)	(0.0607)	(0.0619)
$d_{noreg.movement}$		0.0516	0.173**	0.149***	-0.0448
		(0.0344)	(0.0800)	(0.0477)	(0.0466)
Travel restr in o (1)		-0.309***			
		(0.0555)			
Travel restr in o (2)		-0.716***			
		(0.0690)			
Travel restr in o (3)		-0.805***			
		(0.0662)			
Travel restr in o (4)		-0.608***			
		(0.0945)			
X_{op} (controls)	...	...	...	...	...
FE country#prov#week	Yes	Yes	Yes	Yes	Yes
FE prov#time	Yes	Yes	Yes	Yes	Yes
Pseudo R^2	0.98	0.99	0.99	0.99	0.99
Observations	218665	202046	53422	57580	61358

The table presents estimates of the model 2 estimated over different periods for EU countries, Schengen countries plus United Kingdom. These were the only countries for which after the first wave visits for holiday tourism were allowed without the need to quarantine and accounted for about two-thirds of total tourism receipts in 2020. The 1^{st} wave period (column 1) includes the weeks from 25 February to 2 June 2020). The Summer period (column 2) goes from 3 June to 15 September 2020. The 2^{nd} wave, columns (5), goes from 16 September 2020 onward. Variable $Cases_{ot-1}$ was winsorised at the 1-99% percent level to mitigate possible measurement errors (there are cases in the original database where the number of new cases is negative). The model includes the variables X_{op} (coefficients not shown), namely $d_{\text{Covid19}} * \left(\boldsymbol{\beta}_1'\text{Purpose}_{\text{op}} + \boldsymbol{\beta}_2'\text{Accommodation}_{op} + \boldsymbol{\beta}_3'\text{Transport}_{op}\right)$.. Standard errors, in parenthesis, are clustered by province–time and country of departure–time. ***, **, and * indicate statistical significance at 1, 5, and 10 per cent, respectively. Fixed effects by country of departure - province - week (α_{opw}) and province - time (α_{ot}) are always included.

country of the departure. On one hand, an increase of Covid-19 cases in the home country of the tourists may induce them to raise caution and curb their plans to travel abroad, given the uncertainty on the health situation at home. By the same token, a tightening in containment measures in the home country may produce similar effect, also in consideration that future stronger containment policies may hinder the travel on the way back home or make it more costly (e.g. because of reduced number of flights). On the other hand, a surge of positive cases at home may push the tourist to travel abroad (if the destination is perceived as "safer") in order to minimise contagion risk during holidays and/or avoiding domestic restrictions (substitution effect).

As regards the new Covid-19 cases variable, our results are inconclusive: the coefficient is not significantly different from zero in whole sample (column 1 and 2) in table 4), while it turns out to be negative in one specification on the sub-sample of European countries (table 5, column 2). Moreover, the coefficient is positive during the summer months while negative afterward.[21]

The coefficient of the stringency index is instead more stable, as we find consistent positive estimates over the whole sample (column 1 in tables 4 and table 5). The sign of the stringency index coefficient remains positive even if we separately introduce dummies that control for mobility restrictions at home.

A possible relevant source of cross-country variation that we are not controlling for in column (1) stems from travel restrictions to *outbound* tourism in the countries of origin. Unfortunately, we do not have information on these restrictions. As a proxy remedy to this concern, we include a categorical variable from the Oxford database (Hale et al., 2021) that measures the strictness of travel restrictions to *inbound* tourism in the tourist's home, as we assume that the restrictions to outbound tourism are generally symmetric with restrictions on inbound tourism, as suggested by anecdotal evidence observed for the Italian case. Our assumption seems validated, as we find that the introduction of these measures is negatively associated with a reduction in the number of arrivals, but their inclusion does not alter our results.

4.3 Variance decomposition

As discussed in section 3.2, our empirical approach relies on fixed effects to achieve a clean identification of the variation explained by our set of independent variables. On this respect, this section shows a comparison exercise on the amount of variance our models are able to capture with a view of assessing the relative importance of variables by country of origin and

[21] As an alternative approach, we considered the difference in the number of cases between Italy and the country of departure, distinguishing between positive and negative values. Results remain mixed.

by province.[22] We do this exercise by incrementally adding variables and fixed effects to a model and looking at the square of the correlation between our dependent variable and its fitted values. This is conceptually equivalent to looking at the R^2 in case of a linear model. Results are reported in Table 6.

As a first comparison term, we compute this statistic for a model in which we only include the fixed effects α_{opw} (column 1). These fixed effects, as discussed in section 3.2, control for all factors that render a province more attractive for tourists from a specific country, as well as for possible seasonal patterns in these relationships. This simple model alone is able to explain about 84% of the total variation of the data, leaving 16% residual variance, exhaustively capturing the gravity structure in our tourism data.[23] We then add to the model the time fixed effects α_t (column 2). They capture the effect of time-varying shocks that affect all Italian destinations and flows from all countries of origin in the same way. As expected, this model explains a large share of the residual variance (about 70%), clearly reflecting the nature of the Covid-19 as a common shock that hit international tourism flows. The residual 30% is the variation during the pandemic that was country or destination specific and which is the focus of this paper. In column (3) we thus report the same statistic as we add to the model all our explanatory variables. Overall, augmenting the model with our variables lead to a significant improvement in terms of explained variance (by about 12%).

Table 6: **A variance decomposition**

	(1)	(2)	(3)	(4)	(5)
Explained variance (%)	83.8	95.4	97.3	99	98.7
Residual variance explained (%)	-	71.7	83.4	94	92.1
FE orig#prov#week	Yes	Yes	Yes	Yes	Yes
FE time	No	Yes	Yes	No	No
X_{pt}	No	No	Yes	Yes	No
X_{ot}	No	No	Yes	No	Yes
$d_{covid19}\#X_{op}$	No	No	Yes	Yes	Yes
FE orig # time	No	No	No	Yes	No
FE prov # time	No	No	No	No	Yes

The table shows the variance explained by several models with different sets of fixed effects and variables. The explained variance is the square of the correlation between fitted values and observed values. The residual variance is computed as the share of variance in addition to model (1), taken as a reference term. X_{pt} and $d_{covid19}\#X_{op}$ are the variables included in equation 1; X_{ot} are the variables added in equation 2.

[22] Notice however that since we have data on one country only, we are not able to disentangle push and pull factors operating at the country level.

[23] In fact, there would be no degrees of freedom if our sample was restricted to 2019.

We then look at the explanatory power of our variables along a specific dimension (province versus country origin), controlling for the other with fixed effects. In particular, we first includes country-of-origin fixed effects, leaving the province-time variation explained by our variables (column 4). This model explain 94% of residual variance. Adding province–time fixed effect to the model in column 3 leads to a similar accounting, as it raises the explained variance to 92% (column 5). To sum up, this evidence suggests that province characteristics and country factors played a comparable role in explaining heterogeneous patterns at the country-province level during the pandemic.

5 Concluding remarks

In this paper we analysed inbound tourism to Italy during the Covid-19 pandemic, looking at variation across Italian provinces of destination as well as countries of origin. To this end, we relied on unique mobile phone data on the weekly number of foreign visitors in Italy, broken down by Italian province of stay and by visitors' nationality.

Our main result is that there is a negative and statistically significant relation between the flow of foreign travellers in a given province and the local epidemiological situation, even controlling for restrictive measures at the national and regional level. In other words, tourists seem to pay attention not only to the risk of contagion at the national level but also to that in the local destination. The policy implication is that a substantial reduction of contagion risk, rather than merely lifting restrictions, is necessary to revamp international tourism flows.

We also find that, since the start of the pandemic, provinces specialised in art tourism were hit the most, while provinces with a more prevalent orientation to business tourism were instead significantly more resilient. Furthermore, provinces that used to be more "hotel intensive" in terms of accommodation choices made by visitors were hit harder than provinces characterised by a larger use of private housing and/or rental houses. Finally, we found that arrivals to local destinations more easily reachable by private means of transport (such as cars) decreased significantly less.

This evidence is overall consistent with the hypothesis that contagion risk affected not only tourists' decisions to travel, but also *how* to travel and *where* to stay, thus implying heterogeneous effects across local destinations.

Looking at cross country variation, we found that the intensity and the cross-country differentiation of restrictions to entry was a key factor in explaining cross-country patterns. However, screening requirements at entrance (such as swab tests requirement) do not seem to significantly discourage arrivals. After controlling for these restrictions and for the easiness to arrive by car, we observed that the European travellers from more distant countries generally decreased more, again pointing to renewed importance of distance in shaping tourism patterns during the pandemic.

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A Appendix

A.1 Data annex

In this section we provide further details on the data we used.

Mobile phone data. The total number of foreign SIM cards active in Italy is calculated by the mobile operator on the number of foreign cards detected, taking into account its market shares (as not all foreign SIM cards are provided roaming services by the same Italian mobile operator). A SIM card (Subscriber Identity Module) contains an integrated circuit that stores the subscriber's identity, including the nationality of the operating company that issues the card. This information is what we take as a proxy for the residency (i.e. country of departure) of the card owner. It is a good approximation as far as phone users resort to *resident* mobile companies. It may not be the case for migrants, as mentioned in section 3.1, as they may prefer using SIM cards issued in their home country instead of cards issued in their host country, so to be able to call their relatives at home at cheaper prices. This is why we excluded SIM cards issued in countries associated with large immigrants communities in Italy. As for the location, foreign SIM cards were attributed to Italian provinces on the basis of the "cells" (i.e. mobile phone antenna towers) they were connected with. If a SIM is detected in more than one province in the same day, it is assigned to the province where it was detected for the longest time. The Italian data protection legislation does not allow the diffusion of information derived from mobile phone data referring to less than 15 individual users. Therefore, if the dimensions *day*, *country of origin*, and *province of destination* are populated by 15 or less observations, the *province of destination* is set equal to “other” by the phone operator. The impact of this truncation on the data used in this paper is however quite low: the weight of number of SIMs of the “undisclosed” province is about 1.5 percent in 2019 (2.5 in 2020). Moreover, they partly pertain to relatively minor countries that we excluded from our analysis.

BISIT data. The Bank of Italy Survey on International Tourism (BISIT) is based on two pillars: (i) counting the number of travellers that enter/leave the country at a selected number of border crossing points, and (ii) conducting interviews with a sample of international travellers, both residents and not residents, crossing the Italian borders. The counting process aims at estimating the reference universe (i.e. the total number of inbound and outbound travellers), broken down by country of residence or destination, while the survey collects information about tourists’ expenditure and their personal characteristics..

The BISIT survey asks the surveyed traveller to specify the reason for her trip to Italy choosing one among the possible answers: A) personal reasons (it includes: A1 holidays and leisure; A2 Studying; A3 Pilgrimage or other religious reasons; A4 health or thermal tourism; A5 honeymoon; A6 visiting relatives and/or friends; A7 shopping; A8 other personal reasons. B) Business reasons. C) Transit only. If the respondent chooses A1, she is invited to further specify if it was holidays A1.1 at the beach; A1.2 on the mountains; A1.3 at the lake; A1.4 in a *città d’arte* (city of art); A1.5 green holidays; A1.6 sport and fitness holidays; A1.7 wine & food holidays. The complete questionnaire form can be downloaded from the Bank of Italy website section on international tourism statistics.

List of countries included. For readers’ information, we list here (according to the alphabetical order of their ISO code) the forty countries of origin we have in our sample: United Arab Emirates, Argentina, Austria, Australia, Belgium, Brazil, Canada, Switzerland, Chile, Czech Republic, Colombia, Germany, Denmark, Spain, Finland, France, Great Britain, Greece, Croatia, Hungary, India, Ireland, Israel, Japan, Lithuania, Luxembourg, Latvia, Macedonia, Malta, Mexico, Netherlands, Norway, New Zealand,Portugal, Russia, Sweden, Slovakia, Slovenia, Turkey, United States. From these forty countries are excluded the Principality of Monaco (as it was not identifiable using mobile phone data) and the countries with large foreign resident communities, namely Poland, Romania, Bulgaria, Bosnia and Herzegovina, China, Serbia, Ukraine, Albania, and Moldavia. Table A.1 reports some statistics on their weight on total inbound tourism, both in terms of night spent and in terns of total travellers, and a comparison between BISIT data and mobile phone data.

Table A.1: **Weight of included countries in terms of inbound tourism to Italy**

	BISIT Travellers 2017-2019		BISIT Nights 2017-2019		Daily SIMs 2019	
	number	share	number	share	number	share
First 40 countries (net of excluded countries)	85,973	91.8	344,369	89.2	403,450	85.1
Excluded countries(*)	5,814	6.2	27,978	7.2	52,037	11.0
Other countries	1,842	2.0	13,731	3.6	18,482	3.9
Total	93,629	100.0	386,077	100.0	473,969	100.0

Source: BISIT and mobile phone data.

(*)Countries with a large community resident in Italy: Poland, Romania, Bulgaria, Bosnia and Herzegovina, China, Serbia, Ukraine, Albania, and Moldavia.

A.2 Robustness analysis

Table A.2: **Analysis by province: robustness**

dep. variable:$Tour_{opt}$	(1)	(2)	(3)	(4)	(5)	$log(Tor_{opt})$ (6)	first 40 prov. (7)	Up to dec. 2020 (8)
$cases_{pt-1}$	-0.0645***			-0.0290**	-0.0398***	-0.0420***	-0.0605***	-0.0422***
	(0.00850)			(0.0148)	(0.00648)	(0.00576)	(0.00942)	(0.00460)
$cases_{pt-4}$		-0.0524***						
		(0.00858)						
wins. $cases_{pt-1}$			-0.0749***					
			(0.0108)					
$cases^2_{pt-1}$				-0.00247**				
				(0.00114)				
cumulative $cases_{pt-1}$					-0.0131***			
					(0.00123)			
d_{Covid19} X purpose$_{\text{op}}$:								
nature and beach	-0.716***	-0.715***	-0.722***	-0.713***	-0.762***	-1.045***	-0.778***	-0.516***
	(0.0523)	(0.0548)	(0.0535)	(0.0519)	(0.0507)	(0.0576)	(0.0634)	(0.0477)
art and culture	-1.049***	-1.041***	-1.051***	-1.043***	-1.199***	-1.277***	-1.066***	-0.964***
	(0.0541)	(0.0555)	(0.0550)	(0.0536)	(0.0571)	(0.0494)	(0.0659)	(0.0573)
other personal reasons	-0.713***	-0.716***	-0.728***	-0.702***	-0.783***	-0.645***	-0.630***	-0.701***
	(0.0358)	(0.0361)	(0.0360)	(0.0360)	(0.0365)	(0.0374)	(0.0801)	(0.0378)
d_{Covid19} X accom.$_{\text{op}}$:								
hotels/hostels	-1.296***	-1.313***	-1.300***	-1.307***	-1.078***	-1.522***	-1.610***	-1.244***
	(0.0753)	(0.0772)	(0.0761)	(0.0752)	(0.0763)	(0.0624)	(0.105)	(0.0724)
camping/farmhouse	-0.101	-0.0863	-0.0929	-0.101	-0.103	0.759***	-0.812***	-0.465***
	(0.130)	(0.135)	(0.131)	(0.130)	(0.125)	(0.142)	(0.162)	(0.124)
others	-0.602***	-0.604***	-0.599***	-0.611***	-0.462***	-0.764***	-0.942***	-0.540***
	(0.0428)	(0.0435)	(0.0431)	(0.0432)	(0.0430)	(0.0393)	(0.0615)	(0.0420)
d_{Cov19} X airplane$_{op}$	-0.292***	-0.280***	-0.291***	-0.290***	-0.322***	-0.150***	-0.389***	-0.341***
	(0.0245)	(0.0260)	(0.0248)	(0.0246)	(0.0231)	(0.0149)	(0.0285)	(0.0238)
FE country#prov#week	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
FE country#time	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R^2 / adj.R^2	0.99	0.99	0.99	0.99	0.99	0.90	0.99	0.99
Observations	311606	311606	311606	311606	311606	216368	148841	288930

The table reports estimates of the model 1 on the period January 2019 - February 20201, for different specifications of the variable measuring contagion at local level (columns 1-5). Columns (6) report estimates of the model rewritten in log form and estimated with OLS. Column 7 restricts the sample to the first 40 provinces. Column (8) excludes the first months of 2021.

Table A.3: **Analysis by province: EU, Schengen members, and UK**

dep. var.8: $Tourists_{opt}$	All sample		1^{st} wave	Summer	2^{nd} wave		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$cases_{pt-1}$	-0.0579***	-0.0722***	0.0357		-0.0635***	-0.0592***	-0.0401***
	(0.00925)	(0.00895)	(0.0236)		(0.00719)	(0.00685)	(0.00328)
d_{Cov19} X purpose$_{\text{op}}$:							
nature and beach		-0.478***	-1.110***	-0.389***	-0.454***	-0.458***	-0.525***
		(0.0349)	(0.129)	(0.0447)	(0.0464)	(0.0463)	(0.0426)
art and culture		-1.026***	-1.488***	-0.868***	-1.121***	-1.130***	-1.152***
		(0.0370)	(0.115)	(0.0492)	(0.0533)	(0.0532)	(0.0431)
other pers. reasons		-0.357***	-0.181***	-0.282***	-0.456***	-0.458***	-0.323***
		(0.0266)	(0.0697)	(0.0373)	(0.0340)	(0.0340)	(0.0266)
d_{Cov19} X accomm.$_{op}$:							
hotels/hostels		-0.597***	-0.755***	-0.360***	-0.961***	-0.964***	-0.446***
		(0.0297)	(0.0676)	(0.0393)	(0.0371)	(0.0369)	(0.0224)
camping/farmhouse		-0.136***	-0.264**	-0.457***	0.605***	0.602***	0.390***
		(0.0496)	(0.118)	(0.0525)	(0.0725)	(0.0722)	(0.0442)
others		-0.412***	-0.373***	-0.226***	-0.661***	-0.667***	-0.414***
d_{Cov19} X airplane$_{op}$		-0.341***	-0.329***	-0.394***	-0.225***	-0.225***	-0.485***
		(0.0264)	(0.0711)	(0.0377)	(0.0378)	(0.0378)	(0.0219)
RR index						-0.00641**	
						(0.00283)	
FE country#prov#week	Yes	Yes	Yes	Yes	Yes	Yes	Yes
FE country#time	Yes	Yes	Yes	Yes	Yes	Yes	Yes
FE reg.#time	No	No	No	No	No	No	Yes
Pseudo R^2	0.99	0.99	0.99	0.99	0.98	0.98	0.99
Observations	234761	218665	53422	57580	105346	105346	105346

The table reports estimates of the model 1 over different periods . Column (1) and (2) look at the whole sample (Jan. 2019 to Feb. 2021). The 1$^{\text{st}}$ wave period (column (3)) includes the weeks from 25 February to 2 June 2020.The Summer period (column 4) goes from 3 June to 15 September 2020. The 2$^{\text{nd}}$ wave (columns 5, 6, and 7) goes from 16 September 2020 onward. Standard errors, in parenthesis, are clustered by province–time and country of departure–time. ***, **, and * indicate statistical significance at 1, 5, and 10 per cent, respectively.Fixed effects by country of departure - province - week (α_{opw}) and country of departure - time (α_{ot}) are always included.