### **Online Appendices**

### — Locked Down, Lashing Out: COVID-19 Effects on Asian Hate Crimes in Italy — Dipoppa, Grossman, Zonszein

# A Classification of Victims' Ethnic Background from Description of the Crime

To extract the victims' origins and religions, we first gather lists of countries and their adjectival and demonymic forms, ethnicities, and religions in the Italian language. In addition, we create a list containing terms which refer to immigrants, refugees and asylees (e.g. *immigrati, stranieri, clandestini, rifugiati*, which mean immigrants, foreigners, illegal immigrants and refugees, respectively). Secondly, in order to capture only the crimes against ethnic minority and immigrant groups, we remove from these lists all n-grams which are homonyms (e.g. *Mali*, the West African country is the word *evil* in Italian), particularly homonyms of Italian place names (e.g. *roma* the Indo-Aryan ethnic group also means the capital of Italy), and n-grams that do not indicate an immigrant origin (e.g. *italia, italiana*). Thirdly, we match exactly the country, nationality and ethnicity n-grams to the text of the crime's description and we map the matching n-grams to countries and then to regions of the world to assign a country and region of origin to the victim, and we follow the same process to assign religions. Likewise, we define the victim as an immigrant when the text of the crime's description matches exactly at least one term in the immigrant keywords list.

As a result of these processes, we were able to identify at least one characteristic of the victim as an immigrant or ethnic minority for 92.7% of the total crimes. The description in the majority of the remaining 7.3% cases (577 crimes) does not specify any characteristics of the victim's origin. Among the cases with at least one identified characteristic, 93% (or 6,796 total crimes) correspond to immigrant victims, from which 4,670 are classified into a region of origin —with 48% assigned to Africa, 27% to Eastern and Southern Europe, 11% to Asia, 6% to the Middle East and the rest almost equally divided among other regions— and 2,126 are classified as immigrants, but with an unknown region of origin. The remaining 7% (522 crimes) corresponds to crimes against ethnic minorities based on their religion; about 56% of these are crimes targeted at Muslim people, 24% at Jewish people, 15% at Christians and the rest are targeting people from other non-dominant religions in Italy. Figure A1 presents a summary of the classification results. In the analysis of the Covid-19 effects on hate crimes we use the sample that we can classify as crimes against ethnic minorities and immigrant groups, which corresponds to 92.7% of the total crimes, and we focus on the sample with an assigned region of origin, which includes 4,670 crimes, when we assess crimes targeted at a specific immigrant group. As illustrated in Figure A2, neither the proportion classified as crimes against immigrants or ethnic minorities, nor the proportion which is classified into a region of origin is distinguishable across months before and after Covid-19.





Figure A2: Proportion of classified crimes against ethnic minorities and immigrant groups, and with known victim's region of origin



### **B** Additional Tables and Figures

We start by providing additional details on our dependent variable in Figures B1, B2, B3a and B3b. We plot the frequency of hate crimes by the victim's region of origin, identity of the perpetrator and type of hate crime (Figure B1) and map the distribution of hate crimes across Italian municipalities (Figure B2). In Figures B3a and B3b we present the results of a generalized fluctuation test for structural breaks, which reveals a large break in trends in crimes against Asians in January 2020, but no significant break in crimes against Africans in the same period.

We then include information on our treatments of interest, exposure to Covid-related deaths and unemployment. We start by presenting descriptive statistics by above and below median levels of exposure deaths (Table B3) and unemployment (Table B4). The two tables report the mean and standard deviation of hate crimes, socioeconomic variables and voting behavior before the start of Covid-19. The differences existent between cities in our treatment and control group before Covid, displayed in the last column in the tables, are differenced out by our estimation strategy, which absorbs pre-treatment differences in average outcomes across groups. Focusing on Covidrelated death, Table B5 repeats our main DiD analyses on mortality using exposure to deaths in February 2020 rather than in January 2020. Even when the population is fully aware of the virus and its deadliness – unlike in January, when Covid had just started spreading – exposure to mortality does not predict a higher likelihood to observe hate crimes against Asians. Again focusing on mortality, Figure B4 shows the relation between predicted and observed probability of deaths, indicating that places with high mortality in January 2020 are a good predictor of where high mortality will be concentrated in February 2020. Consistently, the average number of excess deaths by month from 2018 to 2020 (Figure B5) reveals a sudden increase in excess mortality in January 2020, even before the diffusion of Covid was acknowledged in Italy. We repeat a similar exercise for Covid-related unemployment: Figure B6 shows the relation between predicted and observed probability of unemployment in the first two quarters of 2020, again indicating a high accuracy in prediction. Finally, in Figure B7 we show that there is a low correlation between our dichotomized treatment indicators capturing low and high exposure to Covid-related death and unemployment, as the number of municipalities in each of the four possible values taken by these variables is very

similar.

We then present additional analyses discussed in the text. In the manuscript text, Figure 2 presented a snapshot of the effect of Covid-related deaths and unemployment in each month from 2018 to 2020. Here, we include the same figure for the whole period for which we have data, including all months since 2007 (Figure B8). In Figure B9 we show that our DiD result on unemployment is robust to the use of a double DiD estimator Egami and Yamauchi (2019), which accounts for potential violations of the common trends assumption. In Figure B12 we address the concern that the null response we observe to health-related threats might be the result of a larger reduction in mobility in areas affected by a health threat. However, we show that mobility did not decrease differentially in provinces with larger exposure to health-related threats in the period of consideration.

Finally, we present descriptives and analyses on the mechanism in Figures B10 and B11: first, we show that there is a low correlation between our measure of far-right voting at the national level and electing a far-right mayor in Figure B10. Second, we present a generalized fluctuation test on the trend of monthly negative articles about Chinese-origin people which indicates the presence of a structural break in correspondence with the start of Covid-19 (Figure B11).



Figure B1: Hate crimes by victim's region of origin, perpetrator and type

Figure B2: Cities with hate crimes (red) and hate crimes against Asians (black)



Table B1:	Hate	Crime	Examples
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Region	Crime Description
Calabria	In a well-known shopping center, according to a student, a man kicks a 5-year-old boy of Filipino origins (but born in Italy and never gone abroad) only "for the shape of his eyes and for fear of contract the Coronavirus". The child, whose parents have lived in Italy for many years (the mother for over 20), approached the attacker's daughter because he wanted to play. At that point, the man would first simulate a kick and then, seeing the little one try to get closer to his daughter, he would have launched a real one. Thus, the child's father would have intervened seeing the scene and asking the man why he was making that aggressive and gratuitous gesture. "He's a dirty Chinese, he has to go away",
р. ·I·	he replied.
Emilia- Romagna	A young Italian boy of Filipino origin is approached, teased and finally attacked by a group of young people in the center. "Go away, bring us the virus" are the contemptuous words spoken by some of them to the boy who was in the Pilotta area, for a walk with his girlfriend and some friends. According to initial information, after the attack, the friends of the young Filipino reacted and a brief scuffle would ensue. The young men attacked then contacted a lawyer.
Campania	Young Xin Liu, a student of Chinese nationality at the "Domenico Cimarosa" Conservatory, denounces, during the 'Raid' television program broadcast on the 'Primativvu' broadcaster, of having been the object of ridicule and contempt by other young people ("They call me coronavirus"). Another young man, his compatriot, was allegedly attacked and beaten by a group of very young students from other schools. An attack on which the Carabinieri are investigating on delegation from the Prosecutor's Office.
Sardinia	A 31-year-old Filipino waiter, Demetrio Elida, is attacked on a Ctm bus, which leads from the center of Cagliari to Assemini. On board, according to what he reported to the Carabinieri, there were three boys who would have insulted him. They allegedly provoked him by "confusing him for a Chinese citizen" and then hit him in the face, accusing him of carrying the Coronavirus. The three then got out of the vehicle and fled. The young Filipino reached the home of a friend to ask for help and was accompanied to the hospital where he was hospitalized with a 30-day prognosis for facial trauma.
Lazio	Five Chinese boys were insulted and threatened in the afternoon by a group of 3 Italian teenagers: "Go away from Italy because you are infected with Coronavirus", they would have shouted in Piazza dei Consoli, in the Tuscolana area. After the screams, the Italian boys would have fled. Policemen from the Tuscolano police station intervened on the spot and arrested one of the young people, a 15-year-old who had threatened the Chinese boys with a broken bottle. Nobody was hurt. The Chinese girl, who is pregnant, is taken to the hospital emergency room for checks after the fright, but she does not report any consequences. At the end of the checks, the group of Chinese citizens decides not to file a complaint against the teenager
Piedmont	A couple of young Chinese people report to the carabinieri that they were bottle-attacked by two boys, who would have shouted at them "Go away, bring the coronavirus". The episode took place around two o'clock in the Borgo Vittoria district. The boy and the girl were on their way home after a day's work in a supermarket, when they were allegedly approached by two young Italians, who first offended them and then hit them with a broken glass bottle. The carabinieri are viewing the images of the surveillance cameras to trace the attackers.

The table presents examples of hate crime against Asian-origin people during February 2020 as reported by Lunaria.



Figure B3: Generalized fluctuation test for structural breaks

(a) Empirical fluctuation process of crimes against Asian immigrants

(b) Empirical fluctuation process of crimes against African immigrants

Notes: The empirical fluctuation process is computed via moving sums of residuals within a window of 3 months using the R package strucchange. The horizontal red lines indicate the boundaries of the limiting process fluctuation. The vertical line indicates the estimated optimal breakpoint, considering only one breakpoint.

	Befc	ore	After			
	Mean	SD	Mean	SD	Difference in Means	p-value
All hate crimes	0.0031	0.18	0.0017	0.04	-0.0014	0.000
Asian hate crimes	0.0001	0.03	0.0007	0.02	0.0005	0.004
African hate crimes	0.0009	0.07	0.0006	0.03	-0.0003	0.144

Table B2: Hate Crime Before and After Covid-19

The table presents the pre- and post-Covid-19 mean and standard deviation of the outcome variables (hate crimes per 10,000 residents), and the difference in means. The p-values of the difference-in-means test indicate that the covariates are distinguishable across periods. Data are from Lunaria 2007 to March 2020. \*\*\*p < 0.001, \*p < 0.01, \*p < 0.05, °p < 0.1.

	Low Death		High D	Death	
	Mean	SD	Mean	SD	Difference in Means
All hate crime	0.0027	0.19	0.0035	0.17	0.0008*
Asian hate crime	0.0002	0.04	0.0001	0.02	-0.0000
African hate crime	0.0007	0.08	0.0011	0.07	$0.0004^{**}$
Population	3785.5566	7006.55	11278.2209	57441.47	7490.5609***
%~65+	11.6073	4.31	9.9650	3.51	$-1.6423^{***}$
% Foreign population	34.3289	28.73	42.5544	29.80	10.0113***
% Less college	58.4529	8.53	57.0781	8.26	$-1.7268^{***}$
% Unskilled labor	18.7127	6.07	17.0073	4.92	$-1.6388^{***}$
Unemployment rate	11.1076	7.71	9.1920	6.94	$-1.8799^{***}$
% Male unemployed	8.8428	6.64	7.2020	5.91	$-1.5942^{***}$
% Young unemployed	29.9939	17.59	25.7105	15.65	$-4.1151^{***}$
Vote share extreme right	13.4835	9.02	16.4047	10.74	2.7476***
Far-right mayor	0.0125	0.11	0.0278	0.16	$0.0154^{***}$

Table B3: Descriptive Statistics by Covid-19 Related Death

The table presents the pre-Covid-19 mean and standard deviation of the outcome variables (hate crimes per 10,000 residents), sociodemographic and political covariates across municipalities with low and high Covid-19 related deaths, and the difference in means. The p-values of the difference-in-means test indicate that the covariates are distinguishable across groups. In so far as these covariates affect the outcomes, such differences across groups are residualized by the DID approach, which accounts for the pre-Covid-19 difference in average outcomes across groups. In the analysis, we further account for these differences with municipality fixed effect and by controlling flexibly for these covariates. Data are from Lunaria 2007 to March 2020, 2011 Population Housing Census, 2011 Industry and Services Census, and Ministry of Interior. \*\*\*p < 0.001, \*p < 0.01, \*p < 0.05, °p < 0.1.

	Low Unemployment		High Unem	ployment	
	Mean	SD	Mean	SD	Difference in Means
All hate grime	0.0027	0.15	0.0034	0.20	0.0007*
All hate crime	0.0027	0.10	0.0034	0.20	0.0007
Asian hate crime	0.0002	0.04	0.0001	0.02	-0.0000
African hate crime	0.0008	0.08	0.0010	0.06	0.0002
Population	3401.0761	5672.32	11165.2625	55725.74	7740.9268***
% Foreign population	45.4338	30.65	30.9391	26.38	$-13.6860^{***}$
% Less college	59.0927	7.68	56.5164	8.95	$-2.8474^{***}$
% Unskilled labor	17.4664	4.49	18.3399	6.54	$0.9581^{***}$
Unemployment rate	7.3189	5.16	13.0630	8.18	$5.6956^{***}$
% Male unemployed	5.6128	4.46	10.5034	7.00	4.8734***
% Young unemployed	21.2098	12.52	34.6695	17.88	$13.3565^{***}$
Vote share extreme right	18.4216	10.52	11.2901	7.92	$-7.1071^{***}$
Far-right mayor	0.0292	0.17	0.0101	0.10	$-0.0190^{***}$

Table B4: Descriptive Statistics by Covid-19 Related Unemployment

The table presents the pre-Covid-19 mean and standard deviation of the outcome variables (hate crimes per 10,000 residents), sociodemographic and political covariates across municipalities with low and high Covid-19 related unemployment, and the difference in means. The p-values of the difference-in-means test indicate that the covariates are distinguishable across groups. In so far as these covariates affect the outcomes, such differences across groups are residualized by the DID approach, which accounts for the pre-Covid-19 difference in average outcomes across groups. In the analysis, we further account for these differences with municipality fixed effect and by controlling flexibly for these covariates. Data are from Lunaria 2007 to March 2020, 2011 Population Housing Census, 2011 Industry and Services Census, and Ministry of Interior. \*\*\*p < 0.001, \*p < 0.05, °p < 0.1.

	Dependent variable:					
	As	sian Hate C	rimes per 10	),000 resider	nts	
	(1)	(2)	(3)	(4)	(5)	
Excess deaths	0.00008					
	(0.00006)					
After Jan, 2020	$0.00073^{*}$					
	(0.00032)					
After Jan, 2020 $\times$	-0.00043	-0.00043	-0.00069	-0.00062	-0.00062	
Excess deaths	(0.00036)	(0.00036)	(0.00041)	(0.00042)	(0.00042)	
$\mathbb{R}^2$	0.00000	0.00650	0.00706	0.00706	0.00713	
Obs	1253594	1253594	1253594	1253594	1253594	
N Municipalities	7885	7885	7885	7885	7885	
Month FE	Ν	Y	Y	Y	Y	
Municipality FE	Ν	Υ	Υ	Υ	Υ	
Flexible controls	Ν	Ν	Υ	Υ	Υ	
Group-specific linear trends	Ν	Ν	Ν	Υ	Υ	
Province-specific linear trends	Ν	Ν	Ν	Ν	Y	

Table B5: Covid-19 Death Effects on Asian Hate Crimes

The dependent variable is monthly Asian hate crimes in a municipality per 10,000 residents. After Jan, 2020 indicates the period after the first confirmed case of Covid-19 in Italy. Excess deaths indicates municipalities with an above the median number of excess deaths associated to Covid-19 in February 2020. Flexible controls include municipality population shares of foreign born, less than college educated, 65 years and older, and the party label of the head of local government interacted with month indicators. Group-specific linear trends and Province-specific linear trends correspond to the interaction between a continuous time measure and the municipality indicator of death exposure or Province indicators, respectively. Municipality-clustered-robust standard errors reported in parentheses. Data are from Lunaria 2007 to March 2020, Istat death counts 2017-2020, 2011 Population Housing Census. \*\*\*p < 0.001, \*\*p < 0.01, \*p < 0.05.





Notes: Points are the average number of municipalities under high threat of infection in February 2020 for equally spaced bins of the predicted probability of high excess deaths in February 2020 from logistic regression on the number of excess deaths in January 2020. The shaded band indicates 95% confidence intervals. Data are from ISTAT 2017-2020 and the 2011 Industry and Services Census.

Figure B5: Average number of excess deaths by month



Notes: Points are the average number of excess deaths across Italian municipalities. Data are from ISTAT 2017-2020.





Notes: Points are the average number of municipalities under high threat of unemployment for equally spaced bins of the predicted probability of unemployment from logistic regression on regional unemployment rates in the first two quarters of 2020. The shaded band indicates 95% confidence intervals. Data are from ISTAT 2020 and the 2011 Industry and Services Census.

Figure B7: Correlation between local exposure to death and unemployment



Notes: The box's size represents the share of municipalities in each of the four exposure conditions. Data are from ISTAT death counts 2017-2020 and the 2011 Industry and Services Census.



Figure B8: Monthly-varying Covid-19 effects on Asian hate crimes

Notes: Points represent the estimated coefficients from linear regression of Asian hate crimes per 10,000 residents on the interaction between monthly indicators and municipality indicators for (a) above the median deaths associated to Covid-19 and (b) above the median share of workers in affected economic sectors by Covid-19. The model specification includes month and municipality fixed effects. Lines are 95% confidence intervals. Data are from Lunaria 2007 to March 2020, 2011 Industry and Services Census, ISTAT deaths counts 2017-2020.

Figure B9: Covid-19 death and unemployment effects on Asian hate crimes: Accounting for possible violations to the common trends assumption



Notes: Points represent the estimated DiD and double DiD coefficients of effects of excess deaths and expected unemployment due to Covid-19 on Asian hate crimes per 10,000 residents as implemented by the R package DIDdesign. Lines are 95% confidence intervals. Data are from Lunaria 2007 to March 2020, 2011 Industry and Services Census, ISTAT death counts 2017-2020.

Figure B10: Correlation between vote for the extreme right in national elections and far-right mayors



Notes: The box's size represents the number of municipalities in each of the four conditions. Data are from the Ministry of Interior.

Figure B11: Generalized fluctuation test for structural breaks in the number of negative articles about Chinese- and African-origin people



(a) Empirical fluctuation process of negative articles about Chinese people

(b) Empirical fluctuation process of negative articles about African people

Notes: The empirical fluctuation process is computed via moving sums of residuals using the R package **strucchange**. The horizontal red lines indicate the boundaries of the limiting process fluctuation. The vertical line indicates the estimated optimal breakpoint.

Figure B12: Change in mobility across provinces exposed to different levels of Covid excess deaths



Notes: The plotted measure in (a) is based on weekly users' average radius of gyration by province, which captures the extent of individual movements, and in (b) on daily average degree of users' proximity network, which captures the level of social distancing by province. Pre-Covid includes available data from January 2020, and Post-Covid from February and March. The data at hand suggest that spatial variation in hate crimes is not a function of individuals' movement, at least as captured using available mobility data. Data are from Pepe et al. (2020).

# C Hate Crime Analyses Including Periods with Restrictions on Freedom of Movement

In this section we assess our main results on hate crimes accounting for the months after the implementation of measures restricting freedom of movement. These strict measures were imposed by the end of March 2020 and maintained across the year, except for the months of July–October when they were temporarily lifted. Given that such measures greatly affected social dynamics, we first describe in Figure C1 how the patterns of hate crime respond to these measures: hate crimes are way below expected levels when restrictions are imposed in the periods of April–June and November–December (representing 45% and 40%, respectively of the average hate crimes over the previous four years), and at around expected levels when restrictions are lifted in July–October (equivalent to 85% of average hate crimes over the previous four years).

Figure C1: Total number of hate crimes during the lockdown periods



Despite such a disruption to the hate crime patterns, Asian hate crimes continued to be prevalent over this period of lockdowns, reaching a record high when compared to the previous decade. Figure C2 presents the number of hate crimes against Asians as a share of the total number of hate crimes, during these 3 different periods when restrictions were imposed, lifted and imposed again. During April–June and July–October, the share of Asian hate crimes represents at least 200% of that share in the previous four years, and 90% during November–December. These patterns suggest that Asian hate crimes may have persisted across the year of 2020, even with the strict lockdown measures.

In the main text our analyses are centered on the months before the freedom of movement



Figure C2: Share of Asian hate crimes during the lockdown periods

measures were imposed, as we aim to assess the reponse to the pandemic outbreak clean of other dynamics that may have affected the likelihood of hate crimes. However, considering that there may be persistence in the reaction to the pandemic outbreak in the form of Asian hate crimes, despite the disruption to social dynamics, as suggested in Figure C2, here we replicate the main results using the hate crime data from January 2007 to December 2020. The results are broadly consistent with those presented in the main text.

Figure C3 presents the monthly-varying Covid-19 related unemployment and mortality effects on Asian hate crimes for every month until December 2020 (we zoom in on 2018-2020 for illustrative clarity). Consistent with the results presented in the main text, the plots suggest that the effects of Covid-related death are not statistically significant at any month after the Covid outbreak (Figure C3a). In contrast, the effect of Covid-related unemployment on Asian hate crimes is positive and statistically significant only in February 2020. The magnitude of the effects decay after that month and are not statistically significant (Figure C3b).

Table C1 presents the main Covid-related death and unemployment effects on Asian hate crimes including the data from the months after the restriction on movement measures were imposed. The conclusion remains substantively the same as that reached from the results in Table 1: the effect of Covid-related unemployment on Asian hate crimes is positive and statistically significant, although the magnitude of the coefficient is smaller, and the effect of Covid-related deaths is not statistically significant.



Figure C3: Monthly-Varying Covid-19 Effects on Asian Hate Crimes Until December 2020

Notes: Points represent the estimated coefficients from linear regression of Asian hate crimes per 10,000 residents on the interaction between monthly indicators and municipality indicators for (a) above the median deaths associated with Covid-19 and (b) above the median share of workers in affected economic sectors by Covid-19. The model specification includes month and municipality fixed effects. Lines are 95% confidence intervals. Data are from Lunaria 2007 to December 2020, 2011 Industry and Services Census, ISTAT deaths counts 2017-2020. The plot presents a snapshot of the effects since January 2018.

	Dependent variable:					
	As	ian Hate Cri	mes per 10,	000 resident	s	
	(1)	(2)	(3)	(4)	(5)	
Panel A: Health Threat						
Excess	-0.00000					
deaths	(0.00006)					
After Jan, 2020	0.00005					
	(0.00009)					
After Jan, 2020 $\times$	-0.00001	-0.00001	-0.00011	-0.00021	-0.00021	
Excess deaths	(0.00011)	(0.00011)	(0.00013)	(0.00016)	(0.00016)	
Average Hate Crimes	0.00015	0.00015	0.00017	0.00014	0.00014	
$\overline{\mathbb{R}^2}$	0.00000	0.00616	0.00671	0.00637	0.00643	
Obs.	1324559	1324559	1324559	1324559	1324559	
N Municipalities	7885	7885	7885	7885	7885	
Panel B: Economic Threat						
Expected	-0.00002					
unemployment	(0.00006)					
After Jan, 2020	$-0.00015^{**}$					
	(0.00006)					
After Jan, 2020 $\times$	0.00038***	0.00038***	$0.00031^{**}$	$0.00029^{*}$	$0.00029^{*}$	
Expected unemployment	(0.00011)	(0.00011)	(0.00010)	(0.00013)	(0.00013)	
Average Hate Crimes	0.00016	0.00016	0.00014	0.00014	0.00014	
$R^2$	0.00000	0.00616	0.00630	0.00630	0.00636	
Obs.	1330775	1330775	1330775	1330775	1330775	
N Municipalities	7922	7922	7922	7922	7922	
Month FE	Ν	Y	Y	Y	Y	
Municipality FE	Ν	Υ	Υ	Υ	Υ	
Flexible controls	Ν	Ν	Υ	Υ	Υ	
Group-specific linear trends	Ν	Ν	Ν	Υ	Υ	
Province-specific linear trends	Ν	Ν	Ν	Ν	Υ	

Table C1: Covid-19 Effects on Asian Hate Crimes Including all Months Until December 2020

The dependent variable is monthly Asian hate crimes in a municipality per 10,000 residents. After Jan, 2020 indicates the period after the first confirmed case of Covid-19 in Italy. Excess deaths and Expected unemployment indicate municipalities with an above the median number of deaths in January 2020 associated to Covid-19 and share of workers in affected sectors by Covid-19, respectively. Flexible controls include municipality population shares of foreign born and less than college educated interacted with month indicators. The health threat specification includes as well share of the population 65 years and older, and the party label of the mayor interacted with month indicators. Group-specific linear trends and Province-specific linear trends correspond to the interaction between a continuous time measure and the municipality indicator of infection or unemployment exposure, or province indicators, respectively. Municipality-clustered-robust standard errors reported in parentheses. Average Hate Crimes is the effective sample mean pre-Covid-19 hate crime rate in control municipalities, computed following Aronow and Samii (2016). Data are from Lunaria 2007 to December 2020, 2011 Industry and Services Census, Istat death counts 2017-2020. \*\*\*p < 0.001, \*\*p < 0.01, \*p < 0.05.

### D Robustness of Covid-19 Unemployment Effects

In addition to checking in Table 1 that results are robust to accounting for endogeneity due to presence of confounders (with monthly and municipality fixed effects, controlling flexibly for relevant covariates, and province-specific linear trends) and for possible violations to the common trends assumption (with group-specific linear trends), here we explore whether the Covid-19 related unemployment results are robust as well to a series of other specification considerations.

First, we control flexibly for the pre-Covid municipality's size of the East and Southeast Asian communities to correct for potential bias from omitting this variable. We do so with a restricted sample of municipalities that have information about their immigrant population. The patterns presented in the main analysis (in Table 1) remain when we control flexibly for the size of these communities, as shown in Table D1. This suggests that even when we compare within municipalities with similar size of the targeted community, we find a stronger reaction in economically affected municipalities.

Second, we use alternative definitions of exposure to unemployment. In particular, we use the continuous measure of the share of workers in affected sectors as opposed to the dichotomous variable which splits municipalities into below and above the median share. We also present the effect estimates by quartiles of the share of workers in affected sectors. Table D2 and Figure D1 confirm that the results are not sensitive to any specific cutoff of expected unemployment to determine exposures.

Third, we restrict the analysis to a shorter time frame, from January, 2019 to March, 2020, that may guarantee that the reporting standards of hate crimes, as well as relevant aspects of the municipalities, including the number of Asian residents and the political climate, are not changing substantially. These results are very similar to the results in our main specification, suggesting that even when we account for potential endogeneity caused by time-varying municipality characteristics, and also for potential changes in the reporting of crime, the Covid-related unemployment effects are unchanged.

Fourth, we rule out the alternative explanation that the reaction we observe is a response to being exposed to Chinese tourists accused of spreading the virus in Italy, instead of a reaction to

	Dependent variable:					
	As	sian Hate Cr	imes per 10	,000 residen	ts	
	(1)	(2)	(3)	(4)	(5)	
Expected	-0.00002					
unemployment	(0.00007)					
After Jan, 2020	-0.00011					
	(0.00008)					
After Jan, 2020 $\times$	$0.00135^{***}$	$0.00135^{***}$	$0.00089^{**}$	$0.00087^{**}$	$0.00087^{**}$	
Expected unemployment	(0.00039)	(0.00039)	(0.00028)	(0.00029)	(0.00029)	
$\mathbb{R}^2$	0.00001	0.00652	0.00669	0.00669	0.00677	
Obs	1163918	1163918	1163918	1163918	1163918	
N Municipalities	7321	7321	7321	7321	7321	
Month FE	Ν	Y	Y	Y	Y	
Municipality FE	Ν	Υ	Υ	Υ	Υ	
Flexible controls	Ν	Ν	Υ	Υ	Υ	
Group-specific linear trends	Ν	Ν	Ν	Υ	Υ	
Province-specific linear trends	Ν	Ν	Ν	Ν	Υ	

Table D1: Covid-19 Unemployment Effects on Asian Hate Crimes: Accounting for the Size of East and Southeast Asian Communities

The dependent variable is monthly Asian hate crimes in a municipality per 10,000 residents. After Jan, 2020 indicates the period after the first confirmed case of Covid-19 in Italy. Expected unemployment indicates municipalities with an above the median share of workers in affected sectors by Covid-19. Flexible controls include municipality population shares of foreign born, less than college educated, and East and Southeast Asian immigrants interacted with month indicators. Group-specific linear trends and Province-specific linear trends correspond to the interaction between a continuous time measure and the municipality indicator of unemployment exposure, or province indicators, respectively. Municipality-clustered-robust standard errors reported in parentheses. The sample includes only municipalities with immigrant population data (92% of those included in the main analysis). Data are from Lunaria 2007 to March 2020, 2011 Population Housing Census, 2011 Industry and Services Census, Istat death counts 2017-2020. \*\*\*p < 0.001, \*\*p < 0.01, \*p < 0.05.

Covid-related unemployment. Although this alternative explanation is unlikely, given that flights from China to Italy were halted on January 31st, we assess it by redefining our measure of exposure to unemployment. Particularly, we exclude workers in tourism from the share of workers in affected sectors, and therefore, under this definition, the exposed municipalities do not to rely on tourism. Figure D2 shows that the Covid-related unemployment effects on hate crime excluding tourism are not distinguishable from the main effects, suggesting that the increase in hate crimes is not explained by exposure to tourists.

Fifth, we alter the model's functional form to account for nonlinear models which deal with outcome variables of bounded support, and to deal with excess zeros in the outcome variable. In

	$Dependent \ variable:$					
	Asian Hate Crimes per 10,000 residents					
	(1)	(2)	(3)	(4)		
Expected	-0.00000					
unemployment	(0.00000)					
After Jan, 2020	-0.00306**					
	(0.00094)					
After Jan, 2020 $\times$	0.00007**	$0.00007^{**}$	$0.00005^{**}$	$0.00005^{**}$		
Expected unemployment	(0.00002)	(0.00002)	(0.00002)	(0.00002)		
$\mathbb{R}^2$	0.00001	0.00651	0.00665	0.00671		
Obs	1259477	1259477	1259477	1259477		
N Municipalities	7922	7922	7922	7922		
Month FE	Ν	Y	Y	Y		
Municipality FE	Ν	Υ	Υ	Υ		
Flexible controls	Ν	Ν	Υ	Υ		
Province-specific linear trends	Ν	Ν	Ν	Υ		

Table D2: Covid-19 Unemployment Effects on Asian Hate Crimes: Continuous Treatment Measure

The dependent variable is monthly Asian hate crimes in a municipality per 10,000 residents. After Jan, 2020 indicates the period after the first confirmed case of Covid-19 in Italy. Expected unemployment is a continuous measure with the municipality share of workers in affected sectors by Covid-19. Flexible controls include municipality population shares of foreign born and less than college educated interacted with month indicators. Province-specific linear trends correspond to the interaction between a continuous time measure and Province indicators. Municipality-clustered-robust standard errors reported in parentheses. Data are from Lunaria 2007 to March 2020, 2011 Population Housing Census, 2011 Industry and Services Census. \*\*\*p < 0.001, \*\*p < 0.01, \*p < 0.05, °p < 0.1.

particular, using hate crimes as counts as opposed to the number of hate crimes per 10,000 residents, we fit within a DiD framework a negative binomial model and a zero-inflated negative binomial model with the mass points zeros modeled as a function of the size of the East and Southeast Asian communities in a municipality. These models allow for overdispersion, in part caused by excess zeros in the outcome variable. Estimating a DiD model with the standard specification of a nonlinear model does not fulfill the common trend assumption. This is because the common trend assumption relies on differencing out unobservable terms of the potential outcomes, which cannot be differenced out under a nonlinear specification. Moreover, under a nonlinear specification, the Figure D1: Effect of Covid-19 on Asian hate crimes by quartile of share of workers in affected economic sectors



Notes: Points represent the estimated coefficients from linear regression of Asian hate crimes per 10,000 residents on an indicator for above the first, second, and third quartile of share of workers in affected economic sectors by Covid-19. The model specification includes month and municipality fixed effects, flexible controls, group-specific and province-specific linear trends. Lines are 95% confidence intervals. Data are from Lunaria 2007 to March 2020, 2011 Industry and Services Census.

common trend assumption only holds when the group specific differences are exactly zero, which means that the average outcomes cannot be different in levels. Therefore, estimating a DiD with the standard specification of a nonlinear model would produce an inconsistent estimator when the standard common trend assumption holds. In order to address this challenge, as suggested in (Lechner et al., 2011, p. 199–200), we use nonlinear parametric approximations to predict the four components of the conditional effects  $\mathbb{E}(Y_t \mid X = x, D = d)$  for time t and treatment  $d \in \{0, 1\}$ , and then average the conditional effects according to the negative binomial or zero-inflated negative binomial distribution to obtain estimates for the treated population. For inference on the ATT, we permute the municipality's treatment assignment (in this case, their exposure to high or low pandemic-related unemployment) and estimate the ATT to compute the distribution under the null hypothesis of no treatment effects, which we compare with the observed ATT to compute the two-tailed p-value.

	$Dependent \ variable:$					
	As	sian Hate Cr	imes per 10	,000 residen	ts	
	(1)	(2)	(3)	(4)	(5)	
Expected	-0.00001					
unemployment	(0.00007)					
After Jan, 2020	-0.00004					
	(0.00009)					
After Jan, 2020 $\times$	$0.00124^{***}$	$0.00124^{***}$	$0.00102^{**}$	$0.00114^{*}$	$0.00115^{*}$	
Expected unemployment	(0.00036)	(0.00037)	(0.00034)	(0.00048)	(0.00049)	
$\mathbb{R}^2$	0.00048	0.07027	0.07066	0.07066	0.07172	
Obs	118830	118830	118830	118830	118830	
N Municipalities	7922	7922	7922	7922	7922	
Month FE	Ν	Y	Y	Y	Y	
Municipality FE	Ν	Υ	Υ	Υ	Υ	
Flexible controls	Ν	Ν	Υ	Υ	Υ	
Group-specific linear trends	Ν	Ν	Ν	Υ	Υ	
Province-specific linear trends	Ν	Ν	Ν	Ν	Υ	

Table D3: Covid-19 Unemployment Effects on Asian Hate Crimes: Shorter Time Frame

The dependent variable is monthly Asian hate crimes in a municipality per 10,000 residents. After Jan, 2020 indicates the period after the first confirmed case of Covid-19 in Italy. Expected unemployment indicates municipalities with an above the median share of workers in affected sectors by Covid-19. Flexible controls include municipality population shares of foreign born, less than college educated interacted with month indicators. Group-specific linear trends and Province-specific linear trends correspond to the interaction between a continuous time measure and the municipality indicator of unemployment exposure, or province indicators, respectively. Municipality-clustered-robust standard errors reported in parentheses. The sample is restricted to January, 2019 - March, 2020. Data are from Lunaria 2007 to March 2020, 2011 Population Housing Census, 2011 Industry and Services Census, Istat death counts 2017-2020. \*\*\*p < 0.001, \*\*p < 0.01, \*p < 0.05.

We also estimate the changes-in-changes estimator of Athey and Imbens (2006). This framework drops the linearity assumption in the DiD framework and models the outcome with its actual distribution. This allows for the common trend assumption to hold even for skewed variables with bounded support, and therefore to causally identify the ATT. The results of these three models are presented in Table D4, which suggests that the estimated effects are robust to such variations in the model's functional form.

Finally, in Table D5 we re-run our most restrictive specification of the main analysis (Model 5 in Table 1) including flexible controls for youth unemployment (Column 1) and for population density (Column 2). Considering this additional set of controls interacted with month dummies allows us to





Notes: Points represent the estimated coefficients from linear regression of Asian hate crimes per 10,000 residents on an indicator for above the median share of workers in affected economic sectors by Covid-19 excluding tourism. The model specification includes month and municipality fixed effects, flexible controls, group-specific and province-specific linear trends. Lines are 95% confidence intervals. Data are from Lunaria 2007 to March 2020, 2011 Industry and Services Census.

exclude the possibility that the effect we observe are driven by factors correlated with Covid-related unemployment and that might also have a time-varying effect on hate crimes. The robustness of our findings across these analyses suggests that those factors do not explain our results.

Table D4: Covid-19 Unemployment Effects on Asian Hate Crimes: Nonlinear Models

	Depe	endent var	riable:
	Number o	f Asian H	ate Crimes
Model	Estimate	p-value	Obs
Negative binomial model in DiD framework	0.0052	0.0000	1259477
Zero-inflated negative binomial model in DiD framework	0.0056	0.0000	1163918
Changes-in-Changes framework	0.0109	0.0480	1259477

The dependent variable is the number of monthly Asian hate crimes in a municipality (Mean=0.004). Estimates for the Negative binomial model in DiD framework and Zeroinflated negative binomial model in DiD framework are computed by first estimating a negative binomial (or zero-inflated) model on each of the three subsamples (before-control, beforetreated, after-control) to predict the four components of the DiD estimator on the treated sample, and secondly by taking the difference of the two differences and averaging to obtain the ATT. Estimate for Changes-in-Changes framework follows Athey and Imbens (2006) and is implemented using the R package qte. p-value are computed via randomization inference with 500 iterations. The sample in the zero-inflated model includes only municipalities with information about their immigrant population. Data are from Lunaria 2007 to March 2020, 2011 Population Housing Census, 2011 Industry and Services Census.

	Dependent variable:				
	Asian Hate Crimes per 10,000 reside				
	(1)	(2)			
After Jan, 2020 $\times$	0.00083***	0.00097***			
Expected unemployment	(0.00029)	(0.00036)			
$R^2$	0.00675	0.00656			
Obs	$1,\!259,\!318$	$1,\!259,\!477$			
Month FE	Y	Y			
Municipality FE	Y	Y			
Group-specific linear trends	Υ	Y			
Province-specific linear trends	Y Y				

Table D5: Covid-19 Unemployment Effects on Asian Hate Crimes: YouthUnemployment and Population Density Flexible Controls

The dependent variable is monthly Asian hate crimes in a municipality per 10,000 residents. After Jan, 2020 indicates the period after the first confirmed case of Covid-19 in Italy. Expected unemployment is a continuous measure with the municipality share of workers in affected sectors by Covid-19. Flexible controls include youth unemployment (Column 1) or population density (Column 2) interacted with month indicators. Province-specific linear trends correspond to the interaction between a continuous time measure and Province indicators. Municipality-clustered-robust standard errors reported in parentheses. Data are from Lunaria 2007 to March 2020, 2011 Population Housing Census, 2011 Industry and Services Census. \*\*\*p < 0.001, \*\*p < 0.01, \*p < 0.05, °p < 0.1.

### E Testing for reporting bias

Data on hate crimes may be subject to differences in reporting which might bias the estimates in the direction of our findings if reporting is higher in places with highest expected unemployment after Covid. We check for possible bias in the reporting of hate crimes that may have coincided with the pandemic onset in Table E1.

We start by assessing whether the observed effects are an artifact of the increase in salience of hate crimes against Asians in the media. In particular, national newspapers might report crimes against this group at higher rates due to the preponderance of Asia in the news caused by Covid-19. We show that this is not the case in Column 1: when we exclude from the count of hate crimes all instances of crimes reported by national media, we still observe a positive significant impact of Covid-related unemployment on hate crimes.

Second, instead of media paying higher attention, it might be victims of hate crimes that report at higher rates due to the awareness of being singled in relation to Covid. Column 2 shows that our findings are robust also to this concern: findings are robust when dropping all crimes reported by individuals directly to the NGO.

Third, findings are robust to excluding verbal hate crimes: verbal crimes might be less seriously threatening and thus they might be only reported when crimes against Asians are newsworthy, as it might have happened in February and March 2020. However, subsetting to either verbal (42% of the hate crimes, estimates in Column 4) or to non-verbal hate crimes (58% of the hate crimes, estimates in Column 3) we obtain similar findings. We also present results considering exclusively instances of physical violence. There are considerably less cases in which violence manifests physically, reducing the precision of our estimates, but the increase we observe in this case is more than 50 times the mean of the dependent variable in the control group – a much larger increase than both non-verbal (14 times the control group average) and verbal hate crimes (3 times the control group average).

Fourth, we subset the analyses by type of attacker: we consider crimes committed by individuals or groups (74% of the sample) and crimes committed by institutions, media and politicians (26% of the sample). We find that the increase in hate crimes against Asians is entirely driven by attacks committed by individuals or groups (Column 5), while there is no increase for crimes committed by institutions, politicians, or media (Column 6). This finding confirms our interpretation: if the increase in hate crimes is driven by frustration related to loss of income, we should expect crimes being committed by individuals rather than by institutions, politicians, or media.

A related concern is that the location of the hate crime might be misattributed. For example, when institutions, media or politicians commit hate crimes, the location we observe might not be where the attack took place (at the national level, or where the institution or media is located), but rather where the victim lives. The test in Columns 5 and 6 also allows us to account for such potential concern: our findings are entirely driven by crimes committed by individuals, who, unlike institutions, politicians and news media, are likely to be present in the same location as the victim, avoiding the misallocation issue.

Another case in which crimes committed by individuals might be misallocated is when those happen on social media. Lunaria does not report information on whether the hate crime was first published on social media, but rather only reports as source the outlet or the NGO that reported about the hate crime. However, we build this information by searching in the description of the hate crime the words: Facebook, Twitter, Youtube, Instagram, TikTok. If any of the most commonly used social networks in Italy<sup>20</sup> is listed in the description, we conservatively mark the hate crime as happening on social media. In a robustness test now reported in Table E.1, Column 7, we drop hate crimes with descriptions mentioning social media from the analyses (14% of the total number of hate crimes). Our findings are robust to the exclusion of these events, indicating that potential misattribution in location when the true location is unknown does not drive our results.

<sup>&</sup>lt;sup>20</sup>Source: Most commonly used social networks in Italy, 2021

	(8) Where: No social med	$0.00080^{**}$ $(0.00026)$	1,259,477. $00015$	f the follow s that are 1 committed nedia (Colu- icipalities w effects, flexi cators, grountheses. D ntheses. D 11, ** $p < 0$ .
Test	(7) Attacker: Institutions	0.00004 (0.00002)	1,259,477. $00004$	alyses to one c ing only crimes luding crimes ed on social n indicates muni l month fixed ( ith month indi ported in pare is. *** $p < 0.00$
porting Bias	(6) Attacker: Person	$\begin{array}{c} 0.00082^{***} \\ (0.00028) \end{array}$	1,259,477. $00011$	ricting the an an 2); includi alumn 5); inc imes committ ectedunempl nicipality and interacted w ard errors rej ervices Censu
Hate Crimes, Re <sub>l</sub>	(5) Type: Physical Violence	0.00028 ( $0.00021$ )	1,259,477 $0.000005$	<ul> <li>000 residents rest dividuals (Colum ical violence (Cc a 7); dropping cr -19 in Italy. <i>Exp</i> muns include mu college educated red-robust standared-robust standared red-robust standared red-r</li></ul>
tts on Asian ]	(4) Type: Verbal	$0.00031^{**}$ (0.00014)	1,259,477 .00011	aality per 10, a 1) or by in volving phys ians (Column ase of Covid- d-19. All colu- nd less than ipality-clustel Census, 201.
oyment Effec	(3) Type: Not verbal	$0.00053^{**}$ (0.00024)	1,259,477 .00004	s in a municif edia (Column 4) or only in a and politic t confirmed c tors by Covic tors by Covic reign born a sids. Munici tion Housing
ovid-19 Unempl	(2) Source: Drop individuals	$0.00086^{***}$ (0.00028)	1,259,477. $00016$	sian hate crimes I by national me imes (Column - stitutions, medi iod after the firs ion affected sec ion shares of fo pecific linear tre 0, 2011 Populat
Table E1: C	(1) Source: Drop national media	$0.00077^{***}$ $(0.00024)$	1,259,477. $00014$	by the providence of the providence of the providence of the province of the p
		After Jan 2020 $\times$ Expected unemp	Observations Mean DV	The dependent varial categories: dropping verbal (Column 3) ( individuals only (Cc 8). $AfterJan$ , 2020 an above the median controls for the mur specific linear trend- are from Lunaria 20 * $p < 0.05$ , $^{\circ}p < 0.1$ .

### F Auxiliary Analysis of Covid-19 Unemployment Effects

We have shown that the threat of unemployment caused by Covid-19 triggers an increase in hate crimes against Asian-origin people. Here, we conduct additional analyses to first inquire whether such hateful reaction spills over to other ethnic-minority immigrant groups, in particular, people from African origin, given their history as targets of bigoted attacks in Italy. And secondly, to assess whether in addition to an increase in the crime rate (the number of crimes per 10,000 residents), there is as well an increase in the number of municipalities experiencing hate crimes.

A comparison between the unemployment Covid-19 effects on hate crimes against Asians and Africans shown in Figure F1 suggests that the hateful response to economic grievances as a result of the virus outbreak is targeted at the group perceived to be inflicting such grievances, as the effect of unemployment threat on African hate crimes is smaller than the effect on crimes against Asians and it is not statistically significant.

Moreover, not only the number of crimes against Asians increases in February 2020, but also the number of municipalities experiencing Asian hate crimes increases, suggesting that municipalities without a history of attacks on the Asian population are mobilized against Asian-origin immigrants after the virus outbreak. This finding is in accordance with a Bayesian-like rationale suggesting that triggering events can be disproportionally more consequential where initial levels of hateful behaviors are low (Frey, 2020; Ferrín, Mancosu and Cappiali, 2020), given that against their prior beliefs, people from these places perceive immigrants from Asia as a threat perhaps for the first time, and therefore heavily update on this information, evoking a stronger reaction against Asian-origin immigrants. As Figure F1 shows, such increase in the number of municipalities with presence of crimes against Asians is higher and statistically significant in municipalities under the threat of unemployment relative to less economically affected municipalities.

Figure F1: Comparison of Covid-19 unemployment effects across Asian and African number and presence of hate crimes



+ Crime Rate + Crime Presence

Notes: Points represent the estimated coefficients from linear regression of Asian (left side) or African (right side) hate crimes per 10,000 residents (in dark gray and left-axis), or an indicator of hate crimes (in light Gray and right-axis), on an indicator for above the median share of workers in affected economic sectors by Covid-19. The model specification includes month and municipality fixed effects, flexible controls, group-specific and province-specific linear trends. Lines are 95% confidence intervals. Data are from Lunaria 2007 to March 2020, 2011 Industry and Services Census.

# G Covid-19 Effects on Asian Hate Crime: Bayesian Structural Time-Series Model Approach

We estimate the causal effect of the pandemic on the number of hate crimes against Asians at the national-level via a Bayesian structural time-series model, as developed by Brodersen et al. (2015) and as implemented in the CausalImpact R package. This method employs a state-space time series model that regresses the pre-pandemic national trend of Asian hate crimes on the set of pre-pandemic national trends of hate crimes against non-Asian immigrant groups (except for the trend of Caribbean-origin immigrants which shows a significant uptick at the pandemic onset), flexibly accounting for seasonality, to construct a synthetic control trend. Then, it computes the posterior distribution of the counterfactual trend of crimes against Asians using the pre-pandemic national trend of Asian hate crimes and the post-pandemic synthetic trend of hate crimes against other immigrant groups. A semi-parametric Bayesian posterior distribution for the causal effect of the pandemic is obtained by taking the difference between the post-pandemic observed and counterfactual trends of crimes against Asians.

The top panel in Figure G1 shows the observed (solid line) and the predicted counterfactual (dashed line) trends and the bottom panel presents the difference between these two trends (that is, the causal effect). While the pre-pandemic difference between the observed and the predicted counterfactual trends is not distinguishable from zero (which suggests that the computation of the predicted counterfactual is accurate), we observe a large increase in such difference after January 2020. This effect corresponds to an additional 21 crimes against Asians on average during the months of February and March 2020 with a 95% interval of [18.01, 23.29], which corresponds to a relative increase in crimes of 760% with a 95% interval of [659%, 852%]. Considering the cumulative crimes during these two months we have 42 additional crimes. These effects are statistically significant as the Bayesian one-sided tail-area probability is p = 0.0005.

Figure G1: Observed and predicted counterfactual trends and their difference



#### H Additional Information and Tests of Mechanisms

Tables H1 and H2 present the estimated coefficients of the triple-differences models that we use to compute heterogeneous Covid-related unemployment effects on hate crime by prejudice and

far-right mayors in Figure 3. It is important to note that the inference on the coefficient of the triple interaction After Jan,  $2020 \times Expected unemployment \times Far-right$  would suggest that there is no difference in the effect of Covid-related unemployment across cities with and without farright mayors. However, given that the number of municipalities led by far-right mayors is quite small, only 155 out of 7,922, we compute the p-values on the triple interaction coefficient via randomization inference, by permuting the assignment of far-right mayors to municipalities, as described in the main text. In Table H3, we repeat the analyses testing for reporting bias we perform in Section E on the triple-difference model. First, as for the main analyses, results are robust across reporting sources also when we consider differences between cities with and without far-right mayors (Columns 1-2). Second, while nonverbal and physically violent crimes appear less likely in cities with high unemployment and far-right mayors after covid (Column 3), there is no statistically detectable difference in coefficients between this regression and that considering verbal hate crimes only (Column 4). Third, we confirm the finding that most of the effect of covid related unemployment on hate crimes is driven by individuals rather than by institutions, media, or politicians. Also in this case, when we test whether the coefficients in Columns 5 and 6 are statistically different, we reject the hypothesis that they are. Finally, we find consistent results when excluding social-media hate crimes from the count of events (Column 7). As for the main analyses, also in this case the p-value from the randomization inference returns a significant coefficient (p-value=0.0283).

	Dependent variable: Asian Hate Crimes per 10,000 residents						
	(1)	(2)	(3)	(4)	(5)		
Expected	0.00009*	. ,	. ,	. ,			
unemployment	(0.00004)						
After Jan, 2020	$-0.00003^{*}$						
	(0.00002)						
High	$0.00018^{*}$						
prejudice	(0.00008)						
After Jan, 2020 $\times$	-0.00010	-0.00010	-0.00006	-0.00006	-0.00007		
high prejudice	(0.00011)	(0.00011)	(0.00012)	(0.00012)	(0.00013)		
Unemployment $\times$	-0.00013						
high prejudice	(0.00010)						
After Jan, 2020 $\times$	$0.00133^{**}$	$0.00133^{**}$	$0.00106^{*}$	$0.00104^{*}$	$0.00103^{*}$		
unemployment	(0.00047)	(0.00047)	(0.00041)	(0.00042)	(0.00041)		
After Jan, 2020 $\times$	-0.00038	-0.00038	-0.00071	-0.00071	-0.00068		
Unemployment $\times$ high prejudice	(0.00069)	(0.00069)	(0.00075)	(0.00075)	(0.00074)		
$R^2$	0.00001	0.00651	0.00665	0.00665	0.00671		
Obs	1259477	1259477	1259477	1259477	1259477		
N Municipalities	7922	7922	7922	7922	7922		
Month FE	Ν	Y	Y	Y	Y		
Municipality FE	Ν	Υ	Υ	Υ	Υ		
Flexible controls	Ν	Ν	Υ	Υ	Υ		
Group-specific linear trends	Ν	Ν	Ν	Υ	Υ		
Province-specific linear trends	Ν	Ν	Ν	Ν	Υ		

Table H1·	Covid-19	Unemploy	ment Effect	s on Asian	Hate	Crimes h	w	Preiudice
Table III.	C0viu-13	Unumpioyi	ment Linee	5 On Asian	IIauc	OTHICS I	JY	I ICJUUICC

The dependent variable is monthly Asian hate crimes in a municipality per 10,000 residents. After Jan, 2020 indicates the period after the first confirmed case of Covid-19 in Italy. Expected unemployment indicates municipalities with an above the median share of workers in affected sectors by Covid-19. High prejudice indicates municipalities with an above the median vote share for extreme right parties in national elections. Flexible controls include municipality population shares of foreign born and less than college educated interacted with month indicators. Group-specific linear trends and Province-specific linear trends correspond to the interaction between a continuous time measure and the municipality indicator of unemployment exposure, or province indicators, respectively. Municipality-clustered-robust standard errors reported in parentheses. Data are from Lunaria 2007 to March 2020, 2011 Population Housing Census, 2011 Industry and Services Census, Istat death counts 2017-2020. \*\*\*p < 0.001, \*\*p < 0.01, \*p < 0.05.

	Dependent variable:					
		Asian Hate C	rimes per 10	,000 resident	s	
	(1)	(2)	(3)	(4)	(5)	
Expected	0.00000					
unemployment	(0.00006)					
After Jan, 2020	-0.00008					
	(0.00008)					
Far-right	$0.00075^{\circ}$					
mayor	(0.00042)					
After Jan, 2020 $\times$	$-0.00080^{\circ}$	$-0.00080^{\circ}$	$-0.00084^{\circ}$	$-0.00084^{\circ}$	$-0.00115^{*}$	
Far-right mayor	(0.00042)	(0.00043)	(0.00046)	(0.00046)	(0.00050)	
Unemployment $\times$	-0.00051					
Far-right mayor	(0.00048)					
After Jan, 2020 $\times$	0.00119**	$0.00119^{**}$	$0.00082^{**}$	0.00080**	$0.00079^{**}$	
unemployment	(0.00037)	(0.00037)	(0.00027)	(0.00028)	(0.00028)	
After Jan, 2020 $\times$	0.00387	0.00387	0.00309	0.00309	0.00330	
Unemployment $\times$ Far-right mayor	(0.00318)	(0.00319)	(0.00320)	(0.00320)	(0.00320)	
$\mathbb{R}^2$	0.00001	0.00651	0.00665	0.00665	0.00671	
Obs	1253753	1253753	1253753	1253753	1253753	
N Municipalities	7886	7886	7886	7886	7886	
Month FE	Ν	Y	Y	Y	Y	
Municipality FE	Ν	Υ	Υ	Υ	Υ	
Flexible controls	Ν	Ν	Υ	Υ	Υ	
Group-specific linear trends	Ν	Ν	Ν	Υ	Υ	
Province-specific linear trends	Ν	Ν	Ν	Ν	Y	

Table H2: Covid-19 Unemployment Effects on Asian Hate Crimes by Far-right Mayors

The dependent variable is monthly Asian hate crimes in a municipality per 10,000 residents. After Jan, 2020 indicates the period after the first confirmed case of Covid-19 in Italy. Expected unemployment indicates municipalities with an above the median share of workers in affected sectors by Covid-19. Far-right mayor indicates municipalities governed by a far-right mayor. Flexible controls include municipality population shares of foreign born and less than college educated interacted with month indicators. Group-specific linear trends and Province-specific linear trends correspond to the interaction between a continuous time measure and the municipality indicator of unemployment exposure, or province indicators, respectively. Municipality-clustered-robust standard errors reported in parentheses. Data are from Lunaria 2007 to March 2020, 2011 Population Housing Census, 2011 Industry and Services Census, Istat death counts 2017-2020. \*\*\*p < 0.001, \*p < 0.05.

Table H3:	Covid-19 Unemp	loyment Effects	on Asian H	ate Crimes	by Far-right	t Mayors, Rej	porting Bias	Test
	(1) Source: Drop national media	(2) Source: Drop individuals	(3) Type: Not verbal	(4) Type: Verbal	(5) Type: Physical	(6) Attacker: Person	(7) Attacker: Institutions	(8) Where Not: social media
After Jan 2020 × Expected unemp After Jan 2020 × Far-right After Jan 2020 × Unemp × Far-right	$\begin{array}{c} 0.00073^{***}\\ (0.00024)\\ -0.00056^{*}\\ (0.00031)\\ 0.00343\\ (0.00314)\end{array}$	$\begin{array}{c} 0.00082^{***} \\ (0.00028) \\ -0.00089^{*} \\ (0.00046) \\ 0.00316 \\ (0.00318) \end{array}$	$\begin{array}{c} 0.00053^{**} \\ (0.00024) \\ -0.00050^{*} \\ (0.00027) \\ -0.00104^{*} \\ (0.00062) \end{array}$	$\begin{array}{c} 0.00027 \\ (0.00015) \\ -0.00020 \\ (0.00018) \\ 0.00395 \\ (0.00316) \end{array}$	$\begin{array}{c} 0.00029\\ (0.00022)\\ -0.00004\\ (0.00006)\\ -0.00093^{**}\\ (0.00041)\end{array}$	$\begin{array}{c} 0.00079^{***} \\ (0.00028) \\ -0.00035 \\ (0.00039) \\ 0.00256 \\ (0.00318) \end{array}$	$\begin{array}{c} 0.00002 \\ (0.00002) \\ -0.00053** \\ (0.00053** \\ 0.00050** \\ (0.00023) \end{array}$	$\begin{array}{c} 0.00078^{***} \\ (0.00026) \\ -0.00083^{*} \\ (0.00046) \\ 0.00113 \\ (0.00259) \end{array}$
Observations R-squared Mean DV	$\begin{array}{c} 1,253,912\\ 0.00657\\ .00014\end{array}$	$\begin{array}{c} 1,253,912\\ 0.00666\\ .00016\end{array}$	$\begin{array}{c} 1,253,912\\ 0.00714\\ .00004\end{array}$	$\begin{array}{c} 1,253,912\\ 0.00652\\ .00011\end{array}$	$\begin{array}{c} 1,253,912\\ 0.00700\\ 0.000005\end{array}$	$\begin{array}{c} 1,253,912\\ 0.00658\\ .00012\end{array}$	$\begin{array}{c} 1,253,912\\ 0.00730\\ .00004\end{array}$	$\begin{array}{c} 1,253,912\\ 0.00661\\ .00015\end{array}$
The dependent vari of the following cate only crimes that are including crimes com committed on social Unemployment indic indicates municipality for the municipality specific linear trends Data are from Lunar ** $p < 0.01, *p < 0.05$	able is monthly gories: dropping not verbal (Columited by individ- media (Column ' ates municipaliti ies governed by a population share and province-sp ia 2007 to March $^{\circ}p < 0.1$ .	Asian hate crir c crimes reporte ann 3), verbal huals only (Colu (7). After Jan, 2 es with an abo far-right mayou s of foreign bon ecific linear tren ecific linear tren	nes in a mu d by nation hate crimes mn 5) or by 2020 indicat ve the medi r. All colum r. and less t nds. Munici pulation Hol	micipality 1 al media (( (Column 4 (Column 4 institutions es the peric an share of an share of an sinclude r han college pality-clustu using Censu	per 10,000 r Column 1) c Column 1) c s, media and od after the d after the i workers in nunicipality educated in ered-robust is, 2011 Indu	esidents restrant or by individ- involving phy- politicians ( first confirme affected sect and month fi- ateracted wit ateracted wit standard error ustry and Ser	ricting the ar uals (Column ysical violence Column 6); dr ed case of Cov ors by Covid- ors by Covid- n month indi ors reported i ors reported i	allyses to one 2); including e (Column 5); opping crimes rid-19 in Italy. -19. Far-right exible controls cators, group- n parentheses. *** $p < 0.001$ ,

# I Validation of National Far-Right Vote as a Proxy for Prejudice

In the analysis, we use far-right voting in the 2018 national elections as a proxy for prejudice against immigrants. In this section, we test the validity of voting as a measure of prejudice using nationally representative public opinion survey data from Italian National Election Survey (Itanes) 2018 (N respondents=2,573). This survey includes questions on both voting intentions and on attitudes towards immigrants. This allows to test whether, for the same individual, there is a correspondence between hostility against immigrants and voting for far-right parties. A further advantage of this survey as a validation method is that it was administered right before the 2018 elections, meaning that public opinion data refer to the same period as the measure of prejudice based on voting we want to validate. We note that *Itanes* also collected responses after elections from the same individuals, but we use pre-election data for consistency with the voting measure.

The survey gauges attitudes towards immigrants by asking whether Italy receives too many immigrants on a scale from 1 (too few) to 7 (too many). We correlate this measure to voting intentions for the Lega and for Brothers of Italy, the two main far-right parties in this election cycle, in Figure II. For both parties, we observe a strong positive correlation between voting and hostility towards migrants, with Lega prospective voters concentrated in the most hostile group. Since our voting measure includes also other smaller far-right parties for which Itanes did not record voting intentions (small parties are all grouped in 'Other'), we also test the correlation between hostility against immigrants and self-positioning on a left-right scale (1-7), another question included in the survey. Figure I2 shows an almost perfect mapping between each level of hostility against immigrants and self-positioning as right-wing. The correlations highlighted in these figures are robust to the use of individual level controls for education, employment, gender, age as well as province fixed effects, as reported in Table I1.

This evidence confirms that, at least in our context, prejudice towards immigrants is a fundamental component of the far-right voter's ideology, making voting for far-right parties a good proxy for hostility against foreigners.

A related question is whether it is possible to distinguish empirically between voting for far-right

politicians at the national level and electing a far-right mayor. We show that this is the case by presenting robust results when we run the triple-interaction analyses controlling for the prejudice variable in the regression considering far-right mayors and for far-right mayors in the regression with prejudice (Tables I2 and I3, Column (2) controls flexibly for one or the other variable).





Figure I2: Correlation between self-positioning on a left-right scale and antiimmigrant attitudes



	Dep Exclu	endent vari sionary att	<i>able:</i> itudes
	(1)	(2)	(3)
Lega (0-1)	1.525***		
5 ( )	(0.083)		
Brothers of Italy (0-1)		1.358***	
		(0.144)	
Self-positioning left-right (1-7)		· · · ·	0.298***
			(0.012)
Observations	2,488	2,488	1,768
R-squared	0.139	0.103	0.347
Province FE	Υ	Υ	Υ
Controls	Υ	Υ	Υ
Mean DV	5.265	5.265	5.265

Table I1: Effect of far-right on hostility against immigrants, survey data

Note: The dependent variable is the response to the question "Does Italy receive too many immigrants?" on a 1-7 scale. Lega and Brothers of Italy are self-reported voting intentions (0-1) for these parties. Self-positioning is the respondent's reported collocation on a left-right scale (1-7). All regressions control for education, gender, age and employment of the respondent and include province fixed effects.

	Dep Asian Hate C	endent variable: rimes per 10,000 residents
	(1)	(2)
Expected		
unemployment		
After Jan, 2020		
High		
prejudice		
After Jan, 2020 $\times$	-0.00007	-0.00003
high prejudice	(0.00013)	(0.00014)
Unemployyment $\times$		
high prejudice		
After Jan, 2020 $\times$	$0.00103^{*}$	$0.00103^{*}$
unemployment	(0.00041)	(0.00041)
After Jan, 2020 $\times$	-0.00068	-0.00069
Unemployment $\times$ high prejudice	(0.00074)	(0.00074)
$\mathbb{R}^2$	0.00671	0.00706
Obs	1259477	1259477
N Municipalities	7922	7922
Month FE	Y	Y
Municipality FE	Υ	Y
Flexible controls	Υ	Y
Group-specific linear trends	Υ	Y
Province-specific linear trends	Υ	Y

Table I2: Covid-19 Unemployment Effects on Asian Hate Crimes by PrejudiceControlling for Far-right Mayors

The dependent variable is monthly Asian hate crimes in a municipality per 10,000 residents. After Jan, 2020 indicates the period after the first confirmed case of Covid-19 in Italy. Expected unemployment indicates municipalities with an above the median share of workers in affected sectors by Covid-19. High prejudice indicates municipalities with an above the median vote share for extreme right parties in national elections. Flexible controls include municipality population shares of foreign born and less than college educated interacted with month indicators in column (1), and column (2) adds an indicator for a municipality led government by a far-right mayor interacted with month indicators. Group-specific linear trends and Province-specific linear trends correspond to the interaction between a continuous time measure and the municipality indicator of unemployment exposure, or province indicators, respectively. Municipality-clustered-robust standard errors reported in parentheses. Data are from Lunaria 2007 to March 2020, 2011 Population Housing Census, 42

	Deper Asian Hate Cri	<i>ndent variable:</i> mes per 10,000 residents
	(1)	(2)
Expected		
unemployment		
After Jan, 2020		
Far-right mayor		
After Jan, 2020 $\times$	$-0.00115^{*}$	$-0.00102^{*}$
Far-right mayor	(0.00050)	(0.00052)
Unemployment $\times$		
Far-right mayor		
After Jan, 2020 $\times$	$0.00079^{**}$	$0.00064^{*}$
unemployment	(0.00028)	(0.00027)
After Jan, 2020 $\times$	0.00330	0.00336
Unemployment $\times$ Far-right mayor	(0.00320)	(0.00320)
$\mathbb{R}^2$	0.00671	0.00684
Obs	1253753	1253753
N Municipalities	7886	7886
Month FE	Y	Y
Municipality FE	Υ	Υ
Flexible controls	Υ	Υ
Group-specific linear trends	Υ	Y
Province-specific linear trends	Υ	Y

Table I3: Covid-19 Unemployment Effects on Asian Hate Crimes by Far-right Mayors Controlling for Prejudice

The dependent variable is monthly Asian hate crimes in a municipality per 10,000 residents. After Jan, 2020 indicates the period after the first confirmed case of Covid-19 in Italy. Expected unemployment indicates municipalities with an above the median share of workers in affected sectors by Covid-19. Far-right mayor indicates municipalities governed by a far-right mayor. Flexible controls include municipality population shares of foreign born and less than college educated interacted with month indicators in column (1), and column (2) adds an indicator for municipalities with an above the median right-wing vote share in national elections interacted with month indicators. Group-specific linear trends and Province-specific linear trends correspond to the interaction between a continuous time measure and the municipality indicator of unemployment exposure, or province indicators, respectively. Municipality-clustered-robust standard errors reported in parentheses. Data are from Lunaria 2007 to March 2020, 2011 Population Housing Census, 2011 Industry and Services Census, Istat death counts 2017-2020. \*\*\*p < 0.001, \*\*p < 0.01, \*p < 0.05.

# J National Media Analysis: National Newspapers, Tweets, and Sentiment Classification

National Newspaper Data We collected all articles from 2018–2020 from the 17 Italian national newspapers using the following steps. To obtain the articles published by each of these newspapers, we looked up the newspaper URLs in Common Crawl (an open repository of web crawl data containing a snapshot of every web page at the moment of the crawl). Particularly in the Index for 2021-21 crawl, the most recent crawl at that moment. We retrieved the WARC (Web ARChive format) records for each crawled page from the newspaper, and extracted the pages' HTML. From the HTML, we extracted the text, title, and byline using the Python package readabiliPy, and the publication date using the Python library htmldate. In order to select the subset of articles that reference China or Chinese people (Africa and African people), we extracted mentions of the words *cinese, cinesi*, and *cina*, and the top 20 mentions of African countries and nationalities, as well as articles with the word Africa. The sample includes 17,500 articles, with 42% about China or Chinese people.

Twitter Data We acquired a random sample of 1% of all tweets in Italian from January 2018 to April 2020 from the Annenberg School for Communication at the University of Pennsylvania. In order to get a sample of tweets with mentions about China or Chinese people (Africa and African people), as done with newspaper articles, we extracted tweets with the words *cinese*, *cinesi*, and *cina*, and the top 20 mentions of African countries and nationalities, as well as tweets with the words Africa and its derivatives. This sample includes approximately 95,000 tweets, 35% of which contain mentions about China or Chinese people.

Sentiment Classifier and Validation To define the tone of speech about China and Chinese people (Africa and African people) we use the FEEL-IT Python package from Bianchi, Nozza and Hovy (2021) for inferring two-category sentiment from Italian text. In the case of newspaper articles, we classify as positive or negative every mention of our terms of interest (or every sentence including these terms). In the case of tweets, we classify every tweet containing these terms. To validate the

sentiment classification, a human judge annotated in the two-category classification scale a sample of 130 article mentions and 300 tweets. Comparing the human annotations to the classification of the model for the positive and negative categories and defining the positive class as the negative sentiment category, we have that for newspaper article mentions the FEEL-IT sentiment annotator has an accuracy of 67%, weighted accuracy of 67%, precision of 64%, recall (or true positive rate) of 96%, and F1-score (or harmonic mean of precision and recall) of 77%. Although the model overpredicts the negative mentions as compared to the human annotations (the precision is 64%), it gives us a reasonable, if imperfect, measure of negative speech about China and Chinese people in the newspaper articles. This performance is comparable to other classifiers conducting similar tasks in English and Italian. The anti-Muslim speech classifier in Alrababah et al. (2019) achieves 0.7 weighted accuracy, and the hate speech classifier in Del Vigna et al. (2017) achieves 0.73, 0.63, 0.57, 0.59 in accuracy, precision, recall, F1 score, respectively. For tweets, the sentiment annotator has an accuracy of 76%, weighted accuracy of 78%, precision of 79%, recall (or true positive rate) of 93%, and F1-score (or harmonic mean of precision and recall) of 85%. These are reasonable statistics for sentiment classification, as compared to other classifiers performing similar tasks. Given that the FEEL-IT classifier is trained on a sample of annotated tweets from a broad range of topics, it is not surprising that its performance is better on tweets than in news articles.

National Media Analysis with Twitter Data We replicate our findings on the possible mobilization of hatred behavior by the national media with Twitter data. To assess the plausibility of a national shift in social norms we look at the trends of tweets referring to Chinese-origin people. The patterns in Figure J1a suggest that with the virus outbreak the salience of Chinese people in the public discourse increases; both the total number and the number of negative tweets about people from China significantly increase, whereas as a reference, tweets about people from African countries do not increase with the onset of Covid-19. Furthermore, a generalized fluctuation test on the trend of monthly negative tweets about Chinese-origin people confirms a structural break due to Covid-19 (Figure J2). Moreover, the pattern presented in Figure J1b suggests that the attitudes towards Chinese people are more negative than in previous months as the negative tweets' share trend increases with the pandemic's outbreak.



Figure J1: Italian Public Discourse Trends About Chinese People: Using Twitter Data

Notes: In (a) *total tweets* indicates the monthly number of tweets about Chinese- or Africanorigin people, and *negative tweets* the monthly number of negative tweets about these two groups. (b) displays the ratio of negative to total tweets across the two groups. Twitter data is a 1% sample of all tweets in the Italian language.

Negative tweets against China and Chinese people overwhelmingly involve Covid-19 related speech, identifying the country as responsible for the spread of the disease, expressing the belief that China should provide economic reparations to other affected countries, and indicating fear of contagion from Chinese individuals. Text analysis of negative tweets also reveals that those are more likely to include violent terms.<sup>21</sup>

 $<sup>^{21}</sup>$ We search for words related to violence, killings, punching, stabbing and raping. Of the tweets containing violent words, 73% are in the sample of tweets displaying negative sentiment against asians and only 27% in the sample of tweets not classified as negative.

Figure J2: Generalized fluctuation test for structural breaks in the number of negative tweets about Chinese- and African-origin people





(a) Empirical fluctuation process of negative tweets about Chinese people

(b) Empirical fluctuation process of negative tweets about African people

Notes: The empirical fluctuation process is computed via moving sums of residuals using the R package strucchange. The horizontal red lines indicate the boundaries of the limiting process fluctuation. The vertical line indicates the estimated optimal breakpoint.

#### K Media Coverage of Covid-19 and Unemployment

#### K.1 Salience of the Economic Consequences of Covid-19

We conduct a media analysis of the period January-March 2020 examining all news articles containing the words *Covid* and *Unemployment* in the two main Italian newspapers, Il Corriere and La Repubblica. This analysis documents that, already in this early period, media were reporting that unemployment would increase as a consequence of the virus diffusion and of the restrictions adopted to address it. Not only the Italian Institute for Statistical Analyses (ISTAT) anticipated that the tourism, transportation and restaurants sectors would suffer the largest loss in terms of employment in February, as mentioned in the manuscript, but similar information were widely reported by the media. La Repubblica uses the title *"The virus that kills employment"* in an article reporting that there would be *"social and economic consequences on all sectors, including tourism and transports"* (La Repubblica, March 23, 2020). Already in February 2020, labor unions organized a conference to discuss the employment consequences of Covid-19, and asked the government to take actions to face the *"emergency in the tourism industry"* (La Repubblica, March 8, 2020). Consistently with a demand for actions from unions and public opinion, the national and regional governments took initiatives already from February, suggesting that in this period people might have already anticipated the negative impact of Covid-19 on the hospitality industry. After approximately a month of discussion, on March 12th, the Italian government approved and enforced a plan for the suspension of taxation to avoid weighting on workers' income (La Repubblica, March 12, 2020.), and on March 18th the President signed a plan to address the rising unemployment with subsidies directed to any worker, a large expenditure which would have been impossible to approve in absence of a national agreement on the seriousness of the unemployment emergency (La Repubblica, March 18th, 2020).

The results of this media analysis are confirmed by public attitudes towards Covid-19: a survey by the World Economic Forum shows that In February Italians perceived the pandemic as posing a high threat to their jobs and businesses, but less so to their health.

#### K.2 Economic Concerns in Places with High Unemployment

We use Twitter data to capture Italians concerns with Covid-19 since early February 2020. In particular, we approximate the degree of concern with the pandemic's outbreak with the number of Covid-19 mentions as a share of all tweets. To do so, we work with a random sample of 1% of all tweets in Italian from January 2018 to April 2020 that can be georeferenced to a municipality. From this sample, we extract all tweets with mentions of Covid-19 and related terms (e.g. using the stems corona, virus). To get a sense of whether Italians were more concerned in areas expected to suffer economically the most (given a municipality's sectoral composition), in Figure K1a, we compare the share of tweets mentioning Covid-19 across municipalities with a high share of their population employed in the hospitality industry (transportation, restaurants, hotels) versus municipalities with a low share of workers in such an industry. Figure K1a suggests that concerns about the pandemic peaked by the third week of February 2020, and that since early February, Italians in municipalities expected to be economically exposed were more concerned that people in less exposed areas. A difference-in-means test between the share of tweets mentioning Covid-19 during the first two weeks of February across these two types of municipalities is positive and statistically significant at the 0.02 level.<sup>22</sup> To the contrary, we find no difference across municipalities that differ in their number of excess deaths (Figure K1b; the p-value of the difference-in-means test is 0.4).



Figure K1: Trends of tweets with mentions of Covid-19

(a) Comparison of trends by Covid-related unemployment



### **References for Appendix**

- Alrababah, Ala, William Marble, Salma Mousa and Alexandra Siegel. 2019. "Can exposure to celebrities reduce prejudice? The effect of Mohamed Salah on Islamophobic behaviors and attitudes.".
- Athey, Susan and Guido W Imbens. 2006. "Identification and inference in nonlinear difference-indifferences models." *Econometrica* 74(2):431–497.
- Bianchi, Federico, Debora Nozza and Dirk Hovy. 2021. FEEL-IT: Emotion and Sentiment Classification for the Italian Language. In Proceedings of the 11th Workshop on Computational Approaches to Subjectivity Sentiment and Social Media Analysis.
- Brodersen, Kay H, Fabian Gallusser, Jim Koehler, Nicolas Remy and Steven L Scott. 2015. "Inferring causal impact using Bayesian structural time-series models." *The Annals of Applied Statistics* 9(1):247–274.

Del Vigna, Fabio, Andrea Cimino, Felice Dell'Orletta, Marinella Petrocchi and Maurizio Tesconi.

<sup>&</sup>lt;sup>22</sup>The p-value is computed via randomization inference.

2017. Hate me, hate me not: Hate speech detection on facebook. In *Proceedings of the First Italian Conference on Cybersecurity (ITASEC17)*. pp. 86–95.

- Ferrín, Mónica, Moreno Mancosu and Teresa M Cappiali. 2020. "Terrorist attacks and Europeans' attitudes towards immigrants: An experimental approach." European Journal of Political Research 59(3):491–516.
- Frey, Arun. 2020. "Cologne Changed Everything'—The Effect of Threatening Events on the Frequency and Distribution of Intergroup Conflict in Germany." *European Sociological Review*.
- Lechner, Michael et al. 2011. The estimation of causal effects by difference-in-difference methods. Now.
- Pepe, Emanuele, Paolo Bajardi, Laetitia Gauvin, Filippo Privitera, Brennan Lake, Ciro Cattuto and Michele Tizzoni. 2020. "COVID-19 outbreak response, a dataset to assess mobility changes in Italy following national lockdown." *Scientific data* 7(1):1–7.