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Supplementary Information for

Economic and social consequences of human mobility restrictions during COVID-19

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Supporting Information Text

1. Data

In Table S1, we report descriptive statistics for the variables that we have used in our model.

With regards to Facebook human mobility, all data is provided under an academic license agreement with Facebook through its "Data for Good" program (available at: https://dataforgood.fb.com/tools/disease-prevention-maps/). Facebook releases data upon request to non-profit organizations and academics.

As for economic variables, we provide the appropriate references in Table S2 below.

	count	mean	std	min	25%	50%	75%	max
change in efficiency	2368.000	-0.720	0.237	-1.000	-0.865	-0.735	-0.640	0.331
income pc	2368.000	18175.222	3444.856	9711.081	15803.297	18279.182	20508.584	36941.920
deprivation	2368.000	14.592	98.845	-219.828	-51.289	-2.935	66.691	483.306
fiscal capacity	2348.000	478.460	287.863	131.617	352.465	425.662	516.973	5598.250
inequality	2368.000	0.788	0.091	0.454	0.738	0.784	0.833	1.768
real estate pc	2365.000	1.409	0.993	0.428	1.012	1.142	1.430	14.885

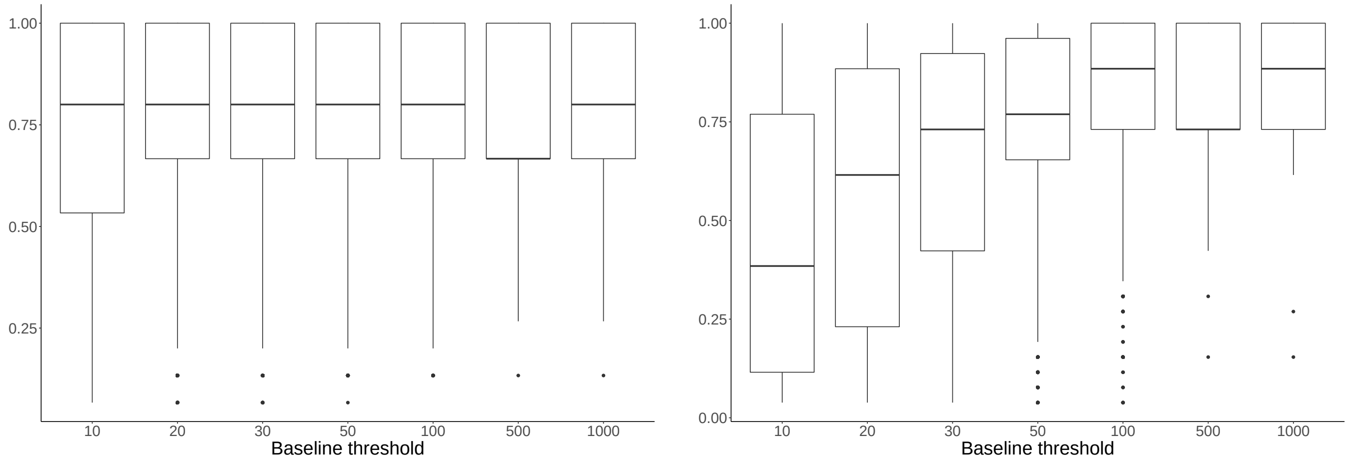
Table S1. Descriptive statistics for the variables used in the regression.

	Calculation	Source	URL
change in efficiency	Rate of change over time of the efficiency calculated on the FB mobility networks	Facebook Data For Good program	https://dataforgood.fb.com/tools/disease-prevention-maps/ (available upon request)
income pc	Total declared income divided by total number of declaring individuals	Istat	http://dati.istat.it/Index.aspx?DataSetCode=MEF_REDDITIIRPEF_COM
deprivation	(see "Materials and Methods" and (1) for detailed methodology)	SOSE	https://www.opencivitas.it/it/dataset/2016-comuni-servizi-totali-indicatori-e-determinanti-0
fiscal capacity	(see "Materials and Methods")	MEF	https://www.gazzettaufficiale.it/do/atto/serie_generale/caricaPdf?cdimg=18A07192001000101100001&dgu=2018-11-16&art.dataPubblicazioneGazzetta=2018-11-16&art.codiceRedazionale=18A07192&art.num=1&art.tiposerie=SG
inequality	Relative difference between mean and median income	MEF	Researchers can obtain it from the Italian Ministry of Economy and Finances (MEF)
real estate pc	Number of available real estates divided by total population	SOSE	https://www.opencivitas.it/it/dataset/2016-comuni-servizi-totali-indicatori-e-determinanti-0

Table S2. Available sources of data with description of the transformation process adopted

2. Human mobility data consistency

We leverage a dataset built by Facebook with proprietary methods. In particular, the number of people travelling between two locations in a given time interval is provided in two forms: a "baseline" value, that is computed as the average over the 45 days preceding day 0 of data collection (February 23rd in our case), and a "crisis" value that corresponds to near real-time data (2). A measurement is retained only if the baseline value exceeds 10, otherwise it is discarded, explaining, in the first place, why we obtain mobility data only for $\sim 1/3$ of overall Italian municipalities. In light of this, we performed a robustness check to ensure that data provides an adequate level of representativity for the real mobility between municipalities. We assessed the amount of links we might be missing due to Facebook processing pipeline by computing the number of paths for which we have at least one daily observation depending on a given threshold applied on the baseline value. In Fig. 1a-b, we show boxplots for the distribution of path coverage, in the period before (February 23th-March 8th) and after (March 10th, April 04th) the day of lockdown, respectively, i.e., for each edge we compute the percentage of days (over the entire period of observation) where we have a measurement. Missing values could be either because their value is lower than 10 or because Facebook erroneously discarded them. We also consider edges increasingly based on their value (and filtering them according to increasing thresholds). We notice that before lockdown, the median coverage is always above 75%, whereas values are slightly smaller for the period after lockdown (especially when considering smaller edges), most likely because of the effective reduction in mobility. We thus assume that the data collection is homogeneous in time and representative enough for the sake of our analysis.



a) Integrity check before lockdown b) Integrity check after lockdown

Fig. S1. Integrity check for Facebook data before and after lockdown.
We show on the x-axis the baseline threshold we use to filter edges and on the y-axis the coverage percentage for each resulting set of edges. We perform this exercise for two periods, respectively: a) Feb 23rd-March 8th, and b) March 10th-April 04th.

3. Comparison with the ISTAT baseline

We further assessed the quality of Facebook mobility data by comparing it with a baseline dataset provided by the Italian National Institute of Statistics (ISTAT, available at https://www.istat.it/it/archivio/139381). This dataset consists of a commuting network of workers/students travelling between municipalities that was recorded with the last national census (2011). Such comparison has indeed a few caveats–it only tracks residents who declared to be travelling for work/study and it is 9 years old–but we believe it is useful for a further validation the situation of Italian mobility before lockdown. We performed a few adjustments in order to make a consistent comparison. First, we filtered out those paths where the number of travelers is less than 10 (as mentioned before, Facebook uses this value as threshold to include a measurement). Secondly, we retained only municipalities that are present in our data. With regards to pre-lockdown mobility, we build an averaged graph over the 14 days before national lockdown, i.e., each edge has a weight that is the average of all the observations in that period. In both cases, we filter self-loops, which are ignored in our analyses. We obtain 2955 nodes and respectively 30,358 edges for the ISTAT network against 17,553 edges in our network. We find a significant positive correlation between Facebook and ISTAT Degree centrality distributions: Pearson $R = 0.80$ $P \sim 0$; Spearman-Rho $R = 0.64$, $P \sim 0$. We also find a significant positive correlation between Facebook and ISTAT edge weights (common to both graphs): Pearson: $R = 0.55$, $P \sim 0$; Spearman-Rho: $R = 0.37$, $P \sim 0$.

4. Centrality measures

We computed the distribution of several node centrality measures for four different snapshots of the Italian mobility network of municipalities. Each snapshot was taken over a distinct window of 7 days, from Feb 23rd to Feb 29th, from March 1st to March 7hth, from March 8th to March 14th and from March 15th to March 21st.

We observed a significant change in the distributions across time for all measures, as shown in Figs. 1-8, where we provide the Complementary Cumulative Distribution function for each week. In Table 1, we provide applications of Kruskal-Wallis test and post-hoc multiple comparison Dunn's test (with Holm's p-value adjustment).

Centrality	Kruskal-Wallis	P-value pairwise tests for different weeks					
		W1 W2	W1 W3	W1 W4	W2 W3	W2 W4	W3 W4
Degree	478.72***	7.62E-01	3.71E-07	3.39E-80	1.24E-06	8.89E-78	1.55E-42
In-Degree	471.44***	8.04E-01	1.73E-07	6.97E-79	4.49E-07	6.16E-77	8.97E-41
Out-Degree	451.76***	6.99E-01	1.60E-06	5.29E-76	7.39E-06	5.42E-73	4.08E-41
Strength	767.54***	5.02E-01	8.48E-24	5.09E-129	4.41E-21	4.01E-122	2.19E-44
In-Strength	761.47***	5.43E-01	9.35E-24	1.19E-127	2.67E-21	2.00E-121	1.19E-43
Out-Strength	724.49***	4.96E-01	9.08E-23	5.96E-122	4.42E-20	3.69E-115	1.09E-41
Clustering Cofficient	89.11***	2.21E-01	5.53E-03	5.45E-18	2.21E-01	2.07E-12	3.98E-08
Nodal Efficiency	2811.91***	1.41E-11	3.64E-119	0.00E+00	7.39E-61	0.00E+00	1.43E-141

Table S3. Application of Kruskal-Wallis and post-hoc Dunn's multiple test comparison (with Holm's pvalue adjustment).
For each centrality measures we performed a Kruskal-Wallis test to assess that the four weekly distributions are signifcantly different (* means significant at alpha=0.001), followed by a multiple pair-wise comparison test using Dunn's procedure with Holm's p-value adjustments.**

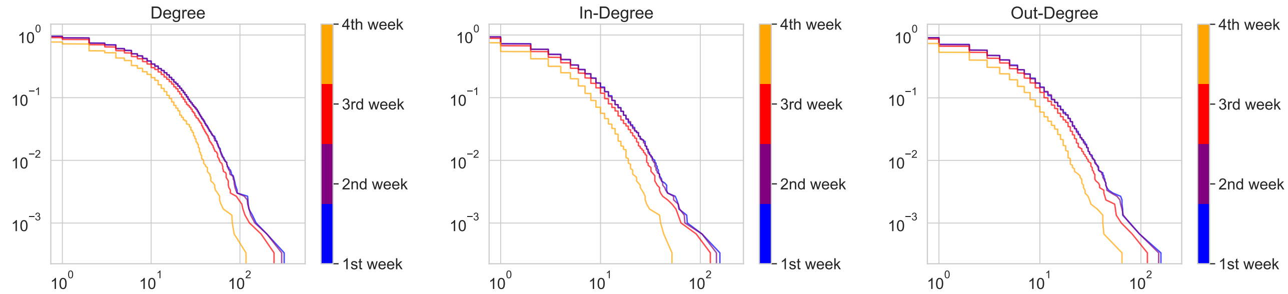


Fig. S2. Distribution of Degree, In-Degree and Out-Degree centrality over 4 consecutive weeks.

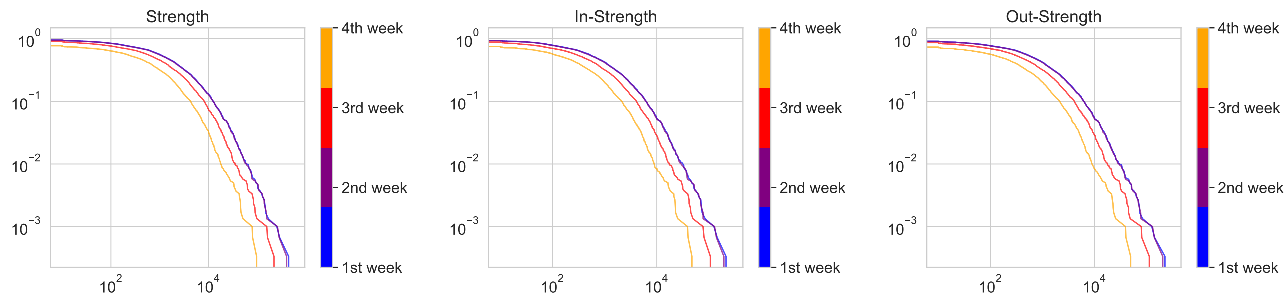


Fig. S3. Distribution of Strength, In-Strength and Out-Strength centrality over 4 consecutive weeks.

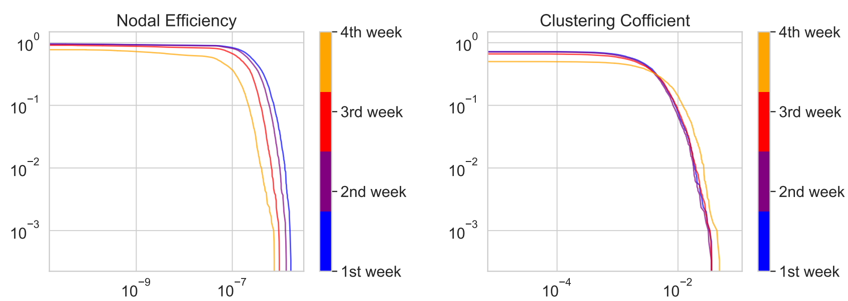


Fig. S4. Distribution of Nodal Efficiency and Clustering Coefficient over 4 consecutive weeks.

5. Correlation between variation in Nodal Efficiency, Degree and Strength

In Table 2, we show an application of Pearson, Spearman-Rho, Theil-Sen and Kendall's Tau test to assess the correlation between relative change (in percentage) between Nodal Efficiency versus Degree and Strength node centralities. We also show two relative scatter plots with a linear regression line (Figs. 10 and 11).

Centrality	Pearson	Spearman-Rho	Theil-Sen	Kendall's Tau
Degree	R=0.61 P=4.35E-300	R=0.63 P=7.10E-320	R=0.63	R=0.47 P=1.17E-303
Strength	R=0.51 P=1.42E-194	R=0.45 P=7.80E-146	R=0.65	R=0.33 P=8.96E-149

Table S4. Correlation tests between relative change (in percentage) in Nodal Efficiency versus Degree and Strength.

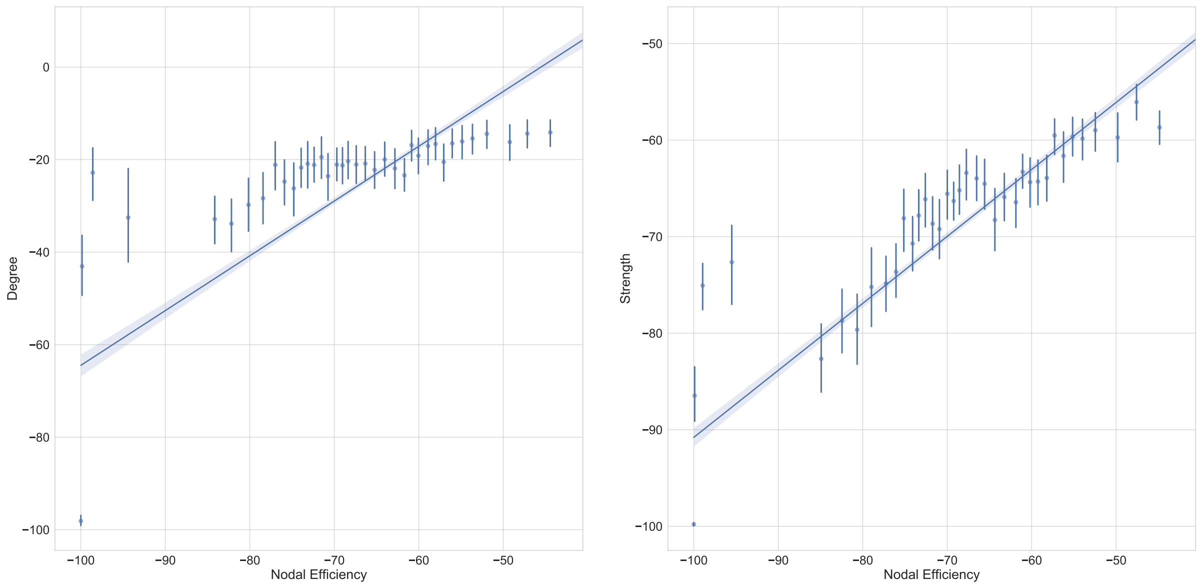


Fig. S5. Scatterplot of relative change in Nodal Efficiency versus Degree (left) and versus Strength (right). We group data points in 40 bins to ease visualization. We also show a linear fitting.

Correlation of economic indexes versus centrality measures

Correlation with centrality measures. We performed correlation exercises between the main economic indexes of interest (declared income per capita and deprivation index) and aforementioned centrality measures (using relative change in percentage). We provide applications of Pearson and Spearman-Rho test (and Theil-Sen coefficient) in Table 2. We provide scatterplots for indexes versus variation in nodal efficiency in Figure 13.

Centrality	Economic Index	Pearson	Spearman-Rho	Theil-Sen	Kendall's Tau
Irpef per Capita	In Degree	R=0.15 P=9.09E-16	R=0.07 P=1.96E-04	R=-0.00	R=0.05 P=2.49E-04
Irpef per Capita	In Strength	R=0.21 P=1.50E-29	R=0.29 P=1.45E-53	R=0.00	R=0.19 P=5.08E-53
Irpef per Capita	Out Degree	R=0.16 P=1.38E-17	R=0.08 P=3.76E-05	R=-0.00	R=0.05 P=5.53E-05
Irpef per Capita	Out Strength	R=0.23 P=2.90E-33	R=0.28 P=1.53E-50	R=0.00	R=0.19 P=3.49E-50
Irpef per Capita	Degree	R=0.18 P=1.20E-22	R=0.13 P=1.64E-11	R=0.00	R=0.09 P=3.90E-11
Irpef per Capita	Strength	R=0.23 P=1.37E-34	R=0.29 P=1.14E-57	R=0.00	R=0.20 P=2.69E-57
Deprivation Index	In Degree	R=-0.07 P=5.54E-04	R=-0.12 P=4.99E-09	R=-0.05	R=-0.09 P=1.66E-09
Deprivation Index	In Strength	R=-0.05 P=1.13E-02	R=-0.09 P=1.10E-05	R=-0.02	R=-0.07 P=3.33E-06
Deprivation Index	Out Degree	R=-0.04 P=8.64E-02	R=-0.08 P=9.35E-05	R=-0.05	R=-0.06 P=3.73E-05
Deprivation Index	Out Strength	R=-0.03 P=1.59E-01	R=-0.06 P=4.05E-03	R=-0.02	R=-0.04 P=1.81E-03
Deprivation Index	Degree	R=-0.05 P=2.95E-02	R=-0.10 P=3.89E-06	R=-0.04	R=-0.07 P=1.18E-06
Deprivation Index	Strength	R=-0.04 P=7.78E-02	R=-0.07 P=8.22E-04	R=-0.03	R=-0.05 P=3.36E-04

Table S5. Correlation tests between several centrality measures and main economic indexes used in our analysis.

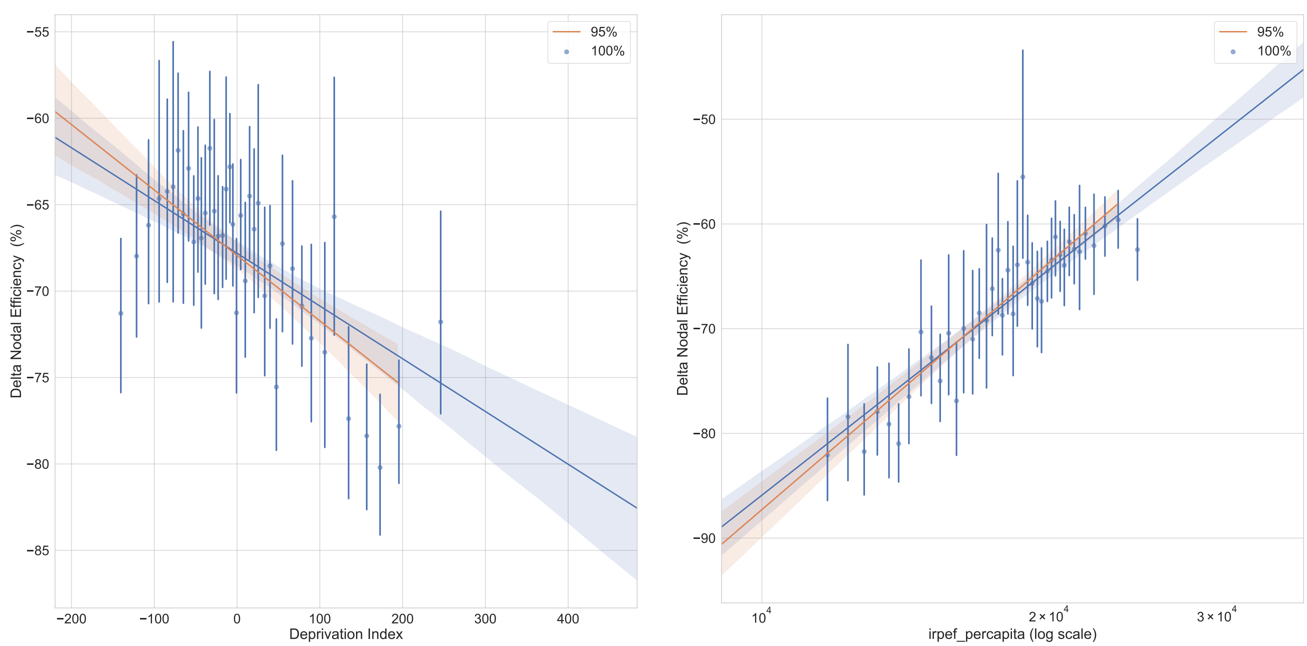


Fig. S6. Correlation of mobility reduction and variation in nodal efficiency.
Plot of the relative change in Nodal Efficiency, between pre- and post- lockdown values for each municipality, versus two different economic indexes, Deprivation Index (top) and Irpef per Capita (bottom, x-axis in logarithmic scale), respectively. For each figure, we provide two linear regression lines, one computed on the entire data (in blue) and one computed after filtering outliers w.r.t the economic index (in orange, using the 95-percentile as threshold). To ease the visualization, we draw the scatterplot by grouping points into 40 discrete bins, and showing mean and 95% confidence interval of each bin. Correlations are significantly negative (Pearson: $R = -0.153$, $P \sim 0$; S-R: $R = -0.235$, $P \sim 0$; T-S: $R = -0.064$; K-T: $R = -0.162$, $P \sim 0$) and significantly positive (Pearson: $R = 0.263$, $P \sim 0$; S-R: $R = 0.404$, $P \sim 0$; T-S: $R = 0.001$; K-T: $R = 0.273$, $P \sim 0$), respectively.

Joint distribution of mobility and economic data

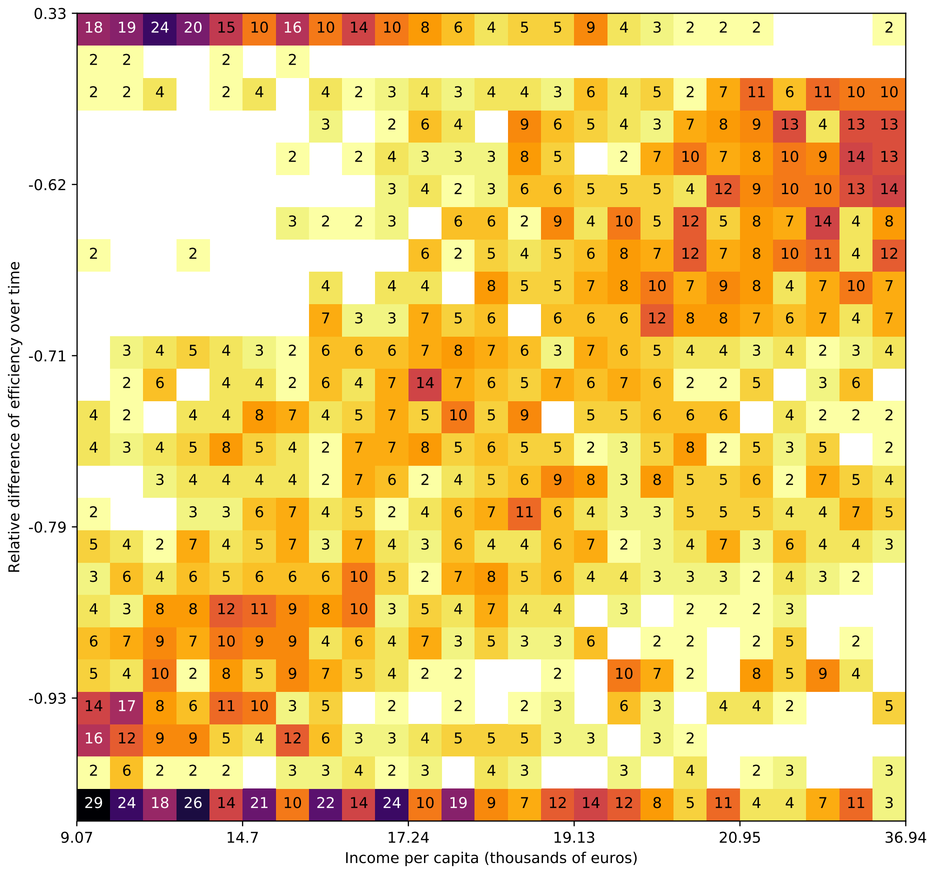


Fig. S7. Joint distribution by percentile of income and change in efficiency over time.

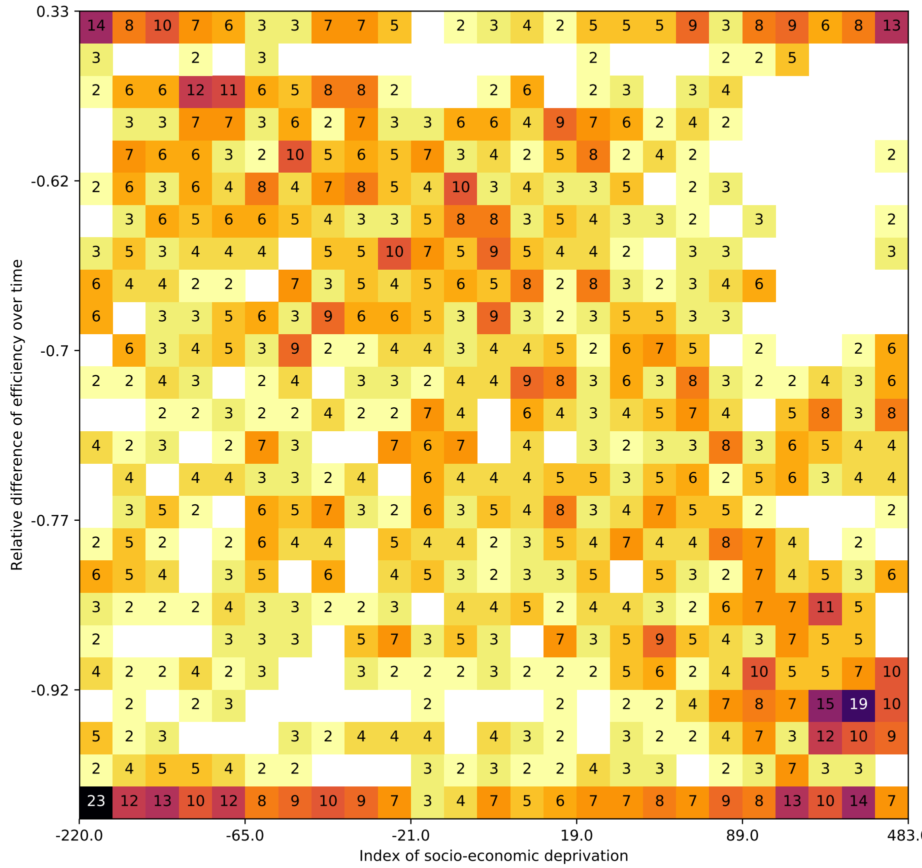
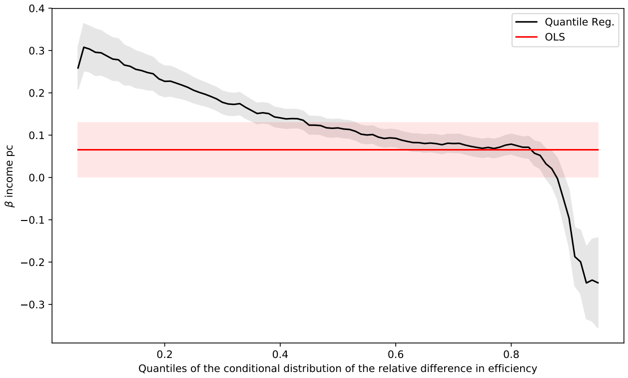
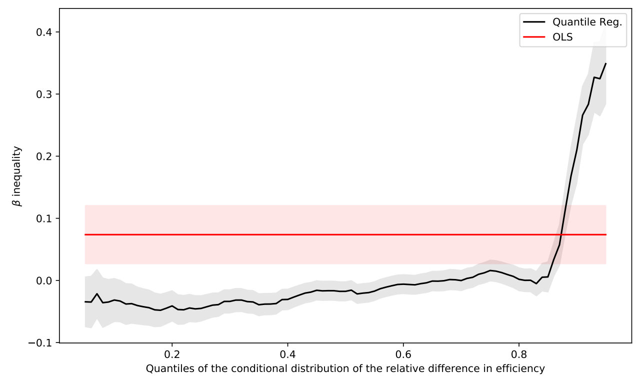


Fig. S8. Joint distribution by percentile of deprivation index and change in efficiency over time.

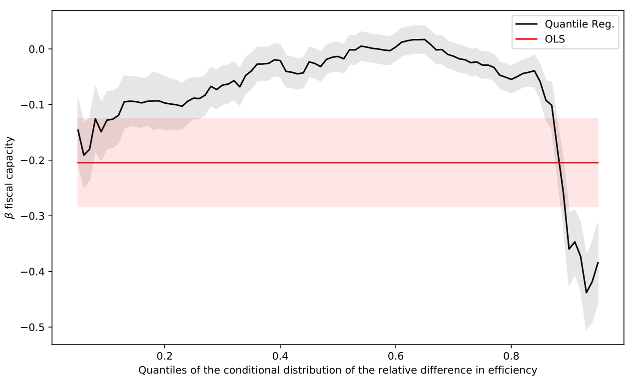
6. Quantile regression



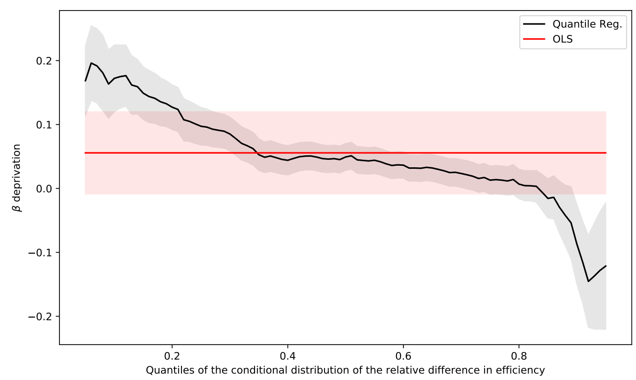
(A) Income per Capita



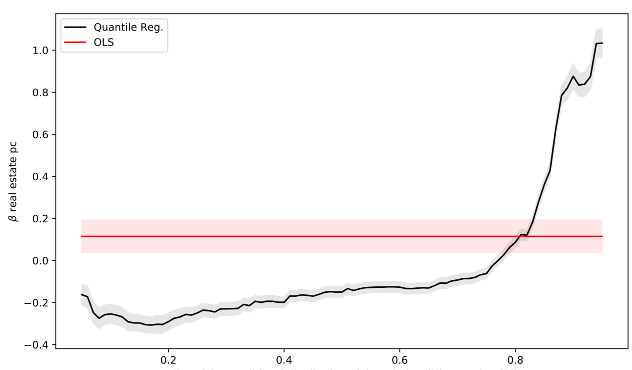
(B) Inequality of income



(C) Fiscal Capacity



(D) Index of Deprivation



(E) Real Estate pc

Fig. S9. Regression coefficients by quantile for the extended model.
Plot of the regression coefficients for each percentile of the relative change in nodal efficiency over time for three of the main independent variables: Income per Capita (A), income Inequality (B), Fiscal capacity (C), Index of Deprivation (D), Real Estate per Capita (E). For each figure, the coefficient of the quantile regression is plotted in black lines with bootstrapped confidence intervals at 95%, as a reference, the OLS regression of the same variables is plotted in red.

q	intercept	income pc	deprivation	fiscal capacity	inequality	real estate pc	(pseudo)R2
0.05	-0.8398***	0.2587***	0.1686***	-0.1461***	-0.0344*	-0.1622***	0.05223
	(0.0491)	(0.0253)	(0.0276)	(0.0286)	(0.0204)	(0.0251)	
0.1	-0.5089***	0.2871***	0.1723***	-0.1280***	-0.0315*	-0.2539***	0.17578
	(0.0456)	(0.0260)	(0.0266)	(0.0261)	(0.0177)	(0.0232)	
0.2	-0.2241***	0.2272***	0.1272***	-0.0972***	-0.0410***	-0.2907***	0.29896
	(0.0317)	(0.0187)	(0.0179)	(0.0242)	(0.0125)	(0.0206)	
0.5	0.1394***	0.1171***	0.0492***	-0.0135	-0.0175**	-0.1500***	0.26163
	(0.0189)	(0.0107)	(0.0107)	(0.0132)	(0.0078)	(0.0130)	
0.8	0.3770***	0.0788***	0.0068	-0.0548***	0.0018	0.0868***	0.14346
	(0.0199)	(0.0121)	(0.0117)	(0.0123)	(0.0094)	(0.0133)	
0.9	0.8644***	-0.0962***	-0.0868***	-0.3598***	0.2099***	0.8759***	0.20012
	(0.0523)	(0.0347)	(0.0319)	(0.0335)	(0.0269)	(0.0304)	
0.95	1.2128***	-0.2489***	-0.1214**	-0.3844***	0.3488***	1.0334***	0.24347
	(0.0761)	(0.0542)	(0.0506)	(0.0362)	(0.0329)	(0.0345)	
OLS	0.1098*	0.0654**	0.0557*	-0.2045***	0.0737***	0.1145***	0.09001
	(0.0576)	(0.0327)	(0.0328)	(0.0404)	(0.0239)	(0.0398)	

(a) Economic variables

q	reg_1	reg_2	reg_3	reg_4	reg_5	reg_6	reg_7	reg_8	reg_9	reg_10	reg_11	reg_12	reg_13	reg_14	(pseudo)R2
0.05	-0.0932	0.3689***	0.1964*	0.1325**	-0.1879**	-0.2542**	-0.2845***	-0.2530***	-0.2861***	-0.5335***	-0.2870***	-0.3779***	-0.4473***	-0.5938***	0.05223
	(0.0600)	(0.0629)	(0.1099)	(0.0671)	(0.0740)	(0.1187)	(0.0920)	(0.0724)	(0.0986)	(0.1462)	(0.1094)	(0.0998)	(0.1328)	(0.1131)	
0.1	-0.2473***	0.4354***	-0.0817	0.0969	-0.3698***	-0.3542***	-0.3492***	-0.4276***	-0.4816***	-0.6444***	-0.5175***	-0.5890***	-0.7631***	-0.8529***	0.17578
	(0.0571)	(0.0607)	(0.1008)	(0.0634)	(0.0688)	(0.1078)	(0.0891)	(0.0717)	(0.0956)	(0.1406)	(0.0978)	(0.0955)	(0.1243)	(0.1056)	
0.2	-0.3221***	0.3025***	-0.1982***	0.1384***	-0.2229***	-0.3834***	-0.3099***	-0.4749***	-0.6979***	-0.8076***	-0.4982***	-0.7460***	-0.9494***	-1.0026***	0.29896
	(0.0405)	(0.0425)	(0.0704)	(0.0449)	(0.0486)	(0.0721)	(0.0619)	(0.0506)	(0.0647)	(0.0971)	(0.0671)	(0.0661)	(0.0843)	(0.0740)	
0.5	-0.3412***	0.2254***	-0.3297***	0.0968***	-0.2263***	-0.4289***	-0.3961***	-0.4394***	-0.8264***	-0.8182***	-0.3381***	-0.7383***	-1.0093***	-1.1624***	0.26163
	(0.0245)	(0.0259)	(0.0431)	(0.0275)	(0.0300)	(0.0443)	(0.0378)	(0.0310)	(0.0386)	(0.0573)	(0.0398)	(0.0406)	(0.0503)	(0.0437)	
0.8	-0.2706***	0.2600***	-0.3589***	0.0973***	-0.1449***	-0.4862***	-0.0062	-0.3609***	-0.8504***	2.6858***	-0.2499***	-0.5961***	2.6744***	-0.9684***	0.14346
	(0.0258)	(0.0276)	(0.0450)	(0.0287)	(0.0315)	(0.0463)	(0.0400)	(0.0336)	(0.0404)	(0.0611)	(0.0400)	(0.0440)	(0.0514)	(0.0478)	
0.9	-0.2940***	0.2198***	0.1769	0.1191	0.4281***	1.1428***	-0.0082	-0.0430	-0.9882***	1.9893***	0.9368***	0.2602**	1.8604***	1.6716***	0.20012
	(0.0671)	(0.0705)	(0.1194)	(0.0768)	(0.0811)	(0.1261)	(0.1038)	(0.0905)	(0.1085)	(0.1570)	(0.1115)	(0.1132)	(0.1480)	(0.1282)	
0.95	-0.2105**	0.2525**	0.4708**	0.1620	1.1993***	1.2534***	0.8698***	0.0467	-0.8832***	1.7031***	1.1913***	1.3511***	1.7371***	1.7002***	0.24347
	(0.0994)	(0.1057)	(0.1877)	(0.1130)	(0.1145)	(0.1956)	(0.1489)	(0.1311)	(0.1581)	(0.2359)	(0.1684)	(0.1622)	(0.2336)	(0.1987)	
OLS	-0.2290***	0.3035***	0.1136	0.2229***	0.0465	-0.0749	-0.1879	-0.3326***	-0.7918***	-0.2630	-0.1500	-0.4551***	0.1752	-0.7034***	0.09001
	(0.0749)	(0.0791)	(0.1314)	(0.0839)	(0.0915)	(0.1352)	(0.1153)	(0.0946)	(0.1177)	(0.1750)	(0.1214)	(0.1239)	(0.1536)	(0.1333)	

(b) Regional controls

Table S6. Extended results for quantile regression of the relative difference of efficiency over time with respect to income per capita with multiple controls. In Table S6a, we report results for social and financial distress in the municipality (deprivation and fiscal capacity), concentration of estates (real estate pc) and income inequality. In Table S6b, we report results for regional controls where Lombardy constitutes the baseline region (see Table S7 for regional codes). Regression obtained with the Iterative Weighted Least Squares method on standardized variables. Standard errors reported in parenthesis are calculated via bootstrap with 1000 iterations. Pseudo R2 are obtained via McFadden's method. Bottom line shows OLS regression as a reference. Number of observations: 2345. *** **p < 0.01,** ** **p < 0.05,** * **p < 0.1**

References

1. Caranci N, et al. (2010) The Italian deprivation index at census block level: definition, description and association with general mortality. *Epidemiologia E Prevenzione* 34(4):167–176.
2. Maas P, et al. (2019) Facebook disaster maps: Aggregate insights for crisis response and recovery in *Proceedings of the 16th International Conference on Information Systems for Crisis Response and Management (ISCRAM), Valencia, Spain. 2019*.

	Regional codes
Piedmont	reg_1
Veneto	reg_2
Liguria	reg_3
Emilia-Romagna	reg_4
Tuscany	reg_5
Umbria	reg_6
Marche	reg_7
Lazio	reg_8
Abruzzo	reg_9
Molise	reg_10
Campania	reg_11
Apulia	reg_12
Basilicata	reg_13
Calabria	reg_14

Table S7. Regional codes for quantile regression results.