Title: “Balancing health and economic impacts from targeted pandemic restrictions”
Authors: Giovanni Bonaccorsi, Francesco Scotti, Andrea Flori and Fabio Pammolli
Journal: Journal of Evolutionary Economics
Publisher: Springer Nature
Year: 2023
Doi: https://doi.org/10.1007/s00191-023-00834-6

Journal of Evolutionary Economics
https://doi.org/10.1007/s00191-023-00834-6

REGULAR ARTICLE

Balancing health and economic impacts from targeted pandemic restrictions

Giovanni Bonaccorsi[1] · **Francesco Scotti**[1] · **Andrea Flori**[1] · **Fabio Pammolli**[1]

Accepted: 27 July 2023
© The Author(s) 2023

Abstract

The COVID-19 pandemic has highlighted the necessity for policymakers to design interventions that allow to promptly resume economic activities while taking control of the healthcare emergency. We analyze the response of differentiated policy measures by exploiting a meta-population SEIR model based on transaction data that map human mobility through daily physical transactions performed by cardholders of a major Italian bank. We calibrate multiple counterfactual scenarios and study the impact of alternative combinations of tailored mobility restrictions with different intensity across sectors. Although the Retail sector accounts for the largest portion of mobility and drive results in terms of infections and consumption dynamics, other economic activities, such as those related to Restaurants, have a relevant role in the design of the optimal policy. Finally, we show how the proposed approach can be used by policymakers to evaluate the trade-off between economic and healthcare impacts by identifying the alternative policy restrictions that minimize either the economic impact given a certain level of infections or the spread of contagion for a target value of economic impact.

Keywords COVID-19 · SEIR model · Consumption · Economic impact · Sector

JEL Classification E21 · I18 · J17

✉ Giovanni Bonaccorsi
giovanni.bonaccorsi@polimi.it

Francesco Scotti
francesco.scotti@polimi.it

Andrea Flori
andrea.flori@polimi.it

Fabio Pammolli
fabio.pammolli@polimi.it

[1] Department of Management, Economics and Industrial Engineering, Politecnico di Milano, Via Raffaele Lambruschini, Milan 20156, Italy

1 Introduction

The 2020 SARS-COV-2 pandemic has represented the most serious health threat in the last 100 years (Huang et al. 2020), involving all world countries with a total number of 5.94 million reported deaths at the global level attributed to the virus outbreak between January 2020 and December 2021 (Dong et al. 2020; Dobson et al. 2020).

As a consequence, besides isolating themselves from other countries by forbidding international travel, during 2020 and in the first half of 2021, national governments resorted to implementing non-pharmaceutical interventions (NPIs) to slow down the diffusion of the virus and reduce the death toll among most susceptible cohorts of citizens (Davies et al. 2020; Flaxman et al. 2020).

Strong and generalized restriction policies have been shown to be effective in containing the virus (Chinazzi et al. 2020; Dehning et al. 2020; Kraemer et al. 2020; Li et al. 2020; Brauner et al. 2021). However, they entail significant economic losses for the affected population whose work and consumption patterns are substantially disrupted, with the real world gross domestic product (GDP) of G20 countries falling by 3.4% during the first quarter of 2020 with respect to the previous quarter according to OECD.[1]

Moreover, strong and generalized restrictive policies have been shown to enhance previous inequalities among territories (Adams-Prassl et al. 2020; Blundell et al. 2020; Hacıoğlu-Hoke et al. 2021; Iacobucci 2020; Jay et al. 2020; Bonaccorsi et al. 2020; Chang et al. 2021), leading to protests (Pavlik 2020) and weaker compliance of individuals toward restrictions (Barrios et al. 2021; Gollwitzer et al. 2020; Wright et al. 2020).

The timing and stringency of the implemented NPIs have differed across countries. In the first months of the pandemic, countries have converged toward very restrictive containment policies, including school and workplace closures, in response to or even anticipating the diffusion of the virus. However, after the first phase of coordinated and generalized restrictions, several countries differentiated their approach along two main dimensions. First, some countries introduced economic relief programs, recognizing a strong and unevenly distributed impact of restrictions on labor and economic conditions. Second, when the number of infected individuals started to grow again during the second part of 2020, several countries adopted a targeted territorial approach instead of a generalized one, recognizing that the diffusion of the contagion exhibits notable territorial differences (Allain-Dupré et al. 2020; Bertuzzo et al. 2020; Chinazzi et al. 2020; Iacobucci 2020) that must be addressed with different intensity.

Interestingly, the adoption of targeted restrictions during the second phase of the pandemic suggests that generalized national lockdowns, while widely effective, entail unsustainable economic trade-offs for unaffected individuals and hence can be recommended only for short periods of time, during which contagion is out of control and public health objectives are of primary importance. As a consequence several works (Baqaee et al. 2020a; Haffajee and Mello 2020; Scala et al. 2020; Acemoglu et al. 2021; Bonaccorsi et al. 2021; Cont et al. 2021; Davies et al. 2021; Birge et al. 2022; Kretzschmar et al. 2022) suggest targeted restrictions as the optimal policy

[1] https://www.oecd.org/sdd/na/g20-gdp-growth-Q1-2020.pdf.

response. In fact, immediate and localized lockdowns as the one observed in Wuhan or in specific Asian territories (such as Singapore, Hong Kong and Taiwan[2]) are difficult to replicate for extended areas, while policy responses tailored on the severity of contagion and on the socio-economic features of territories may instead constitute a sustainable response for pandemic events, even though with some caveats (Holtz et al. 2020; Chandrasekhar et al. 2021).

Despite the effort to highlight the detrimental and unequal socio-economic consequences related to generalized restrictions (Adams-Prassl et al. 2020; Blundell et al. 2020; Bonaccorsi et al. 2020; Tisdell 2020; Hacıoğlu-Hoke et al. 2021), there are only a few empirical studies analyzing how targeted restrictions can entail a more sustainable trade-off between public health and socio-economic objectives (Bargain and Aminjonov 2020; Spelta et al. 2020; Kochańczyk and Lipniacki 2021; Galanis and Hanieh 2021; Bonfiglio et al. 2022).

Moreover, several models at the intersection of epidemiology and economics often do not explicitly introduce interventions targeted toward specific sectors and/or territories and focus instead on differentiating intervention by age or infectious status inside the population (Acemoglu et al. 2021; Makris 2021). This is in part due to the adoption of models where the use of mobility data is limited or where the population is assumed to mix homogeneously, hence preventing the introduction of a precise channel to model targeted restrictions. However, current literature on COVID-19 has strongly highlighted the role of mobility as a relevant dimension for the control of COVID-19 diffusion (Flaxman et al. 2020; Kraemer et al. 2020; Maier and Brockmann 2020; Brauner et al. 2021; Nouvellet et al. 2021; Franks et al. 2022) and we believe that to assess more precisely the diffusion of contagion and the socio-economic consequences of such policy interventions, it is worth introducing additional complexity in the models and adopt mobility-based analyses.

Finally, due to the lack of precise and real-time data on both the economic and public health effects of restrictions, models often rely on data with insufficient granularity and on simplifying assumptions. However, a growing stream of research (Andersen et al. 2020; Bounie et al. 2020; Carvalho et al. 2020; Chetty et al. 2020; Sheridan et al. 2020; Chen et al. 2021; Hacıoğlu-Hoke et al. 2021; Kubota et al. 2021; Vavra 2021) has shown the relevance of the use of granular transaction data to track the evolution of the pandemic and assess heterogeneous responses of different economic sectors. Among these, several contributions have also shown the importance of studying consumption patterns during pandemic events (Baker et al. 2020; Dong et al. 2021; Dietrich et al. 2022), since they represent the largest share of countries' GDP and have been shown to promptly react to restrictions, constituting a reliable first proxy of the economic impact of policy intervention. Furthermore, the growing availability of data is becoming an invaluable resource to design rapid response during epidemic events (Scotti et al. 2022; Zelner and Eisenberg 2022) and we believe that this approach should be mirrored also in economic analyses.

Against this background, we rely on a novel dataset of transactions from a major Italian bank to assess both the epidemic and economic impacts of targeted restrictions in Italy during the second phase of the pandemic. Our proposed approach exploits the

[2] https://www.nytimes.com/2020/03/17/world/asia/coronavirus-singapore-hong-kong-taiwan.html.

fact that restrictions targeting the mobility of individuals simultaneously affect both their patterns of consumption and their social interactions. Such a dataset tracks physical transactions on a daily basis over the entire Italian territory allowing to disentangle the business category of the merchant. Hence, we leverage aggregate information related to the merchant category, location and number of transactions to infer the mobility network of individuals moving for consumption reasons and train a SEIR epidemiological model in line with Chang et al. (2021) on this bipartite network, accurately fitting the observed dynamics of infected individuals. We then use such calibrated model to run multiple counterfactual scenarios regarding the adoption of differentiated policy interventions and study the impact of alternative combinations of restrictions across sectors both in terms of contagion and consumption patterns.

We illustrate the functioning of our approach for the case of the Lombardy region as it represents the Italian region most severely hit by the COVID-19 pandemic. Indeed, at the end of 2020, it accounted for more than 22% of total national infections and almost 34% of the overall number of deaths. Furthermore, with around 10 million inhabitants it is the most populated region in Italy, the territory producing the largest share of GDP in the country (more than 20%) and the richest area with the highest GDP per capita. We find that mobility restrictions bring out a trade-off between the containment of the pandemic and the contraction of consumption, with more stringent policies allowing to shrink the spread of the virus at the cost of reduced economic activity. Furthermore, we show that alternative policy interventions with different restriction intensity across sectors generate heterogeneous results, suggesting that, in correspondence with target values of infections or consumption reduction, some combinations of policy restrictions across sectors can be preferred with respect to the other dimension. In addition, we highlight the pivotal role of the Retail sector in our framework by exhibiting a resurgence of infections and resumption of economic consumption as restrictions are progressively lifted in such sector. However, other sectors, such as Restaurants activities, also significantly affect infections and economic dynamics, demonstrating how carefully tailored restrictions should be designed to obtain the optimal policy outcome.

Overall, our work aims to provide policymakers with a tool that can support the definition of the restriction intensity across sectors in order to either achieve a certain level of contagion that minimizes economic losses or a target consumption reduction with the lowest number of infections.

Our results show that targeted restrictions, similarly to generalized ones, are effective against a highly infectious virus such as COVID-19. Contrary to generalized policies, however, targeted and tiered NPIs can reduce the economic impact on territories where contagion is weaker by selecting combinations of sectorial restrictions that are more favorable, allowing for a better trade-off between the economic and health objectives.

The paper is organized as follows: we first review the literature on epidemiological models applied to COVID-19 and the estimation of socio-economic impacts in Section 2. Then we introduce the data and the mobility model in Section 3.1, while Section 4 presents the calibration of the proposed approach. Section 5 shows the results of the epidemic model and discusses the trade-off between contagion and economic impact. Finally, Section 6 concludes and presents limitations and future research directions.

2 Related literature

The pressing urgency to resume business activities calls for carefully tailored containment measures aiming to balance infections and economic losses. As a consequence, researchers have developed numerous scientific works at the intersection of economics and epidemiology in order to support policymakers to identify the best trade-off between the spread of the virus and economic contraction (Atkeson 2020; Boucekkine et al. 2021; Eichenbaum et al. 2022; Fernández-Villaverde and Jones 2022).

Such studies clearly highlight how governments cannot minimize both contagions and economic downturn, as measures to keep as low as possible infections exacerbate economic results and significantly reduce national GDP at the aggregate level while re-opening business activities may trigger the resurgence of the pandemic (Jena et al. 2021; Škare et al. 2021).

These models usually employ a simple SIR epidemic structure, assuming homogeneous mixing of the population, and have been used to show that in equilibrium solutions without interventions are suboptimal and lockdowns strategies do not harm total output once health costs are accounted for. For instance, Eichenbaum et al. (2022) show that with optimal containment measures in terms of infections, the expected consumption reduction drops by 15% with respect to a scenario without social restrictions, but it allows to reduce the mortality rate from 0.40% to 0.26% with half a million of saved lives.

Despite the widespread use of SIR-based economic models, the building evidence on the epidemiological features of the SARS-CoV2 virus has led to the development of more accurate epidemiological models which have been integrated into the economic analyses. A SEIR-like model has been used by Glover et al. (2020) to show that once differences in age and sector are accounted for, optimal restriction solutions may differ according to the specific class of individuals which is targeted. Droste and Stock (2021) employ a SEIRD model to show that generalized lockdowns disproportionately affect economic activities, while low-cost mechanisms such as the usage of masks, screening tests, telework, and goods delivery replacing in-person purchases can simultaneously support the healthcare and the economic dimensions. Finally, in Aspri et al. (2021) a SEAIRD model is embedded in a framework where only realistic restrictions are available to the policymaker, showing the existence of multiple equilibria where laissez-faire is an optimal solution when the evaluation of statistical life reaches a certain threshold.

In this work, we adopt a basic SEIR model as a reference, but to better assess the development of contagion we developed a meta-population SEIR model, adapting the work of Chang et al. (2021) to the Italian case. This marks the first difference of our work with respect to the existing literature since economic analyses through meta-population models are not commonly employed, despite their popularity for epidemic predictions (Chinazzi et al. 2020).[3]

The adoption of a meta-population model entails also another difference with respect to existing models for the evaluation of the economic impact of policy intervention, which is the use of granular mobility data to model the diffusion of the virus.

[3] Among the works similar to ours we can acknowledge Fajgelbaum et al. (2021); Spelta et al. (2020).

Mobility-based models have lately been developed to account for the growing evidence on the importance of movement and contact patterns in the diffusion of contagion (Flaxman et al. 2020; Kraemer et al. 2020; Maier and Brockmann 2020). Among the recent works employing mobility-based epidemic models, we have Akbarpour et al. (2020); Azzimonti et al. (2020); Baqaee et al. (2020b); Bisin and Moro (2022); Fajgelbaum et al. (2021). However, only a few of these works employ mobility data with sufficient granularity, namely Azzimonti et al. (2020) and Fajgelbaum et al. (2021), and all of them use data to calibrate their model in a speculative manner.

Our work, on the contrary, employs granular data as input to provide accurate predictions of the contagion dynamics, which we validate by measuring the goodness of fit of our model with respect to the actual data. This data-driven approach is unique in the context of economic modeling and is more similar to other works in the epidemiology field (Chinazzi et al. 2020; Chang et al. 2021). However, we differentiate from pure epidemic modeling since we focus on the economic consequences of restrictions, studying the existence of alternative restriction scenarios where contagion is maintained fixed and the decision maker attempt to maximize the economic outcomes.

In this sense, we also contribute to a stream of literature analyzing the health-economic trade-off during the pandemic based on agents based models. Such studies highlight the need to balance mortality rates and GDP losses, with the most effective solutions involving the adoption of early containment measures and expansionary policy support packages to avoid a strong economic recession (Basurto et al. 2020; Mellacher 2020). Indeed, closing sectors with limited customer interaction, such as Construction and Manufacturing, may significantly raise unemployment, while enabling a limited contraction of the virus spread (Pangallo et al. 2022). Overall, through an integrated analysis combining the health and the economic dimensions, we thus extend previous studies just focusing on the economic impact of the lockdown in Italy (Reissl et al. 2022).

We assess the impact of alternative policy restrictions exploiting a unique database on transaction data which allows us to model simultaneously the evolution of contagion and consumption in the population as suggested in Murray (2020). This sets us apart also from other works which have recently shown the effectiveness of high-frequency transaction data for empirical analysis (Carvalho et al. 2020; Chetty et al. 2020; Scotti et al. 2023 among the many), since in these studies the data are not employed for epidemic modeling.

In addition, by analyzing the period October-December 2020, we have the opportunity to investigate the impact of tailored restrictions targeting specific sectors, thus expanding the empirical evidence produced by previous studies assessing the effect of alternative non-pharmaceutical interventions such as lockdowns and social distancing in Italy during the first wave of the COVID-19 pandemic (Delli Gatti and Reissl 2022). This is particularly relevant, considering that restrictions had heterogeneous economic effects across sectors, with Transportation, Restaurants and Tourism mainly constrained by demand shocks, while Manufacturing activities are strongly affected by supply reduction (del Rio-Chanona et al. 2020).

Other studies, introducing models with differentiation of agents with respect to age and health status (Acemoglu et al. 2021; Baqaee et al. 2020b; Farboodi et al. 2021;

Fabbri et al. 2021; Scala et al. 2020), show that targeting groups with tailored restrictions can lead to better equilibrium solution with respect to generalized restrictions. Similarly to these works our model entails differentiated restrictions, but we adopt a targeting by territory and productive sector, using the Italian pattern of restrictions as a case study (Di Porto et al. 2022). Therefore, we provide a more realistic pattern of restrictions, since targeting by health status or age has been demonstrated to be difficult in practice. In this sense our model is more similar to Baqaee et al. (2020b), Bisin and Moro (2022), Glover et al. (2020) and Kaplan et al. (2020).

Several studies have studied how modulating the intensity of restrictions may increase the effectiveness of interventions. For instance Makris (2021) identify that a good balance between economic and epidemiological results can be obtained through milder but longer restrictions in less essential sectors. This result is confirmed by Federico and Ferrari (2021) who show that the optimal containment policy should alternate a first phase without restrictions where the virus is free to spread, a second stage characterized by a strict lockdown, and a final period with less stringent measures, where the product between the reproduction number and the percentage of susceptible is kept below the threshold value of 1. Similarly to these works, we also propose restrictions with different intensity by sector.

Finally, regarding the approach to assess the economic impact of restrictions, since our data allow us to obtain a reliable measurement we adopt a conservative approach and measure economic losses directly as reduction of consumption. Indeed, by employing a similar dataset, Scotti et al. (2023) show that these transaction data are highly representative of the consumption dynamics in Italy disclosed by official statistics and can be used to study the impact of tailored restrictions by sector during Autumn 2020.

3 Materials and methods

3.1 Data

Our main variables of interest are movements associated with consumption and their corresponding monetary value spent in specific locations. We use a novel anonymized database of transactions from a major Italian bank with a market share larger by at least 15% in each Italian region. Our data measure at the municipality level the aggregate daily number and value of the transactions from all the bank card-holders to all point-of-sales (POSs) in the territory. POSs are additionally identified by their specific merchant category.

The data cover the years 2019 and 2020 without missing days and encompasses the entire Italian territory. This allows us to monitor the evolution of mobility before and after restrictions during the year 2020. In addition, we can use the data from 2019 as a reference for a period where both the effects of the COVID-19 pandemic and of the restrictions were absent. We use data regarding all transactions made in person (i.e., no online purchases). Regarding the representativity of the data as a sample of

the consumption in the Italian population, the data have been shown to closely track official statistics on consumption.[4]

We restrict the analysis to three dimensions. First, we focus on the time range from the 9th of October 2020 to the 8th of December 2020 to capture the second phase of targeted restrictions in Italy.[5] Second, we analyze only the Lombardy region, which is the richest and the most populated Italian region and has been the most affected territory during the pandemic.

Finally, to study the effect of different policy interventions, we match POS merchant categories to ATECO codes,[6] which is the sector categorization used by the Italian government to identify differentiated mobility restrictions with respect to economic activities. To simplify the analysis and maintain a computationally feasible size for the mobility matrices we map merchant categories to 3-digit ATECO codes, restricting the categories from 276 to 80 through aggregation.

Furthermore, partially inspired by policy restrictions implemented in Italy we select only a subset of relevant sectors to study.[7] Our final mapping from merchant codes to ATECO codes is the following: Retail with code 470, Restaurants with code 560, Accommodation with code 550 and Health with code 860.[8] These sectors account for 82.79%, 2.69%, 0.04% and 5.81% of total consumption across all sectors in the

[4] Scotti et al. (2023) show that our transaction data adequately match official statistics disclosed by the national office. For instance, the correlation of the share of total consumption measured by transactions at the province level with the share of GDP in the year 2020 and income for the year 2019 at the same level of aggregation is equal to 0.955 (P-value $\simeq$ 0) and 0.934 (P-value $\simeq$ 0), respectively. Furthermore, the correlation between the year-on-year growth rates of total national quarterly consumption levels calculated based on either transaction or ISTAT over the time frame 2019-2020 ranges between 0.616 (P-value = 0.103) and 0.875 (P-value = 0.004) considering consumption in the Retail, Accommodation, Restaurants and Healthcare sectors.

[5] We stop our exercise at the 8^{th} of December 2020 to avoid the effects of the Christmas holidays and of an additional policy intervention based on cashback that occurred in Italy to stimulate consumption and started on that date. During the period of differentiated policy restrictions starting from the 6^{th} of November 2020, Lombardy was classified as a high-risk region until the 28^{th} of November 2020. After that, due to the reduction of the local severity of the COVID-19 pandemic, it was classified as a medium-risk region for the remaining portion of the analyzed period (it was classified as a low-risk region starting from the 13^{th} of December 2020).

[6] ATECO codes are a hierarchical classification system used to categorize Italian economic activities. ATECO codes are consistent with NACE codes, the classification of activities used in the European Union, up to the 4^{th} digit.

[7] The DPCM n. 275 provides specific information related to differentiated restrictions targeting business activities in Italian regions characterized by low, medium and high epidemiological risk, respectively. More specifically, low-risk areas were subject to the complete closure of motion picture projection activities and the majority of activities associated with the Arts, Entertainment and Recreation sector such as theatres, libraries, museums, gambling centers, swimming pools, gyms, discos, night clubs and other leisure centers for physical well-being activities. In addition to this, medium-risk regions experienced the closure of bars and restaurants for 7 days per week, although food delivery was allowed every day until 10 p.m. More stringent restrictions were applied in high-risk regions targeting the majority of business activities within the wholesale and retail trade sector not related to the sale of primary need goods. Such closed activities encompass retail sale of textiles, retail sale of carpets, rugs, wall and floor coverings, retail sale of electrical household appliances, retail sale of music and video recordings, retail sale of watches and jewelry, and retail sale of second-hand goods. In addition, closures applied also to sports and recreation education activities.

[8] The Health sector includes also the data regarding ATECO codes 870 and 880 which refer to nursing homes and home health assistance.

considered period which corresponds to over 7.7 million bank transactions for a total associated value of approximately 390 million EUR.

3.2 The base SEIR model

The starting point in our investigation framework is the basic SEIR model, which has been the cornerstone of several epidemiological works in the literature on COVID-19 (Davies et al. 2020; Di Domenico et al. 2020; IHME COVID-19 forecasting team 2020; Kucharski et al. 2020; Prem et al. 2020). We assume that the total population N is large and constant during the period due to the rapid diffusion of the virus with respect to the natural birth/death processes in the population.

At each time t the population can be divided according to the equation:

$$N = S_t + E_t + I_t + R_t \tag{1}$$

where each letter identifies the share of the population belonging to the following compartments (or health states):

- S_t: susceptible individuals who have never been infected but can transition to the infected state upon contact with infected individuals.
- E_t: individuals who have been exposed to the virus but are not infectious yet. They transition to the infected state with a rate inversely proportional to the mean latency period, i.e. the average span of time between the moment individuals have been exposed to the virus and the moment they become infective.
- I_t: infected individuals. The duration of the infective period is inversely proportional to the mean infectious period, i.e. the average span of time until recovery or death, after which these individuals transition to the removed compartment.
- R_t: individuals who cannot be exposed and transmit the virus either because they have recovered or because they have died. Here we assume that recovery grants immunization: this is common with these types of models since we are concerned with the short-run consequences of contagion and COVID-19 recovery grants a temporary immunity from re-infection.[9]

The transition among states happens at each step t and is governed by the following set of equations:

$$\frac{dS}{dt} = -\lambda_t^b S_t \tag{2}$$

$$\frac{dE}{dt} = \lambda_t^b S_t - \mu_e E_t \tag{3}$$

$$\frac{dI}{dt} = \mu_e E_t - \mu_i I_t \tag{4}$$

$$\frac{dR}{dt} = \mu_i I_t \tag{5}$$

[9] Recent studies (Kojima and Klausner 2022) show that risk of re-infection for recovered individuals is below 1% in the first 6-8 months after infection.

where λ_t^b is the base infection rate, i.e. the rate at which susceptible individuals become infected once they have been in contact with an infected individual. Without explicit modeling on the contact patterns of individuals, we assume homogeneous mixing in the population, hence $\lambda_t^b = \beta\gamma = \beta\frac{I_t}{N_t}$, i.e. the product of the base transmission rate β and the probability of encountering infected individuals in the population γ. The base transmission rate is the probability of infection upon contact, which corresponds to the mean number of infections in a susceptible population exposed to infected individuals and is common to the entire population. γ instead is the proportion of infected individuals in the population at time t.

Furthermore, $\mu_e = \frac{1}{\delta_e}$ is the inverse of the mean latency period and $\mu_i = \frac{1}{\delta_i}$ is the inverse of the mean infectious period. Transition in each of the equations is equivalent to sampling from a Binomial distribution where the number of trials is equal to the size of the starting compartment and the success rate is equal to the transition parameter.

3.3 The metapopulation SEIR model on a bipartite network

We step away from the basic model with two changes. First, we move from a uniform population to a metapopulation model (Chinazzi et al. 2020; Chang et al. 2021; Lai et al. 2020). Adapting the framework from Chang et al. (2021) to the Italian case, individuals are additionally distributed in separate and homogeneous communities where the epidemic process is simultaneously replicated with a specific set of compartments for each sub-territory. In our case, communities represent all the Italian municipalities (the smallest administrative units in Italy) inside the same Region (the largest administrative unit in Italy). As a consequence for each municipality m_i Eq. 1 now becomes:

$$N^{m_i} = S_t^{m_i} + E_t^{m_i} + I_t^{m_i} + R_t^{m_i} \tag{6}$$

with Eqs. 2-5 now being indexed by each municipality m_i. Moreover the probability of encountering infected individuals, γ, is now different across all municipalities: $\gamma_t^{m_i} = \frac{I_t^{m_i}}{N_t^{m_i}}$, leading us to a specific parameter $\lambda_t^{m_i}$ for each m_i.

The second way our model differs from the basic SEIR model is that we introduce a mechanism through which contagion may spill across communities. Susceptible individuals may move from their communities toward other locations for consumption reasons and encounter infectious individuals, exposing themselves to the virus. Hence, if members of different communities move to the same POS for a sufficient time, then contagion may spread between them. Moreover, we restrict mobility to movements for consumption reasons only, since they represented an important driver of differentiated policy restrictions in Italy for the period we are considering.[10]

We define the municipality-POS network $G = (M, P, E)$ as a bipartite network with two disjointed sets of nodes, one corresponding to municipalities M and the other to POS P. Two nodes m_i, p_j are connected if an individual from municipality m_i has made a purchase in POS p_j at time t, with each POS being characterized by

[10] Additional information related to the implementation of differentiated policy restrictions in Italy refer to the DPCM n. 275 and are available at the following link: https://www.gazzettaufficiale.it/eli/gu/2020/11/04/275/so/41/sg/pdf.

a geographic position and a specific merchant category. POS nodes are characterized by unique categories, hence all money spent in a specific POS is assumed to refer to a single category only. Furthermore, connections among nodes of the same type (i.e., among nodes inside the set M or P) are not allowed: two communities m_i and m_j are never directly connected, their members can meet only by visiting the same POSs at the same time.

Aggregating the number of all purchases from individuals from a specific node m_i to a specific node p_j at a certain time t we obtain a weighted municipality-POS network where edges represent the number of individuals moving for consumption reasons related to a specific product category, hence the mobility bipartite network. Aggregating instead the value of all purchases for the same pair, we obtain a weighted municipality-POS network where edges represent the amount spent by individuals of municipality m_i on the product category in POS p_i, the consumption bipartite network.

We represent the two networks with two weighted adjacency matrices where the elements w_{ij} and v_{ij} in each matrix represent the number of transactions and the amount spent by individuals from the municipality i in the specific POS j at time t, respectively:

$$\mathbf{B}_t^{mov} = \left\{ w_t^{ij} \right\}^{M \times P} \quad \text{with} \quad w_t^{ij} \in \mathbb{R}_{\geq 0} \tag{7}$$

$$\mathbf{B}_t^{cons} = \left\{ v_t^{ij} \right\}^{M \times P} \quad \text{with} \quad v_t^{ij} \in \mathbb{R}_{\geq 0} \tag{8}$$

The empirical matrices $\mathbf{B}_t^{mov}$ and $\mathbf{B}_t^{cons}$ have $M = 1220$ rows corresponding to the set of municipalities in Lombardia from which individuals move for consumption reasons and $P = 3842$ columns corresponding to POSs located in the territory which are the destinations of movements. Each POS is localized in a specific municipality, however not all POSs are present in all municipalities, hence $P < 4 \cdot M$. In particular, the distribution of POSs by sector in our analysis is 1157 Retail, 1135 Restaurants, 685 Accommodation, 865 Health. The mobility related to each sector differs from one of the others not only regarding the number of affected POSs but also by the specific number of individuals moving for consumption reasons, which is affected by the habits of individuals and by the effect of government intervention. Figure 4 shows the evolution over time of the number of transactions (i.e., individuals moving for consumption reasons) in all the 4 sectors we analyze, during 2019 and 2020, reported as a percentage of the maximum. We can observe that the Retail and Health sectors are less affected by the introduction of restrictions while mobility related to the Restaurants and Accommodation sectors is heavily affected. Finally, we observe also a good correlation between our empirical matrices and other sources of mobility that have been used to model COVID-19 contagion, namely Google Mobility reports. [11]

[11] More precisely: we have compared the year-on-year variation of the Retail sector with the "Supermarket and pharmacy" category and the year-on-year variation of the Restaurant sector with the "Retail and recreation" category of Google mobility reports obtaining correlation coefficients of 0.89 and 0.93, both significant at 0.01 level. Google mobility reports define the "Supermarket and pharmacy" category as "Mobility trends for places such as supermarkets, food warehouses, farmers markets, specialty food shops and pharmacies.", and the "Retail and recreation" category as "Mobility trends for places such as restaurants, cafés, shopping centers, theme parks, museums, libraries and cinemas."

Our measurements are collected daily, however, to simulate the actual dynamics of POS visits, we use the hour as the time reference by distributing daily visits and expenditures in three time frames of 8 h each, corresponding to 10%, 60%, and 30% of daily transactions. Finally, within each time frame, we distribute visits and expenditures evenly to obtain hourly matrices.

Introducing mobility among communities in the basic SEIR model affects the probability of susceptible individuals being exposed to the virus, which now may happen in their origin territory or in a POS in another territory (with a potentially different rate of infection).

As a consequence, Eqs. 2-3, which regulate the transition of an individual into the exposed and infected states, must be updated as follows:

$$\frac{dS^{m_i}}{dt} = -\lambda_t^{m_i} S_t^{m_i} - \Lambda_t^{m_i} \frac{S_t^{m_i}}{N^{m_i}} \tag{9}$$

$$\frac{dE^{m_i}}{dt} = \lambda_t^{m_i} S_t^{m_i} + \Lambda_t^{m_i} \frac{S_t^{m_i}}{N^{m_i}} - \mu_e E_t \tag{10}$$

In both equations, we observe a first term reflecting new exposures arising from municipality-specific local contagion ($\lambda_t^{m_i} S_t^{m_i}$). The second term instead represents exposures imported from visits to POSs for consumption reasons ($\Lambda_t^{m_i} \frac{S_t^{m_i}}{N^{m_i}}$).

Specifically, the rate of contagion deriving from visiting external POSs, $\Lambda_t^{m_i}$, depends on the number of individuals moving from municipality m_i to visit POS p_j at time t, w_t^{ij}, i.e., the element i, j in $\mathbf{B}^{mov}$. Among the w_t^{ij} visitors only a fraction $\frac{S_t^{m_i}}{N^{m_i}}$ would be susceptible to being exposed to the infection with a time- and POS-specific rate of infection equal to $\lambda_t^{p_j}$. As was the case with the base model, the new cases from each POS are sampled from a Binomial distribution with a number of trials equal to $w_t^{ij} \frac{S_t^{m_i}}{N^{m_i}}$ and success probability equal to $\lambda_t^{p_j}$. However, since the first parameter is sufficiently large and the rate of infection is sufficiently small we can approximate the Binomial distribution with a Poisson with a rate equal to $w_t^{ij} \frac{S_t^{m_i}}{N^{m_i}} \lambda_t^{p_j}$ and obtain the sum of all new cases from POS exposures as a single sample from a Poisson with parameter[12]:

$$\eta_{m_i} = \frac{S_t^{m_i}}{N^{m_i}} \Lambda_t^{m_i} = \frac{S_t^{m_i}}{N^{m_i}} \sum_{j=1}^{P} w_t^{ij} \lambda_t^{p_j} \tag{11}$$

As with the base case, $\lambda_t^{p_j}$, is the product of the transmission rate and the probability of encountering infected individuals in the population. However, both terms now

[12] A distribution $Y \sim \text{binomial}(n, p)$ can be approximated by a distribution $Y \sim \text{Poisson}(\lambda)$ with $\lambda = np$ if the number of trials of the distribution, n, is large and the product between the success rate, p, and n is small (see Example 2.3.13 in Casella and Berger (2021), for instance). Usual rules of thumb for these values are $n \geq 100$ and $np \leq 10$, which hold in our case.

depend on the specific POS visited by the individual, with a POS-specific transmission rate $\beta_t^{p_j}$ and a share of infected individuals encountered depending on the total number of visitors from all municipalities:

$$\lambda_t^{p_j} = \beta_t^{p_j} \frac{I_t^{p_j}}{\sum_{i=1}^{M} w_t^{ij}} \tag{12}$$

Moreover, we model $\beta_t^{p_j}$ as a function of the structural characteristics of each POS, ϕ^{p_j}, of the number of visitors it receives and of a base transmission constant τ, equal for all POSs:

$$\beta_t^{p_j} = \tau \phi^{p_j} \sum_{i=1}^{M} w_t^{ij} \tag{13}$$

The structural characteristics of POS can be defined as $\phi^{p_j} = \frac{l^{p_j^2}}{a^{p_j}}$, i.e. as the ratio of two factors affecting the density of visitors in the POS. The first factor is the average length of time a visitor stays in the POS, l^{p_j} which has a quadratic effect on ϕ^{p_j} since it affects both the probability of two visitors to be simultaneously in the same POS and the time duration visitors remain exposed to each other. The second factor is the surface area of the POS, a^{p_j}, which affects the closeness of visitors and hence has an inverse effect. Smaller POSs, where visitors use to stop for a longer time, are those where the transmission rate is higher.

Finally, the probability of a random visitor encountering an infectious individual, $I_t^{p_j}$, depends on the number of visitors from all municipalities and on the share of infected individuals among them:

$$I_t^{p_j} = \sum_{k=1}^{M} w_t^{kj} \frac{I_t^{m_k}}{N_t^{m_k}} \tag{14}$$

All in all, for a given municipality m_i, the number of individuals moving from the susceptible state to the exposed one due to a visit to POS can be modeled as a Poisson distribution with parameter η_{m_i} equal to:

$$\eta_{m_i} = \frac{S_t^{m_i}}{N^{m_i}} \Lambda_t^{m_i} = \frac{S_t^{m_i}}{N^{m_i}} \tau \sum_{j=1}^{P} w_t^{ij} \phi^{p_j} \sum_{k=1}^{M} w_t^{kj} \frac{I_t^{m_k}}{N_t^{m_k}} \tag{15}$$

We initialize the model assuming that no infections and recoveries have occurred, $I_0^{m_i}$, $R_0^{m_i}$. This is a simplification, since, as we show in the next section, our period of analysis relates to the last part of 2020 when daily infections were at a low level but not absent. However, using initial empty compartments for infected and recovered has the advantage that we can evaluate all the results of the model as separate from the past development of the virus, at the price of a small initial mismatch between the model estimates and the actual number of cases. Furthermore, we compensate for this simplification by allowing the initial share of exposed individuals, p_0, to be a large percentage and we initialize their compartment with a sample from a Binomial with a size equal to the municipality population and success rate p_0. The initial number of

susceptible individuals is finally obtained as the difference between the total population in the municipality and the number of initially exposed individuals: $S_0^{m_i} = N^{m_i} - E_0^{m_i}$.

3.4 Targeted government interventions

In our framework, we assume that vaccines are not available since we want to study the impact of non-pharmaceutical interventions (NPIs). As a consequence, the only way the government can intervene to limit the spreading of the contagion is by reducing the number and riskiness of interactions among individuals. Furthermore, in our model, we introduce only one type of NPIs, namely social distancing, and we do not model the impact of other types such as mask mandates.

Then, the mobility-based metapopulation SEIR model allows us to model in a very transparent way the introduction of NPIs. In fact, the main channel adopted by the Italian government to impose social distancing was the regulation of movements for work and consumption reasons, differentiating the severity of restrictions between essential and non-essential sectors.

Hence, without requiring any additional assumption, government interventions are introduced in the model through the variation in the matrix $\mathbf{B}_t^{mov}$ that, after the introduction of restrictions, will reflect directly the reduction of mobility due to NPIs and will impact the number of infections through the parameter v_i.

Furthermore, since mobility restrictions in Italy have been targeted to specific sectors, through the specific bipartite structure of the $\mathbf{B}_t^{mov}$ matrix we can model restrictions hitting only specific categories of POSs (i.e., specific columns in the matrix $\mathbf{B}_t^{mov}$) while leaving other sectors unaffected.

Let $\tilde{\mathbf{p}}_t$ be the set of targeted sectors at the time of restrictions, t_r, we now define the updated mobility adjacency matrix as:

$$\tilde{\mathbf{B}}_t^{mov} = \left\{ \tilde{w}_t^{ij} \right\}^{M \times P} \tag{16}$$

$$\tilde{w}_t^{ij} = \begin{cases} (1 - \pi_t^{rj}) w_t^{ij}, & \text{if } j \in \tilde{\mathbf{p}}_t \\ (1 - \pi_t^{sj}) w_t^{ij}, & \text{otherwise} \end{cases} \tag{17}$$

$$w_t^{ij} \in \mathbb{R}_{\geq 0}, \pi_t^{sj} \in \{0, 1\}, \pi_t^{rj} \in (0, 1], t \geq t_r \tag{18}$$

Hence, the number of individuals moving for consumption reasons from a certain municipality i to a specific POS j will be a strictly smaller fraction of the number of individuals moving before restrictions ($\pi_t^{rj} > 0$); in addition, the mobility behavior in non-targeted sectors may also react to restrictions with a spontaneous non-negative rate of reduction ($\pi_t^{sj} \geq 0$). Furthermore, by assuming π_t^{rj} is not strictly equal to 1 we allow for a certain degree of non-compliance (which is suggested by the data we will use to calibrate the model). Finally, we allow for varying rates of reductions across sectors to model their different sensitivity toward mobility restrictions.

Regarding the timing of restrictions, there have been two different approaches to social distancing in Italy before the massive introduction of vaccines in the first quarter of 2021. We can identify a first phase starting in March 2020 and ending in June 2020, where contagions needed to be addressed rapidly and effectively through a

national lockdown due to a high mortality rate, especially in the elderly population. In this phase, productive sectors were divided among essential and non-essential ones, with the latter allowed to operate only remotely. Importantly, restrictions were applied regardless of the level of local contagion. When infections started to rise again after summer 2020, new restrictions were required and a second phase started in autumn. In this second phase, restrictions were differentiated among Italian regions and graduated with respect to the severity of contagion inside each region. Starting from the 6^{th} of November 2020, three levels of risk (low, medium and high) were identified through multiple contagion indicators. Moreover, three regional regimens were devised (yellow, orange and red zones) corresponding to an increasing reduction of movements across territories and an enlarged number of productive sectors which were required to be closed or affected by limitations in their economic activities.

In this work, we focus on the second phase of Italian restrictions. Moreover, since targeted restrictions in the second phase were region-specific, we illustrate the functioning of our proposed approach by modeling a single Italian region and simulating the decision process of a local policymaker that needs to optimize the severity of restrictions across different sectors while balancing health and economic targets.

3.5 Direct economic impact of restrictions

As we have shown in the previous section, mobility restrictions in specific sectors affect the level of contagion by reducing the number of individuals visiting specific POSs over time.

At the same time, the reduction in movements for consumption reasons affects also the total value of consumption in the targeted sectors, leading to a direct economic loss equal to the difference in consumption with respect to a period without restriction.

To reflect this negative economic impact, the consumption bipartite network will be updated as follows:

$$\tilde{\mathbf{B}}_t^{cons} = \left\{ \tilde{v}_t^{ij} \right\}^{M \times P} \tag{19}$$

$$\tilde{v}_t^{ij} = \begin{cases} (1 - \rho_t^{rj}) v_t^{ij}, & \text{if } j \in \tilde{\mathbf{p}}_t \\ (1 - \rho_t^{sj}) v_t^{ij}, & \text{otherwise} \end{cases} \tag{20}$$

$$v_t^{ij} \in \mathbb{R}_{\geq 0}, \rho_t^{pj} \in \{0, 1\}, \rho_t^{rj} \in (0, 1], t \geq t_r \tag{21}$$

Hence, similarly to the variation in the number of movements for consumption, the total value of consumption after restriction will be a share of the value before restriction, with targeted sector shares being strictly lower than 100%.

However, while the number of transactions and their value are obviously correlated, the latter may vary with a rate of reduction ρ_t different from π_t, due to changes not only in the number of transactions but also in the average amount spent in a certain POS with respect to a period without restrictions.

Table 1 Exogenous model parameters employed in the SEIR model

Par	Value	Explanation	Source
δ_e	96 h	mean latency period	(Li et al. 2020; Kucharski et al. 2020)
δ_i	84 h	mean infectious period	(Li et al. 2020)
r_c	10%	detection rate	(Li et al. 2020; Kucharski et al. 2020)
r_d	0.66%	infection fatality rate	(Verity et al. 2020)
l_{p_j}	Exp(λ=75)	average length of POS visits in minutes	SafeGraph data
a_{p_j}	$\mathcal{N}(\mu = 1076.39, \sigma = 250)$	average POS surface area in square feet	

To maintain the simplicity of the model,[13] we do not introduce other types of economic losses which may arise from restrictions, either directly or indirectly (see, e.g., Acemoglu et al. (2021); Makris (2021). Hence, our results must be interpreted as a lower bound estimate of the full effect of restrictions on consumption levels.

4 Calibration and scenarios

4.1 Calibration

Our meta-population model requires several parameters as input which we provide with three different approaches. First, mobility, consumption and population data have been recovered from public sources and from a novel transaction dataset. Second, several epidemiological parameters have been sourced from studies related to the COVID-19 epidemic. Third, when the above approaches were not feasible, we estimated the parameters by selecting those in line with observed infection data.

Fixed parameters

The following table contains the list of parameters obtained from external sources and their references (Table 1):

Since we do not have any available information regarding the duration of visits in our data, we have utilized another data source (namely, SafeGraph[14]) to obtain an estimate of the shape of the distribution of visit duration and approximated it with an exponential distribution with parameter λ equal to 75 min. For the same reason, we

[13] This is a simplistic representation of the economy which ignores at least two relevant phenomena: public interventions implemented to support specific economic activities and the switch of consumption habits towards online expenditures.

[14] SafeGraph is a data company specializing in geospatial data and location-based insights which provide information on movements of individuals near POSs and on POS features. We have used data provided by SafeGraph to academic researchers on the duration of visits to US POS locations before stay-at-home orders as an estimate of the visit duration in Italian POSs.

approximate the surface area of POSs with a normal distribution with parameter μ equal to 1076 square feet (100 square meters) and parameter σ equal to 250 square feet (approximately 23 square meters).[15]

Estimated parameters

There are only three parameters that needed to be estimated: the base transmission rate β, common among all municipalities; the base transmission constant τ, common among all POSs; the initial percentage of exposed individuals p_0.

To estimate these three parameters, we perform a grid search over three ranges of plausible parameters. For β and τ we use the same range of parameters employed in Chang et al. (2021). For p_0 we use instead a range shifted toward higher values to account for the higher diffusion of the virus in the last months of 2020.

We run all combinations of these parameters within the chosen ranges in order to find the best ones which fit the observed number of new confirmed cases as reported by the Italian Civil Protection Department for each Italian province.[16]

Our model outputs the hourly number of new cases at the municipal level, $\chi_t^{m_i}$, which we match with the daily number of reported cases aggregating over all municipalities in a certain province, M_{prov}, for all hours in a certain day d. Since only a certain percentage r_c of new cases is detected (Li et al. 2020; Kucharski et al. 2020), we rescale the sum by that factor:

$$\chi_d^{prov} = r_c \sum_{i=1}^{M_{prov}} \sum_{t=24(d-1)}^{24d} \chi_t^{m_i} \tag{22}$$

Let $\hat{\chi}_d^{prov}$ be the observed number of newly confirmed cases. We evaluate each combination of parameters by calculating the root-mean-square error (RMSE) between χ_d^{prov} and $\hat{\chi}_d^{prov}$:

$$RMSE_{comb} = \sqrt{\frac{1}{D} \sum_{d=1}^{D} \left(\chi_d^{prov} - \hat{\chi}_d^{prov}\right)^2} \tag{23}$$

Furthermore, we select models using the average of $RMSE_{comb}$ over 30 stochastic realizations of the same configuration defined by the chosen parameters combination. Finally, to capture the uncertainty in our estimates, we accept results across all models which are within a threshold of 15% of the best one, pooling together their prediction from all stochastic realizations.

[15] Using alternative distribution assumptions on the visiting duration (a lognormal model) and on the distribution of POS areas (a uniform and a constant distribution model) delivers qualitatively similar results to the one shown in the paper that has been omitted for the sake of brevity.

[16] The Italian Civil Protection Department reports only the cumulative sum of cases, which we convert to daily new cases by making the difference across days (Dipartimento della Protezione Civile 2020).

4.2 Baseline scenario: Assessment of actual policy restrictions

We first show how our model is able to capture the contagion dynamics when we use as input the observed pattern of mobility from our transaction dataset. This represents the baseline scenario from which we depart to study how targeting specific sectors may affect the health and economic consequences related to policy restrictions. To assess the economic impact of restrictions in the baseline scenario, we measure the variation in the total value of transactions with respect to the corresponding period of the year 2019.

Figure 1 shows the relative variation of the daily total number of transactions in 2020, with respect to the same measure in 2019. This corresponds to the sum of matrix $\mathbf{B}_t^{mov}$ before the date of policies and of matrix $\tilde{\mathbf{B}}_t^{mov}$ after that date. We observe that before the date of policy kickoff, the 2020 mobility patterns were similar to 2019, while they diverged after that date with a 7-day average relative variation between -20% and -40%.

Figure 2 reports the performance of our model when the observed variation in mobility is used as input. The figure compares the prediction of all best performing models (i.e., within the acceptance threshold with respect to the best model overall) with the observed number of confirmed cases per day, using the 5th and 95th percentile to draw a confidence interval for the model predictions. We perform both full sample and out-of-sample fitting using as train-test split the date of the policy kickoff.

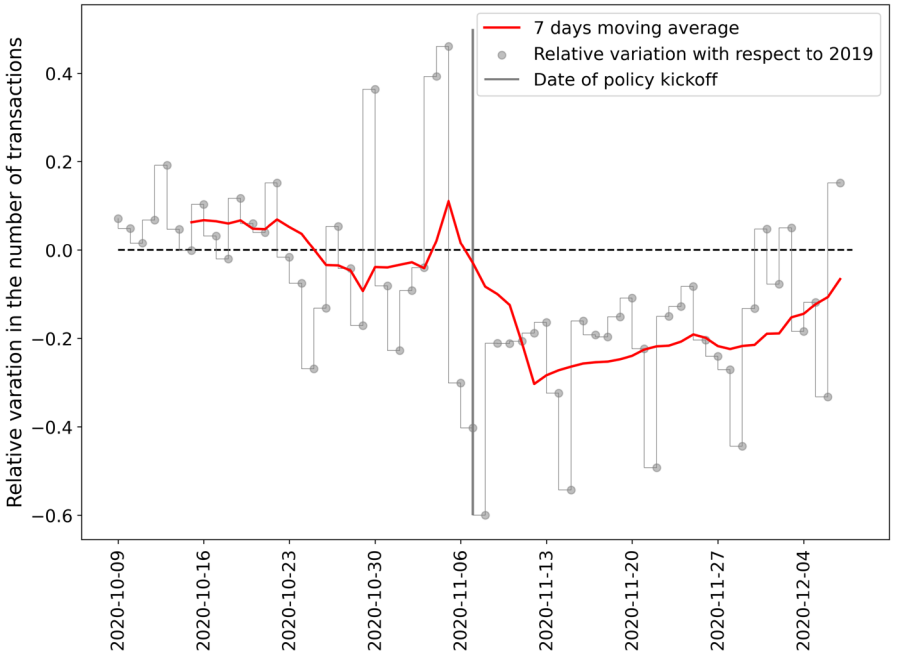


Fig. 1 Relative variation of the daily total number of transactions in 2020, with respect to the same measure in 2019

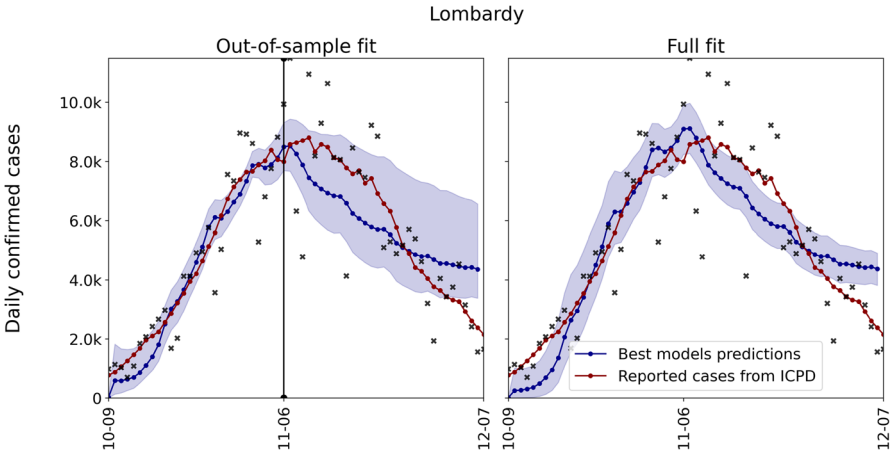


Fig. 2 Out-of-sample and full sample fit of our SEIR model in Lombardy. The black crosses represent the actual reported cases from ICPD, while the red and blue lines depict 7-day centered moving averages of the reported cases and best models predictions, respectively. The dashed curve reports 5%-95% confidence intervals for best models predictions

From Fig. 2 we can assess a good predictive performance of the model in both the full sample and the out-of-sample fitting experiment. The range of parameters for all combinations selected from the grid search is reported in Table 2 with minimum and maximum values in parenthesis.

We report in Fig. 3 the cumulative sum of the value of all transactions for 2020, starting from the day of the policy kickoff and the 2019 corresponding series. At the end of the considered period, restrictions accounted for a reduction in the total value of transactions equal to 18.28%.

4.3 Counterfactual scenarios

Starting from the baseline scenario we study how reopening specific sectors, or to put it differently how less severe policy restrictions, may affect the number of infected individuals and the total value of consumption.

To do so, we modify only the matrix $\tilde{\mathbf{B}}_t^{mov}$ by increasing the mobility of specific sectors towards their reference value of 2019. In particular, using the optimal combination of parameters obtained from the best-fit procedure, we then re-run our model with the updated mobility matrix and measure the variation in the total number of infected individuals.

Table 2 The estimated value of parameters of the best model selected through grid search

Num. best models	β	τ	p_0
60	0.014 (0.009, 0.014)	1139 (827, 4886)	$5 \cdot 10^{-3}$ ($5 \cdot 10^{-6}$, $1 \cdot 10^{-2}$)

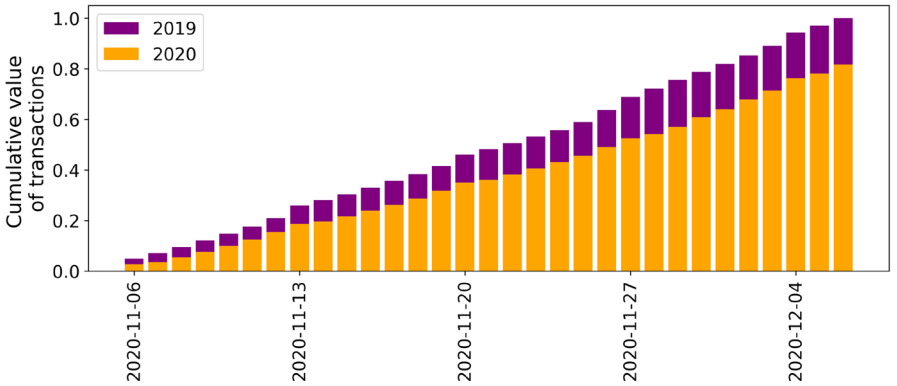


Fig. 3 Cumulative sums of the total value of transactions for 2019 and 2020. Purple bars refer to 2019, orange bars refer to 2020. All values are expressed as a percentage of the maximum

Finally, to obtain the variation in the total value of consumption, we adopt a simplifying assumption and update the matrix $\tilde{\mathbf{B}}_t^{cons}$ by the same proportion of the matrix $\tilde{\mathbf{B}}_t^{mov}$, hence assuming that the variation in the number of transactions is reflected by the variation in the average value of transactions in a one-to-one manner.

We do however differentiate among sectors, reflecting their different patterns of variation with respect to the 2019 baseline. In Fig. 4 we show the variation in the number of transactions between 2020 and 2019 for the four sectors we have chosen to analyze. We can observe a different degree of variation, with the Restaurants and Accommodation sectors showing a higher negative variation with respect to the Retail and Health sectors. To account for this, we have used as a reference for the year 2019 the mean value of each sector after the date of the kickoff of the policies, and gradually increased each sector's 2020 value toward such 2019 value with 4 steps of equal size. Hence, each step accounts for an increase of 25% with respect to the 2020 value, but we use steps of different sizes for each sector reflecting their relative size.

As a consequence, each sector will be updated as follows:

- **Retail sector:** since the average mobility level of the Retail sector in 2020 corresponds to about 83% of the 2019 level, we will increase the Retail mobility by 16.875% in 5 equal steps starting from the 2020 level and reaching the 2019 level, with steps corresponding to 3.375%.
- **Restaurants sector:** since the average mobility level of the Restaurants sector in 2020 corresponds to about 6% of the 2019 level, we will increase the Restaurants mobility by 94% in 5 equal steps starting from the 2020 level and reaching the 2019 level, with steps corresponding to 18.8%.
- **Accommodation sector:** since the average mobility level of the Accommodation sector in 2020 corresponds to about 3% of the 2019 level, we will increase the Restaurants mobility by 97% in 5 equal steps starting from the 2020 level and reaching the 2019 level, with steps corresponding to 19.4%.
- **Health sector:** since the average mobility level of the Health sector in 2020 corresponds to about 95.13% of the 2019 level, we will increase the Health mobility

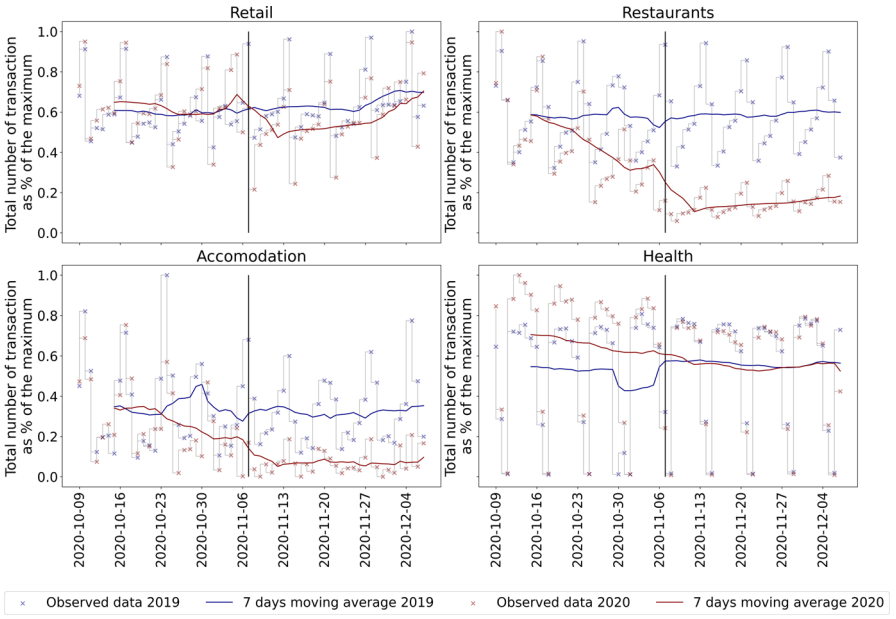


Fig. 4 Total value of transactions performed in 2019 and 2020 in the Retail, Restaurants, Accommodation and Health sectors. The blue line refers to a 7 days moving average in 2019. The red line refers to a 7 days moving average in 2020. All values are expressed as a percentage with respect to the maximum number of daily transactions in the corresponding sector experienced either in 2019 or in 2020

by 4.86% in 5 equal steps starting from the 2020 level and reaching the 2019 level, with steps corresponding to 0.97%.

We run all combinations of (less severe) policy restrictions for all 4 sectors, resulting in 625 possible cases.[17] Each of these combinations is used to vary the mobility matrix $\tilde{\mathbf{B}}_t^{mov}$ by altering only the columns corresponding to POS in the 4 targeted sectors; then, the matrix is used as input of the model which runs all best experiments (60 in our cases) with 30 stochastic realizations. Finally, each combination of alternative restrictions is associated with a certain level of consumption obtained by looking at the sum of the modified $\tilde{\mathbf{B}}_t^{cons}$ matrix and a certain level of mobility obtain by looking at the sum of the modified $\tilde{\mathbf{B}}_t^{mov}$ matrix. We consider this value as the proxy for economic impact due to consumption in the counterfactual scenarios.

[17] All combinations of 5 degrees of openness for all 4 sectors, i.e. 5^4 combinations.

5 Results

5.1 Trade-off mobility vs. contagion and economic impact

The proposed investigation framework aims at exploiting the information embedded in mobility patterns to extract informative signals for both contagion dynamics and economic impact. Mobility restrictions determine a trade-off between the purpose of containing the spread of the pandemic and the economic losses that such limitations induce on economic activity. In addition, different patterns may arise as a consequence of competitive policies, potentially with different intensity, targeting specific sectors rather than others. This calls for the emergence of combinations of policy restrictions across sectors that are preferred in terms of economic impact for a given level of contagion or, vice versa, that limit more effectively the severity of the contagion given a certain target of economic loss.

In our framework, mobility is a key dimension for the assessment of both measures of impact. The relationships between mobility patterns and both contagion and consumption are shown in Fig. 5. Different levels of mobility restrictions affect both contagion levels and economic loss, with more severe interventions limiting the number of infected cases but at the cost of reduced consumption. However, heterogeneous responses arise when the sectors targeted by policy restrictions, or their intensity, vary. From a policymaker's perspective, it means that once a certain target level of either contagion or economic impact is fixed, then some combinations of policy restrictions can be preferred with respect to the other dimension. Figure 5 clarifies this aspect. Notice how by selecting a certain mobility level, different combinations of impacts

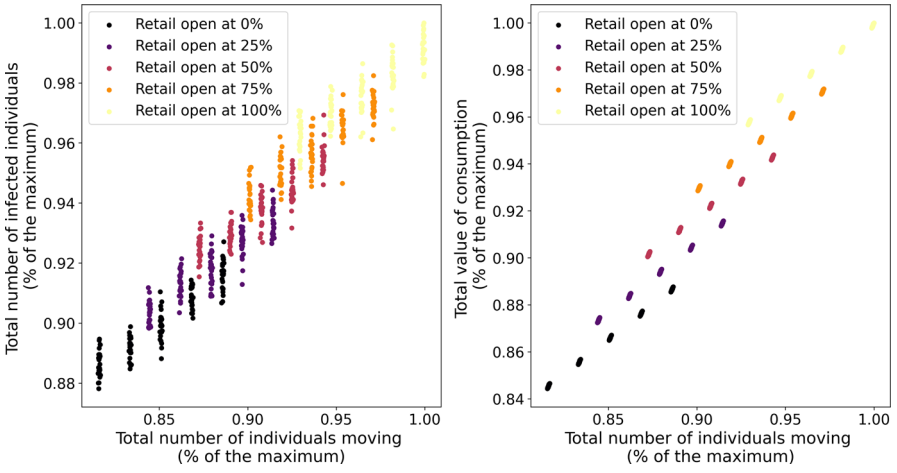


Fig. 5 Left panel shows the relationship between human mobility and COVID-19 infections in correspondence with alternative policy restrictions targeting specific sectors with different intensity. The right panel shows the relationship between human mobility and economic consumption in correspondence with alternative policy restrictions targeting specific sectors with different intensity. All values are expressed as a percentage of the corresponding maximum. The color of the dots refers to the openness degree of the Retail sector, with darker colors meaning less openness

in both consumption and infections may arise depending on how policy restrictions target specific sectors. Also, the Retail sector, which is central in our framework as will be discussed in Section 5.2, seems to dominate aggregate mobility patterns. Still, different levels of restrictions applied to the Retail sector may generate almost equivalent results in terms of either consumption or infections depending on the alternative combinations of restrictions implemented in the other sectors. More generally, this heterogeneity may induce policymakers to select the best alternative that minimizes economic impact given a certain level of infection or, alternatively, that minimizes the spread of contagion given a certain target of economic loss.

Figure 6 directly compares contagion and consumption levels, supporting a clear positive relationship between higher consumption patterns and the spread of the pandemic. However, for the same impact of contagion, different economic scenarios can occur, while the same level of consumption can be associated with different contagion scenarios. Targeting specific economic activities influences the corresponding mobility patterns, impacting therefore both consumption and contagion levels.

5.2 The role of the retail sector

Policy interventions applied in Italy in the autumn of 2020 to limit the spread of the contagion were particularly careful to ensure that relevant sectors, especially those related to expenditures for essential goods and services, remained weakly penalized by mobility restrictions. In this section, we discuss the role of the Retail sector in shaping the dynamics of both contagion and economic impact. Section 5.1 introduces this aspect, with weaker restrictions on the Retail sector typically corresponding in the aggregate to a less severe economic loss but a more serious contagion. Given the

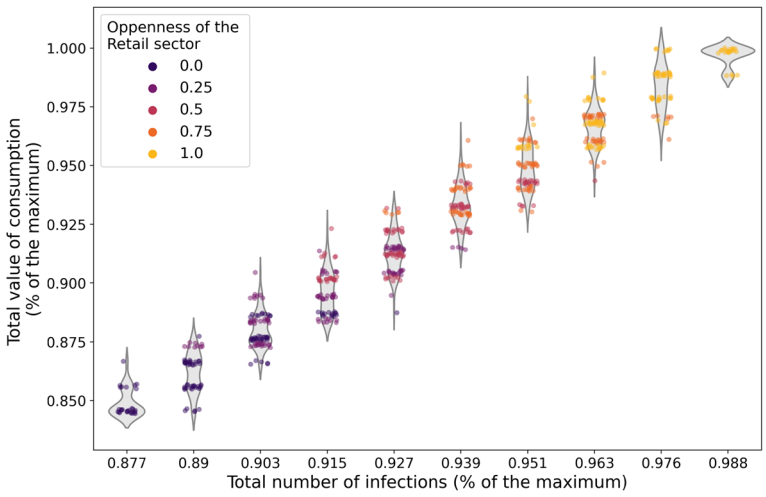


Fig. 6 The relationship between the total number of infections and the total value of consumption, conditioning on the level of openness of the Retail sector (color scale). All values are expressed as a percentage of the corresponding maximum

relevance of the economic activities encompassed in this sector and their consistent mobility flows, it is not surprising that Retail influences consumption and infections more than niche sectors.

A more detailed investigation of the role of Retail is exhibited in Fig. 7 for different values of restrictions ranging from more severe limitations on mobility (corresponding to 0%) to the absence of restrictions (open at 100%). Notice how by lifting mobility restrictions for Retail, both contagion and consumption increase to the top right of the diagram, with combinations of policy restrictions for the other sectors determining the amplitude and dispersion of the impacted area.

We have also calculated the first order (S_1) and the total (S_T) Sobol indices to measure the sensitivity of the total number of infections with respect to the openness degree of each sector. We report the indices in Fig. 8. The results confirm the relevant role of the Retail sector which is the only sector showing an S_1 statistically different from 0 and with an S_T index greater than all other sectors. Furthermore, the differences between the S_T and the S_1 indices suggest that interactions with an order greater than 1 among sectors should explain the remaining variability in the number of infected individuals.

To better gauge the role of Retail, we deepen in Fig. 9 how different levels of intervention impact consumption and contagion. When relaxing the restrictions for Retail, the distribution of infections moves to the right indicating an increase in the number of cases (Fig. 9 left panel). When we combine infections with the economic impact (Fig. 9 right panel), we clearly observe also the key role of Retail in guiding

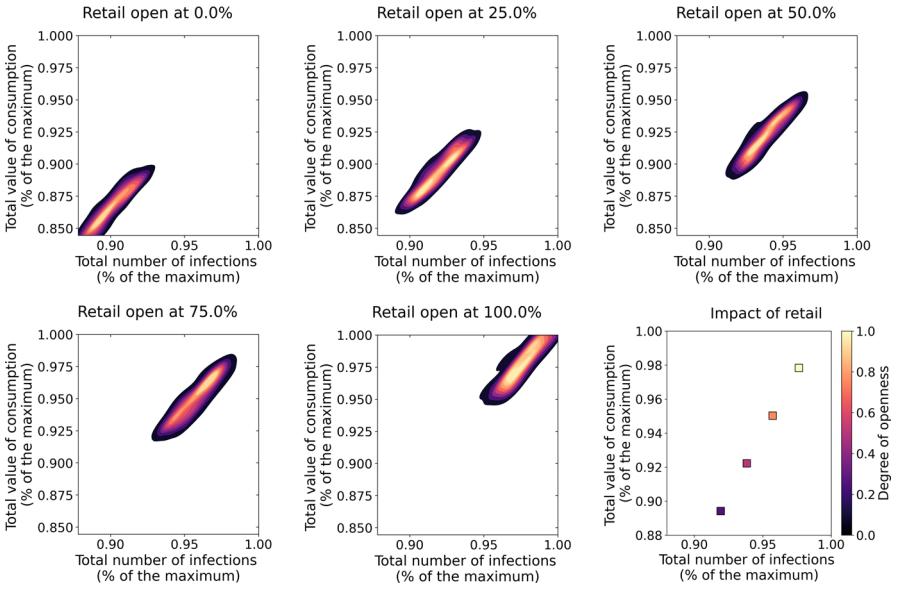


Fig. 7 The relationship between the total number of infections and the total value of consumption for alternative degrees of openness in the Retail sector. All values are expressed as a percentage of the corresponding maximum. The last panel of the plot reports the average number of infected individuals and the average value of consumption across all scenarios for specific degrees of openness for the Retail sector

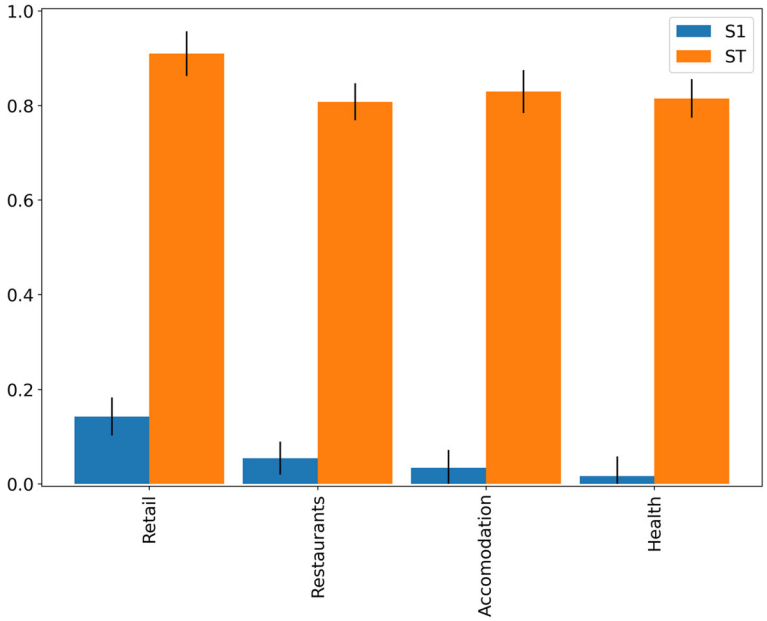


Fig. 8 S_1 and S_T Sobol indices measuring the impact of the openness of the Retail sector on the variance of model results, measured by the total number of infected individuals. S_1 index measures the impact of Retail alone, while S_T measure the effect of Retail to account for any possible interactions with all the other sectors. Indices are calculated using a sample of 2^{11} model observations obtained with the Sobol sampling algorithm

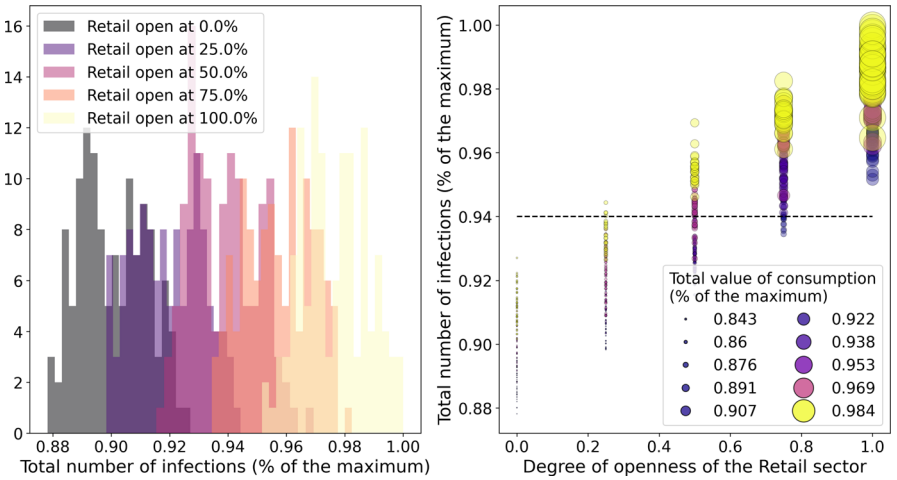


Fig. 9 Left panel shows the distribution of the total number of infections (expressed as a percentage of the maximum) for alternative degrees of openness in the Retail sector. The right panel shows the total number of infections (expressed as a percentage of the maximum) and the total value of consumption (expressed as a percentage of the maximum) for alternative degrees of openness in the Retail sector

consumption and, as a consequence, our estimated economic losses due to mobility restrictions. Specifically, the two extremes (0% vs. 100%) in the grid of restrictions for Retail indicate two completely opposite patterns in terms of contagion and economic impact for the entire system, with more severe restrictions limiting contagion but with a detrimental effect on consumption and the opposite when restrictions are absent. More interesting is the result at the body of the grid distribution, where the same amount of infections, but with different consumption levels, can be associated with competing policy restrictions. For instance, if we select a total number of infections equal to 94% of the maximum, this level can be reached for a wide set of Retail restrictions ranging from 0.25 to 0.75 and, importantly, these different combinations relate to heterogeneous impacts in terms of variations of consumption. Given the relevance of the Retail sector for both dimensions of impact under analysis, the remaining sections will discuss the trade-off between contagion and economic impact for selected levels of Retail restrictions.

5.3 Counterfactual scenarios

We exploit our proposed approach to discuss how different combinations of policy restrictions across sectors impact contagion and consumption levels. In so doing, we seek to emphasize how the same impact on one of the two dimensions can be obtained by competing policies that are likely to generate heterogeneous responses on the other dimension under analysis. Hence, this approach aims at providing policymakers with a tool for the design of more effective policies able to minimize negative impacts on society.

To illustrate it, we consider different combinations of policy restrictions for Restaurants, Accommodation and Health given a certain level of Retail mobility restriction (see Fig. 10). As expected, the role of the Retail sector dominates the overall patterns of infections, with higher cases (lighter yellow color) associated with cells corresponding to scenarios in which the Retail sector does not have restrictions. However, given a certain level of restrictions for Retail, we can explore how competing policies across the other three sectors generate more or less severe contagion dynamics. From Fig. 10, we observe that more risky scenarios in terms of contagion arise when both sectors reported on the axes do not have restrictions, while the opposite occurs when policy restrictions for both sectors are at the maximum. More importantly, similar results in terms of infections emerge for several possible combinations of restrictions across the sectors, meaning that alternative policy restrictions are likely to generate comparable impacts in terms of contagion.

Table 3 reports the combinations of restrictions across sectors that provide the highest (top) and the lowest (bottom) impact in terms of infections. We present the results for the grid of values for policy restrictions referring to the Retail sector. To provide a synthetic representation, we show groups of five combinations for both bottom and top combinations. This helps us to recognize that, as expected, more stringent policy restrictions are typically placed in correspondence with bottom combinations, whose difference in terms of infected cases with respect to top combinations is about 5%. This difference is confirmed across the grid of values of Retail restrictions, which

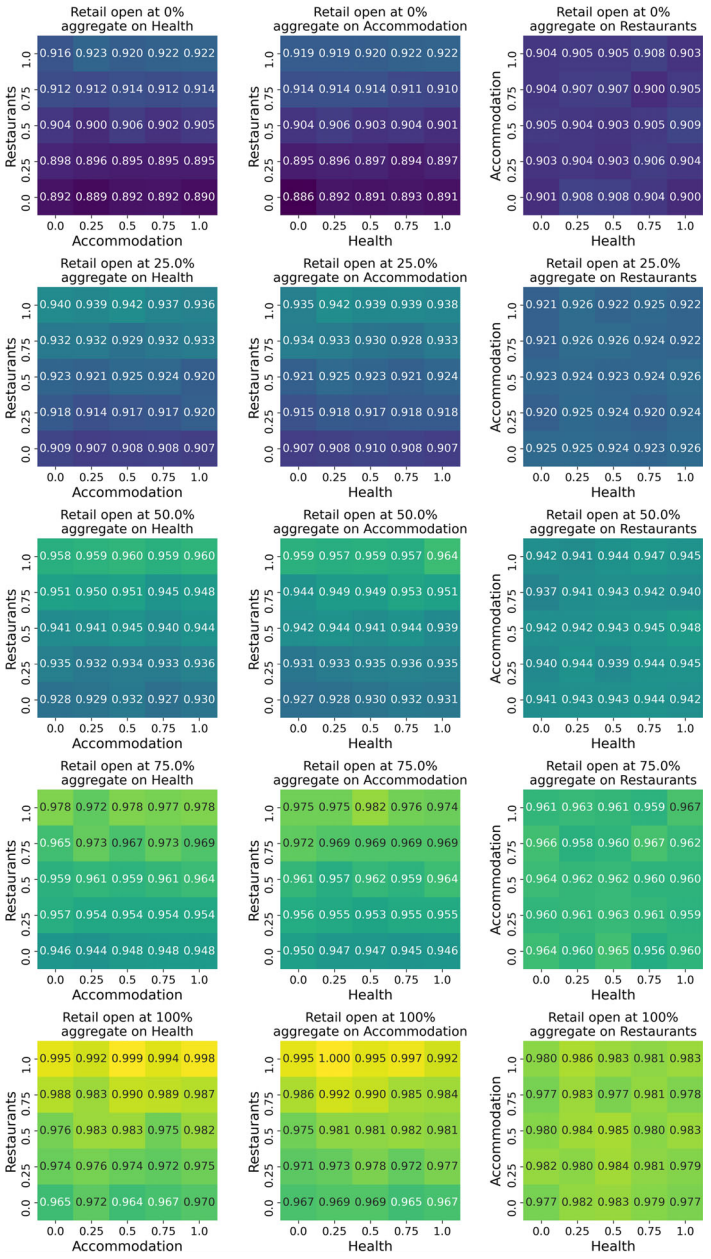


Fig. 10 Levels of contagions for different combinations of policy interventions for Restaurants, Accommodation and Health sectors in correspondence of alternative degrees of openness of the Retail sector. All values are expressed as a percentage of the maximum value of contagions across all combinations

Table 3 Top-Bottom combinations

Position		Degree of openness of the Retail sector				
		0.00	0.25	0.50	0.75	1.00
bottom 1	% infections	0.8782	0.8983	0.9155	0.9345	0.9516
	combinations	(0.0, 0.75, 0.0)	(0.0, 0.0, 0.5)	(0.0, 0.75, 0.0)	(0.0, 0.75, 1.0)	(0.0, 0.0, 1.0)
bottom 2	% infections	0.88	0.8985	0.9187	0.9355	0.9529
	combinations	(0.0, 0.25, 0.0)	(0.0, 0.25, 0.0)	(0.0, 0.0, 0.25)	(0.0, 0.0, 0.75)	(0.0, 0.0, 0.75)
bottom 3	% infections	0.8801	0.8987	0.9191	0.9359	0.9542
	combinations	(0.0, 1.0, 0.0)	(0.0, 1.0, 1.0)	(0.0, 1.0, 0.25)	(0.0, 1.0, 0.5)	(0.0, 0.5, 0.75)
bottom 4	% infections	0.882	0.8988	0.9205	0.9374	0.9573
	combinations	(0.0, 0.75, 0.75)	(0.0, 0.25, 0.25)	(0.0, 1.0, 0.0)	(0.0, 0.25, 0.75)	(0.0, 1.0, 0.0)
bottom 5	% infections	0.8827	0.8991	0.9209	0.9377	0.9578
	combinations	(0.0, 1.0, 1.0)	(0.0, 0.5, 1.0)	(0.0, 0.25, 0.75)	(0.0, 0.25, 0.25)	(0.0, 0.5, 0.0)
top 1	% infections	0.9212	0.9385	0.9572	0.9762	0.9962
	combinations	(1.0, 0.5, 1.0)	(1.0, 1.0, 0.25)	(1.0, 1.0, 0.0)	(0.75, 0.75, 0.75)	(1.0, 1.0, 0.0)
top 2	% infections	0.9214	0.9401	0.9587	0.977	0.9976
	combinations	(1.0, 0.25, 0.75)	(1.0, 0.0, 1.0)	(1.0, 0.0, 0.0)	(1.0, 0.0, 0.5)	(1.0, 0.5, 0.5)
top 3	% infections	0.9218	0.9411	0.9591	0.9772	0.998
	combinations	(1.0, 0.25, 1.0)	(1.0, 0.5, 0.5)	(1.0, 1.0, 1.0)	(1.0, 1.0, 0.5)	(1.0, 1.0, 0.25)
top 4	% infections	0.9223	0.9412	0.9628	0.9776	0.9992
	combinations	(1.0, 0.75, 0.25)	(1.0, 0.5, 0.75)	(1.0, 0.5, 1.0)	(1.0, 0.0, 0.0)	(1.0, 0.5, 0.25)
top 5	% infections	0.9271	0.9443	0.9693	0.9824	1
	combinations	(1.0, 1.0, 0.75)	(1.0, 0.25, 0.25)	(1.0, 0.25, 1.0)	(1.0, 0.5, 0.5)	(1.0, 0.5, 0.75)
reference bottom	% infections	0.8832	0.9118	0.9263	0.9466	0.9689
	combinations	(0.0, 0.0, 0.0)	(0.0, 0.0, 0.0)	(0.0, 0.0, 0.0)	(0.0, 0.0, 0.0)	(0.0, 0.0, 0.0)
reference top	% infections	0.92	0.9284	0.9591	0.9738	0.9879
	combinations	(1.0, 1.0, 1.0)	(1.0, 1.0, 1.0)	(1.0, 1.0, 1.0)	(1.0, 1.0, 1.0)	(1.0, 1.0, 1.0)

The Table reports for each value of Retail restrictions (from 0 to 1, step 0.25) the corresponding combinations of restrictions across the other three sectors that provide the lowest impact in terms of infections (bottom) or the highest impact (top). The combination in the vector of restrictions refers to the following order of sectors: Restaurants, Accommodation, Health. We consider subsets of five combinations for each tail of the distribution to take into account noisy figures that may affect single rankings

strongly influence the total amount of infections. It means that once fixed the policy restriction for Retail, restrictions in the other sectors can generate a dispersion of infections within a range of 5% between the minimum and maximum. Moreover, the two extremes of the Retail restrictions do not present overlapping combinations, with infections of the top group for the case Retail=0 which are below the values for the bottom group of Retail=1 (as also discussed in Section 5.2). Nevertheless, it is clear that the same order of magnitude of impact in terms of contagion can be reached across several different combinations of restrictions across sectors. This is a relevant aspect since the Retail sector is likely to be characterized by consumption related to essential goods and services, which the policymaker may decide not to penalize or to reduce to a much lesser extent than in other sectors. In particular, we notice that the Restaurants sector plays a key role in the contagion dynamics, with its restrictions almost always at 0% in the bottom combinations and 100% in the top ones, a piece of evidence that appears very coherent with the actual policies set in Italy to contain the spread of the virus during the second wave of contagion. Instead, more mixed results emerge for the remaining sectors Accommodation and Health. More in general, such representation may help guide policymakers to select the sectors more able to determine a certain target of contagion and prioritize interventions.

We finally combine both measures of impact in a single synthetic representation provided by Table 4, which reports top and bottom combinations along restrictions across the four considered sectors. The impact in terms of consumption clearly indicates that more stringent restrictions generate lower values of contagion but also a detrimental effect on economic activity. By contrast, when the Retail and the Restaurants sectors are less affected by mobility restrictions, then typically the contagion reaches higher values and the economic impact is less relevant. Notice how the dispersion of consumption within the same level of infections suggests the existence of several different combinations that basically provide comparable results in terms of contagion containment but with heterogeneous responses in terms of economic impact. Similarly, a certain level of economic impact can be associated with different combinations of infections. Overall, this may support policymakers in the selection of the appropriate policy that can limit the economic impact given a target of contagion or that minimizes infections given a certain consumption level. These findings suggest that alternative policies may correspond to the same targets of either contagion or consumption dynamics, but when jointly considered in the decision process some may be preferred over others.

6 Conclusions

Motivated by the strong impact of the COVID-19 pandemic on human society and the need to identify viable policy interventions that allow taking the contagion under control with sustainable economic losses, we estimate a SEIR model with a metapopulation approach and mobility data disaggregated by economic sector. We calibrate our model based on a unique novel Italian dataset tracking transactions on a daily basis over the Lombardy region and across different consumption sectors.

Table 4 Top-Bottom combinations for economic impact

Position		Total number of infected individuals (% of the maximum)					
		0.90	0.92	0.94	0.96	0.98	1.00
bottom 1	% consumption	0.8444	0.8652	0.8849	0.9141	0.9391	0.9708
	combinations	(0.0, 0.0, 0.0, 0.0)	(0.0, 0.5, 0.5, 0.0)	(0.25, 0.25, 1.0, 1.0)	(0.25, 1.0, 0.25, 0.25)	(0.75, 0.25, 0.5, 0.0)	(0.75, 1.0, 0.5, 0.5)
bottom 2	% consumption	0.8445	0.8654	0.8863	0.9147	0.9434	0.9782
	combinations	(0.0, 0.0, 0.25, 0.0)	(0.0, 0.5, 0.0, 0.25)	(0.0, 1.0, 0.75, 0.25)	(0.25, 1.0, 0.5, 0.5)	(0.5, 1.0, 0.25, 1.0)	(1.0, 0.5, 0.25, 0.5)
bottom 3	% consumption	0.8447	0.8655	0.8869	0.9151	0.9436	0.9782
	combinations	(0.0, 0.0, 0.5, 0.0)	(0.0, 0.5, 1.0, 0.0)	(0.0, 1.0, 0.25, 0.75)	(0.25, 1.0, 0.5, 0.75)	(0.5, 1.0, 0.5, 1.0)	(1.0, 0.5, 1.0, 0.25)
bottom 4	% consumption	0.8448	0.8656	0.8873	0.9152	0.9496	0.9783
	combinations	(0.0, 0.0, 0.0, 0.25)	(0.0, 0.5, 0.5, 0.25)	(0.0, 1.0, 0.25, 1.0)	(0.25, 1.0, 0.0, 1.0)	(0.75, 0.5, 0.75, 0.0)	(1.0, 0.5, 0.5, 0.5)
bottom 5	% consumption	0.8448	0.8658	0.8873	0.9214	0.95	0.9785
	combinations	(0.0, 0.0, 0.75, 0.0)	(0.0, 0.5, 0.0, 0.5)	(0.0, 1.0, 1.0, 0.75)	(0.5, 0.5, 0.5, 0.0)	(0.75, 0.5, 0.0, 0.5)	(1.0, 0.5, 0.0, 0.75)
top 1	% consumption	0.8726	0.9009	0.9304	0.9578	0.9887	0.9996
	combinations	(0.25, 0.0, 0.25, 0.0)	(0.5, 0.0, 0.0, 0.25)	(0.75, 0.0, 1.0, 0.75)	(1.0, 0.0, 0.5, 0.5)	(1.0, 0.75, 0.0, 0.75)	(1.0, 1.0, 0.25, 1.0)
top 2	% consumption	0.873	0.9009	0.9305	0.9579	0.9889	0.9996
	combinations	(0.25, 0.0, 0.25, 0.25)	(0.5, 0.0, 0.75, 0.0)	(0.75, 0.0, 0.5, 1.0)	(1.0, 0.0, 0.0, 0.75)	(1.0, 0.75, 0.25, 0.75)	(1.0, 1.0, 1.0, 0.75)
top 3	% consumption	0.8733	0.9015	0.9307	0.9582	0.989	0.9997
	combinations	(0.25, 0.0, 0.0, 0.5)	(0.5, 0.0, 1.0, 0.25)	(0.75, 0.0, 0.75, 1.0)	(1.0, 0.0, 0.5, 0.75)	(1.0, 0.75, 0.5, 0.75)	(1.0, 1.0, 0.5, 1.0)
top 4	% consumption	0.8744	0.9044	0.9316	0.9583	0.9893	0.9999
	combinations	(0.25, 0.0, 0.5, 1.0)	(0.25, 0.75, 0.5, 0.5)	(0.5, 0.75, 0.5, 0.0)	(1.0, 0.0, 0.0, 1.0)	(1.0, 0.75, 0.25, 1.0)	(1.0, 1.0, 0.75, 1.0)
top 5	% consumption	0.8747	0.905	0.9318	0.9607	0.9893	1
	combinations	(0.25, 0.0, 1.0, 1.0)	(0.25, 0.75, 0.75, 0.75)	(0.5, 0.75, 0.75, 0.0)	(0.75, 0.75, 0.0, 0.75)	(1.0, 0.75, 1.0, 0.75)	(1.0, 1.0, 1.0, 1.0)

We report in each column the impact on contagion, measured by the total number of infected individuals as the percentage of the maximum, using a grid of values that approximately ranges between the minimum and the maximum obtained in the simulations. We report the 5 combinations of sector restrictions achieving the smallest (top) and greatest (bottom) levels of economic impact, measured by the variation in consumption as a percentage of the maximum. Each combination reports in the parenthesis the degree of openness of each sector in the following order: Retail, Restaurants, Accommodation, Health

We aim to analyze the response of differentiated policy measures and study the heterogeneous effects generated by alternative combinations of restrictions characterized by different intensity across sectors. Our results highlight the trade-off between the epidemiological and economic dimensions, showing how more stringent policy measures allow to limit the contagion but with a high economic contraction, while a progressive resumption of economic activities is associated with also a resurgence of infections.

However, we show that alternative policy interventions with different restriction intensity across sectors may generate heterogeneous epidemiological and economic patterns. From a policymaker perspective, this result means that a target level of infections can be achieved at the lowest economic loss, or equivalently, that a specific value of consumption reduction can be obtained by minimizing infections. Furthermore, we clarify the impact of restrictions carefully targeting the mobility associated with different sectors in terms of infections and consumption dynamics. We highlight that the Retail sector accounts for the largest portion of mobility flows. Therefore, restrictions targeting this sector mainly drive our results with a lower policy stringency applied to Retail activities typically corresponding in aggregate to a less severe economic loss but a more serious contagion. Although in our framework the Retail sector has a central role in explaining contagion and economic dynamics, also niche sectors should be taken into account to design the optimal policy. Indeed, a certain level of contagion can be achieved in correspondence with significantly different levels of restriction intensity in the Retail sector, with heterogeneous impacts in terms of variations of consumption depending on the combination of policy interventions defined for the other sectors.

Such results demonstrate the relevance of carefully analyzing the effects generated by restriction measures targeting economic sectors with different intensity levels in order to support policymakers in taking optimal decisions under both the epidemiological and economic dimensions. Overall, our proposed approach provides policymakers with a quantitative tool, combining epidemiological and economic modeling, that may allow the investigation of alternative scenarios in terms of policy interventions across sectors, selecting tailored restrictions that minimize the economic loss in correspondence with a target contagion, or that shrink infections at the lowest possible value given a certain target level of consumption.

Further research can extend this approach in several directions. We limit our analysis to a single region focusing on an illustrative application tailored to the specific Italian policies during the second half of 2020, but the same approach can be easily applied to contagion and consumption dynamics at the country level, potentially enriching sector representation. Also, the epidemiological model can be amended by including more compartments describing the evolution of the disease transmission, assuming for instance some discrepancies between observed infected cases and real infections. Importantly, the tuning of some hyperparameters of the model, such as the time spent in POS and their size, could be optimized to more accurately fit the spread of the virus. Finally, although our proposed approach to study the trade-off between contagion and economic impact benefits from the use of detailed and daily transaction data to map both mobility and consumption patterns, other data sources can be adapted for a similar task, for instance using publicly available commuting flows and official

statistics on expenditures and income levels to infer some measures of economic impact in aggregate.

Acknowledgements The authors would like to thank Intesa Sanpaolo S.p.A. for sharing the transaction data with them. The authors would like also to thank two anonymous reviewers for their useful comments and suggestions that have helped improve the content of the paper.

Author Contributions Conceptualization: [Giovanni Bonaccorsi, Andrea Flori, Francesco Scotti];
Methodology: [Giovanni Bonaccorsi, Andrea Flori, Francesco Scotti];
Formal analysis and investigation: [Giovanni Bonaccorsi, Andrea Flori, Francesco Scotti];
Writing - original draft preparation: [Giovanni Bonaccorsi, Andrea Flori, Francesco Scotti, Fabio Pammolli];
Writing - review and editing: [Giovanni Bonaccorsi, Andrea Flori, Francesco Scotti, Fabio Pammolli];
Supervision[Andrea Flori, Fabio Pammolli].

Funding Open access funding provided by Politecnico di Milano within the CRUI-CARE Agreement. No funding was received to assist with the preparation of this manuscript.

Availability of data and materials Not applicable.

Code Availability Not applicable.

Declarations

Ethics approval Not applicable.

Consent to participate Not applicable.

Consent for publication Not applicable.

Competing interests The authors have no competing interests to declare that are relevant to the content of this article.

Open Access This article is licensed under a Creative Commons Attribution 4.0 International License, which permits use, sharing, adaptation, distribution and reproduction in any medium or format, as long as you give appropriate credit to the original author(s) and the source, provide a link to the Creative Commons licence, and indicate if changes were made. The images or other third party material in this article are included in the article's Creative Commons licence, unless indicated otherwise in a credit line to the material. If material is not included in the article's Creative Commons licence and your intended use is not permitted by statutory regulation or exceeds the permitted use, you will need to obtain permission directly from the copyright holder. To view a copy of this licence, visit http://creativecommons.org/licenses/by/4.0/.

References

Acemoglu D, Chernozhukov V, Werning I, Whinston MD (2021) Optimal Targeted Lockdowns in a Multi-group SIR Model. American Economic Review Insights 3(4):487–502. https://doi.org/10.1257/aeri.20200590

Adams-Prassl A, Boneva T, Golin M, Rauh C (2020) Inequality in the impact of the coronavirus shock: Evidence from real time surveys. J Public Econ 189:104245. https://doi.org/10.1016/j.jpubeco.2020.104245

Akbarpour M, Cook C, Marzuoli A, Mongey S, Nagaraj A, Saccarola M, Tebaldi P, Vasserman S, Yang H (2020) Socioeconomic network heterogeneity and pandemic policy response. Technical report, National Bureau of Economic Research

Allain-Dupré D, Chatry I, Michalun V, Moisio A (2020) The territorial impact of COVID-19: Managing the crisis across levels of government. Technical report, OECD

Andersen AL, Hansen ET, Johannesen N, Sheridan A (2020) Consumer Responses to the COVID-19 Crisis: Evidence from Bank Account Transaction Data. SSRN Electronic Journal. https://doi.org/10.2139/ssrn.3609814

Aspri A, Beretta E, Gandolfi A, Wasmer E (2021) Mortality containment vs. economics opening: optimal policies in a seiard model. J Math Econ 93:102490

Atkeson A (2020) What will be the economic impact of covid-19 in the us? rough estimates of disease scenarios. Technical report, National Bureau of Economic Research

Azzimonti M, Fogli A, Perri F, Ponder M (2020) Pandemic control in econ-epi networks. Technical report, National Bureau of Economic Research

Baker SR, Farrokhnia RA, Meyer S, Pagel M, Yannelis C (2020) How Does Household Spending Respond to an Epidemic? Consumption during the 2020 COVID-19 Pandemic. The Review of Asset Pricing Studies 10(4):834–862. https://doi.org/10.1093/rapstu/raaa009

Baqaee D, Farhi E, Mina M, Stock JH (2020a) Policies for a Second Wave. Brookings Papers on Economic Activity 385–431

Baqaee D, Farhi E, Mina MJ, Stock JH (2020) Reopening scenarios. Technical report, National Bureau of Economic Research

Bargain O, Aminjonov U (2020) Trust and compliance to public health policies in times of COVID-19. J Public Econ 192:104316. https://doi.org/10.1016/j.jpubeco.2020.104316

Barrios JM, Benmelech E, Hochberg YV, Sapienza P, Zingales L (2021) Civic capital and social distancing during the Covid-19 pandemic. J Public Econ 193:104310. https://doi.org/10.1016/j.jpubeco.2020.104310

Basurto A, Dawid H, Harting P, Hepp J, Kohlweyer D (2020) Economic and epidemic implications of virus containment policies: insights from agent-based simulations

Bertuzzo E, Mari L, Pasetto D, Miccoli S, Casagrandi R, Gatto M, Rinaldo A (2020) The geography of COVID-19 spread in Italy and implications for the relaxation of confinement measures. Nature Communications 11(1):4264. https://doi.org/10.1038/s41467-020-18050-2

Birge JR, Candogan O, Feng Y (2022) Controlling epidemic spread: Reducing economic losses with targeted closures. Manag Sci

Bisin A, Moro A (2022) Spatial-sir with network structure and behavior: Lockdown rules and the lucas critique. Journal of Economic Behavior & Organization 198:370–388

Blundell R, Costa Dias M, Joyce R, Xu X (2020) COVID-19 and inequalities. Fisc Stud 41(2):291–319

Blundell R, Dias MC, Joyce R, Xu X (2020) COVID-19 and Inequalities*. Fisc Stud 41(2):291–319. https://doi.org/10.1111/1475-5890.12232

Bonaccorsi G, Pierri F, Cinelli M, Flori A, Galeazzi A, Porcelli F, Schmidt AL, Valensise CM, Scala A, Quattrociocchi W et al (2020) Economic and social consequences of human mobility restrictions under COVID-19. Proceedings of the National Academy of Sciences 117(27):15530–15535. https://doi.org/10.1073/pnas.2007658117

Bonaccorsi G, Pierri F, Scotti F, Flori A, Manaresi F, Ceri S, Pammolli F (2021) Socioeconomic differences and persistent segregation of italian territories during covid-19 pandemic. Scientific reports 11(1):1–15

Bonfiglio A, Coderoni S, Esposti R (2022) Policy responses to covid-19 pandemic waves: Cross-region and cross-sector economic impact. J Policy Model

Boucekkine R, Carvajal A, Chakraborty S, Goenka A (2021) The economics of epidemics and contagious diseases: An introduction. J Math Econ

Bounie D, Camara Y, Galbraith JW (2020) Consumers' Mobility, Expenditure and Online-Offline Substitution Response to COVID-19: Evidence from French Transaction Data. SSRN Electronic Journal. https://doi.org/10.2139/ssrn.3588373

Brauner JM, Mindermann S, Sharma M, Johnston D, Salvatier J, Gavenčiak T, Stephenson AB, Leech G, Altman G, Mikulik V, Norman AJ, Monrad JT, Besiroglu T, Ge H, Hartwick MA, Teh YW, Chindelevitch L, Gal Y, Kulveit J (2021) Inferring the effectiveness of government interventions against COVID-19. Science 371(6531):eabd9338. https://doi.org/10.1126/science.abd9338

Carvalho VM, Garcia JR, Hansen S, Ortiz Á, Rodrigo T, Rodriguez Mora JV, Ruiz P (2020) Tracking the covid-19 crisis with high-resolution transaction data. Royal Society Open Science 8(8):210218

Casella G, Berger RL (2021) Statistical inference. Cengage Learning

Chandrasekhar AG, Goldsmith-Pinkham P, Jackson MO, Thau S (2021) Interacting regional policies in containing a disease. Proceedings of the National Academy of Sciences 118(19)

Chang S, Pierson E, Koh PW, Gerardin J, Redbird B, Grusky D, Leskovec J (2021) Mobility network models of covid-19 explain inequities and inform reopening. Nature 589(7840):82–87
Chen H, Qian W, Wen Q (2021) The impact of the covid-19 pandemic on consumption: Learning from high-frequency transaction data. AEA Papers and Proceedings 111:307–11
Chetty R, Friedman JN, Hendren N, Stepner M, Team TOI (2020) The Economic Impacts of COVID-19: Evidence from a New Public Database Built Using Private Sector Data. Technical Report w27431, National Bureau of Economic Research
Chinazzi M, Davis JT, Ajelli M, Gioannini C, Litvinova M, Merler S, Piontti Py MuK, Rossi L, Sun K, Viboud C, Xiong X, Yu H, Halloran ME, Longini IM, Vespignani A (2020) The effect of travel restrictions on the spread of the 2019 novel coronavirus (COVID-19) outbreak. Science. https://doi.org/10.1126/science.aba9757. https://arxiv.org/abs/https://science.sciencemag.org/content/early/2020/03/05/science.aba9757.full.pdf
Cont R, Kotlicki A, Xu R (2021) Modelling covid-19 contagion: risk assessment and targeted mitigation policies. Royal Society open science 8(3):201535
Davies NG, Barnard RC, Jarvis CI, Russell TW, Semple MG, Jit M, Edmunds WJ (2021) Association of tiered restrictions and a second lockdown with COVID-19 deaths and hospital admissions in England: A modelling study. The Lancet Infectious Diseases 21(4):482–492. https://doi.org/10.1016/S1473-3099(20)30984-1. arXiv:abs/3335.7518
Davies NG, Kucharski AJ, Eggo RM, Gimma A, Edmunds WJ, Jombart T, O'Reilly K, Endo A, Hellewell J, Nightingale ES et al (2020) Effects of non-pharmaceutical interventions on COVID-19 cases, deaths, and demand for hospital services in the UK: a modelling study. The Lancet Public Health. https://doi.org/10.1016/S2468-2667(20)30133-X
Dehning J, Zierenberg J, Spitzner FP, Wibral M, Neto JP, Wilczek M, Priesemann V (2020) Inferring change points in the spread of COVID-19 reveals the effectiveness of interventions. Science 369(6500). https://doi.org/10.1126/science.abb9789. arXiv:3241.4780
del Rio-Chanona RM, Mealy P, Pichler A, Lafond F, Farmer JD (2020) Supply and demand shocks in the covid-19 pandemic: An industry and occupation perspective. Oxford Review of Economic Policy 36(Supplement1):S94–S137
Delli Gatti D, Reissl S (2022) Agent-based covid economics (abc): Assessing non-pharmaceutical interventions and macro-stabilization policies. Ind Corp Chang 31(2):410–447
Di Domenico L, Pullano G, Sabbatini CE, Boëlle PY, Colizza V (2020) Impact of lockdown on covid-19 epidemic in île-de-france and possible exit strategies. BMC medicine 18(1):1–13
Di Porto E, Naticchioni P, Scrutinio V (2022) Lockdown, essential sectors, and covid-19: Lessons from italy. J Health Econ 81:102572
Dietrich AM, Kuester K, Müller GJ, Schoenle R (2022) News and uncertainty about covid-19: Survey evidence and short-run economic impact. J Monet Econ
Dipartimento della Protezione Civile (2020) Italian covid-19 data. https://github.com/pcm-dpc/COVID-19
Dobson AP, Pimm SL, Hannah L, Kaufman L, Ahumada JA, Ando AW, Bernstein A, Busch J, Daszak P, Engelmann J et al (2020) Ecology and economics for pandemic prevention. Science 369(6502):379–381
Dong D, Gozgor G, Lu Z, Yan C (2021) Personal consumption in the United States during the COVID-19 crisis. Applied Economics 53(11):1311–1316. https://doi.org/10.1080/00036846.2020.1828808
Dong E, Du H, Gardner L (2020) An interactive web-based dashboard to track COVID-19 in real time. The Lancet Infectious Diseases 20(5):533–534. https://doi.org/10.1016/S1473-3099(20)30120-1
Droste M, Stock JH (2021) Adapting to the covid-19 pandemic. AEA Papers and Proceedings 111:351–55
Eichenbaum MS, Rebelo S, Trabandt M (2022) The macroeconomics of testing and quarantining. J Econ Dyn Control 138:104337
Fabbri G, Gozzi F, Zanco G (2021) Verification results for age-structured models of economic-epidemics dynamics. J Math Econ 93:102455
Fajgelbaum PD, Khandelwal A, Kim W, Mantovani C, Schaal E (2021) Optimal lockdown in a commuting network. American Economic Review: Insights 3(4):503–22
Farboodi M, Jarosch G, Shimer R (2021) Internal and external effects of social distancing in a pandemic. J Econ Theory 196:105293
Federico S, Ferrari G (2021) Taming the spread of an epidemic by lockdown policies. J Math Econ 93:102453
Fernández-Villaverde J, Jones CI (2022) Estimating and simulating a sird model of covid-19 for many countries, states, and cities. J Econ Dyn Control 104318

Flaxman S, Mishra S, Gandy A, Unwin HJT, Mellan TA, Coupland H, Whittaker C, Zhu H, Berah T, Eaton JW et al (2020) Estimating the effects of non-pharmaceutical interventions on COVID-19 in Europe. Nature 1–8. https://doi.org/10.1038/s41586-020-2405-7

Franks J, Gruss B, Mulas-Granados C, Patnam M, Weber S (2022) Reopening strategies, mobility and COVID-19 infections in Europe: Panel data analysis. BMJ Open 12(2):e055938. https://doi.org/10.1136/bmjopen-2021-055938

Galanis G, Hanieh A (2021) Incorporating social determinants of health into modelling of covid-19 and other infectious diseases: A baseline socio-economic compartmental model. Social Science & Medicine 274:113794

Glover A, Heathcote J, Krueger D, Ríos-Rull JV (2020) Health versus Wealth On the Distributional Effects of Controlling a Pandemic. Technical report, National Bureau of Economic Research

Gollwitzer A, Martel C, Brady WJ, Pärnamets P, Freedman IG, Knowles ED, Van Bavel JJ (2020) Partisan differences in physical distancing are linked to health outcomes during the COVID-19 pandemic. Nature Human Behaviour 4(11):1186–1197. https://doi.org/10.1038/s41562-020-00977-7

Hacıoğlu-Hoke S, Känzig DR, Surico P (2021) The distributional impact of the pandemic. Eur Econ Rev 134:103680. https://doi.org/10.1016/j.euroecorev.2021.103680

Haffajee RL, Mello MM (2020) Thinking Globally, Acting Locally–The U.S. Response to Covid-19. N Engl J Med 382(22):e75. https://doi.org/10.1056/NEJMp2006740

Holtz D, Zhao M, Benzell SG, Cao CY, Rahimian MA, Yang J, Allen J, Collis A, Moehring A, Sowrirajan T et al (2020) Interdependence and the cost of uncoordinated responses to covid-19. Proceedings of the National Academy of Sciences 117(33):19837–19843

Huang C, Wang Y, Li X, Ren L, Zhao J, Hu Y, Zhang L, Fan G, Xu J, Gu X et al (2020) Clinical features of patients infected with 2019 novel coronavirus in wuhan, china. The Lancet 395(10223):497–506

Iacobucci G (2020) Covid-19: Deprived areas have the highest death rates in England and Wales. BMJ 369:m1810. https://doi.org/10.1136/bmj.m1810

IHME COVID-19 forecasting team (2020) Modeling covid-19 scenarios for the united states. Nat Med

Jay J, Bor J, Nsoesie EO, Lipson SK, Jones DK, Galea S, Raifman J (2020) Neighbourhood income and physical distancing during the COVID-19 pandemic in the United States. Nature Human Behaviour. https://doi.org/10.1038/s41562-020-00998-2

Jena PR, Majhi R, Kalli R, Managi S, Majhi B (2021) Impact of covid-19 on gdp of major economies: Application of the artificial neural network forecaster. Economic Analysis and Policy 69:324–339

Kaplan G, Moll B, Violante GL (2020) The great lockdown and the big stimulus: Tracing the pandemic possibility frontier for the us. Technical report, National Bureau of Economic Research

Kochańczyk M, Lipniacki T (2021) Pareto-based evaluation of national responses to covid-19 pandemic shows that saving lives and protecting economy are non-trade-off objectives. Scientific Reports 11(1):1–9

Kojima N, Klausner JD (2022) Protective immunity after recovery from sars-cov-2 infection. The Lancet infectious diseases 22(1):12–14

Kraemer MUG, Yang CH, Gutierrez B, Wu CH, Klein B, Pigott DM, du Plessis L, Faria NR, Li R, Hanage WP, Brownstein JS, Layan M, Vespignani A, Tian H, Dye C, Pybus OG, Scarpino SV (2020) The effect of human mobility and control measures on the COVID-19 epidemic in china. Science. https://doi.org/10.1126/science.abb4218. https://arxiv.org/abs/https://science.sciencemag.org/content/early/2020/03/25/science.abb4218.full.pdf

Kretzschmar ME, Ashby B, Fearon E, Overton CE, Panovska-Griffiths J, Pellis L, Quaife M, Rozhnova G, Scarabel F, Stage HB, Swallow B, Thompson RN, Tildesley MJ, Villela D (2022) Challenges for modelling interventions for future pandemics. Epidemics 38:100546. https://doi.org/10.1016/j.epidem.2022.100546

Kubota S, Onishi K, Toyama Y (2021) Consumption responses to COVID-19 payments: Evidence from a natural experiment and bank account data. Journal of Economic Behavior & Organization 188:1–17. https://doi.org/10.1016/j.jebo.2021.05.006

Kucharski AJ, Russell TW, Diamond C, Liu Y, Edmunds J, Funk S, Eggo RM, Sun F, Jit M, Munday JD et al (2020) Early dynamics of transmission and control of covid-19: a mathematical modelling study. The Lancet Infectious Diseases 20(5):553–558

Lai S, Ruktanonchai NW, Zhou L, Prosper O, Luo W, Floyd JR, Wesolowski A, Santillana M, Zhang C, Du X et al (2020) Effect of non-pharmaceutical interventions to contain covid-19 in china. nature 585(7825):410–413

Li R, Pei S, Chen B, Song Y, Zhang T, Yang W, Shaman J (2020) Substantial undocumented infection facilitates the rapid dissemination of novel coronavirus (sars-cov-2). Science 368(6490):489–493

Li Y, Campbell H, Kulkarni D, Harpur A, Nundy M, Wang X, Nair H (2020) The temporal association of introducing and lifting non-pharmaceutical interventions with the time-varying reproduction number (R) of SARS-CoV-2: A modelling study across 131 countries. The Lancet Infectious Diseases. https://doi.org/10.1016/S1473-3099(20)30785-4

Maier BF, Brockmann D (2020) Effective containment explains subexponential growth in recent confirmed COVID-19 cases in China. Science 368(6492):742–746

Makris M (2021) Covid and social distancing with a heterogenous population. Economic Theory: 1–50

Mellacher P (2020) Covid-town: an integrated economic-epidemiological agent-based model. arXiv preprint arXiv:2011.06289

Murray EJ (2020) Epidemiology's time of need: Covid-19 calls for epidemic-related economics. J Econ Perspect 34(4):105–20

Nouvellet P, Bhatia S, Cori A, Ainslie KEC, Baguelin M, Bhatt S, Boonyasiri A, Brazeau NF, Cattarino L, Cooper LV, Coupland H, Cucunuba ZM, Cuomo-Dannenburg G, Dighe A, Djaafara BA, Dorigatti I, Eales OD, van Elsland SL, Nascimento FF, FitzJohn RG, Gaythorpe KAM, Geidelberg L, Green WD, Hamlet A, Hauck K, Hinsley W, Imai N, Jeffrey B, Knock E, Laydon DJ, Lees JA, Mangal T, Mellan TA, Nedjati-Gilani G, Parag KV, Pons-Salort M, Ragonnet-Cronin M, Riley S, Unwin HJT, Verity R, Vollmer MAC, Volz E, Walker PGT, Walters CE, Wang H, Watson OJ, Whittaker C, Whittles LK, Xi X, Ferguson NM, Donnelly CA (2021) Reduction in mobility and COVID-19 transmission. Nat Commun 12(1):1090. https://doi.org/10.1038/s41467-021-21358-2

Pangallo M, Aleta A, Chanona R, Pichler A, Martín-Corral D, Chinazzi M, Lafond F, Ajelli M, Moro E, Moreno Y et al (2022) The unequal effects of the health-economy tradeoff during the covid-19 pandemic. arXiv preprint arXiv:2212.03567

Pavlik M (2020) A great and sudden change: the global political violence landscape before and after the covid-19 pandemic. Armed Conflict Location & Event Data Project

Prem K, Liu Y, Russell TW, Kucharski AJ, Eggo RM, Davies N, Flasche S, Clifford S, Pearson CA, Munday JD et al (2020) The effect of control strategies to reduce social mixing on outcomes of the covid-19 epidemic in wuhan, china: a modelling study. The Lancet Public Health 5(5):e261–e270

Reissl S, Caiani A, Lamperti F, Guerini M, Vanni F, Fagiolo G, Ferraresi T, Ghezzi L, Napoletano M, Roventini A (2022) Assessing the economic impact of lockdowns in italy: A computational input-output approach. Ind Corp Chang 31(2):358–409

Scala A, Flori A, Spelta A, Brugnoli E, Cinelli M, Quattrociocchi W, Pammolli F (2020) Time, space and social interactions: exit mechanisms for the COVID-19 epidemics. Scientific Reports 10(11):13764. https://doi.org/10.1038/s41598-020-70631-9

Scotti F, Flori A, Bonaccorsi G, Pammolli F (2023) Do we learn from errors? the economic impact of differentiated policy restrictions in italy. International Regional Science Review: 01600176231168027

Scotti F, Pierri F, Bonaccorsi G, Flori A (2022) Responsiveness of open innovation to covid-19 pandemic: The case of data for good. PLoS ONE 17(4):e0267100

Sheridan A, Andersen AL, Hansen ET, Johannesen N (2020) Social distancing laws cause only small losses of economic activity during the COVID-19 pandemic in Scandinavia. Proceedings of the National Academy of Sciences 117(34):20468–20473. https://doi.org/10.1073/pnas.2010068117

Škare M, Soriano DR, Porada-Rochoń M (2021) Impact of covid-19 on the travel and tourism industry. Technol Forecast Soc Chang 163:120469

Spelta A, Flori A, Pierri F, Bonaccorsi G, Pammolli F (2020) After the lockdown: Simulating mobility, public health and economic recovery scenarios. Scientific Reports 10(1):16950. https://doi.org/10.1038/s41598-020-73949-6

Tisdell CA (2020) Economic, social and political issues raised by the covid-19 pandemic. Economic Analysis and Policy 68:17–28

Vavra J (2021) Tracking the Pandemic in Real Time: Administrative Micro Data in Business Cycles Enters the Spotlight. J Econ Perspect 35(3):47–66. https://doi.org/10.1257/jep.35.3.47

Verity R, Okell LC, Dorigatti I, Winskill P, Whittaker C, Imai N, Cuomo-Dannenburg G, Thompson H, Walker PGT, Fu H, Dighe A, Griffin JT, Baguelin M, Bhatia S, Boonyasiri A, Cori A, Cucunubá Z, FitzJohn R, Gaythorpe K, Green W, Hamlet A, Hinsley W, Laydon D, Nedjati-Gilani G, Riley S, van Elsland S, Volz E, Wang H, Wang Y, Xi X, Donnelly CA, Ghani AC, Ferguson NM (2020) Estimates of the severity of coronavirus disease 2019: A model-based analysis. The Lancet Infectious Diseases. https://doi.org/10.1016/S1473-3099(20)30243-7

Wright AL, Sonin K, Driscoll J, Wilson J (2020) Poverty and economic dislocation reduce compliance with COVID-19 shelter-in-place protocols. Journal of Economic Behavior & Organization 180:544–554. https://doi.org/10.1016/j.jebo.2020.10.008

Zelner J, Eisenberg M (2022) Rapid response modeling of sars-cov-2 transmission. Science 376(6593):579–580

Publisher's Note Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.