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https://escholarship.org/uc/item/6pz797k7

Journal

Journal of Population Economics, 34(1)

ISSN

0933-1433

Author

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Publication Date

2021

DOI

10.1007/s00148-020-00792-4

Peer reviewed

COVID-19 outbreak, social response, and early economic effects: a global VAR analysis of cross-country interdependencies

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Abstract

This paper studies the social and economic responses to the COVID-19 pandemic in a large sample of countries. I stress, in particular, the importance of countries' interconnections to understand the spread of the virus. I estimate a global VAR model and exploit a dataset on existing social connections across country borders. I show that social networks help explain not only the spread of the disease but also cross-country spillovers in perceptions about coronavirus risk and in social distancing behavior. In the early phases of the pandemic, perceptions of coronavirus risk in most countries are affected by pandemic shocks originating in Italy. Later, the USA, Spain, and the UK play sizable roles. Social distancing responses to domestic and global health shocks are heterogeneous; however, they almost always exhibit delays and sluggish adjustments. Unemployment responses vary widely across countries. Unemployment is particularly responsive to health shocks in the USA and Spain, while unemployment fluctuFations are attenuated almost everywhere else.

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1 Introduction

After being identified in December 2019 in Wuhan, China, the novel coronavirus (SARS-CoV-2) initially spread in the Hubei region and later across mainland China. Although the rest of the world soon learned about the first publicly known cases, several countries did not perceive an immediate risk for their populations. Starting in January 2020, the epidemic spread outside China, first in Thailand, South Korea, Japan, and in the USA, and in many cases it was connected to recent travelers to the country. In Europe, Italy reported its first official community-based case on February 20, and, very quickly, clusters of cases developed in the Lombardy region. It was later discovered that the virus had been circulating in Lombardy since at least early January (Cereda et al. 2020) and, possibly, since December. By mid-March, the vast majority of countries in the world had multiple cases, with the centers of the outbreak moving first to Europe and later to the USA.

Most countries responded by requiring their populations to adhere to some form of social distancing to reduce the rate of infection and lessen the strain on health-care providers. Responses, however, have been widely heterogeneous. Italy reacted with a few-days delay after the outbreak and then implemented restrictive stay-at-home policies. A minority of countries initially experimented with laxer restrictions, either based on a misguided attempt to have their populations achieve herd immunity on their own (the UK, which soon moved away from the policy), or because of an unwritten "social contract" with citizens rather than enforcement from policymakers (Sweden). Others acted quickly and decisively to attempt to eradicate the disease before it became widespread (New Zealand).

The spread of coronavirus has highlighted the importance of interdependencies across different regions. Depending on business links and other existing relationships, the virus rapidly moved across borders. Perceptions about the crisis and social behavior responded generally with lags, but they were also likely affected by observed experiences abroad. Countries had the opportunity of learning from others about social adjustments that were more or less effective in containing the disease.

The main objective of this work is to study these global interrelationships in the early response to COVID-19 shocks. In particular, this paper exploits information about social networks across countries to study interdependencies in the number of disease cases, in the perceptions of their citizens about coronavirus risk, and in their social responses. I also provide some preliminary evidence on the early economic effects of the pandemic by looking at a potential leading indicator of unemployment.

I include in my sample 41 countries and use a variety of data sources. To capture the extent of pairwise country social connections, I use data obtained from Facebook, which measure the total number of friendships across pairs of countries as a fraction of the total number of combined users in the two countries. This Social Connectedness indicator allows me to have a measure that can account for different types of relationships: regular friendships, business links, family ties, relations based on older and more recent patterns of immigration, and tourism flows. Social networks can help explain the transmission of COVID-19 cases across borders, and they are likely to represent a superior measure compared with the use of geographic

distance alone.[1] Other contemporaneous papers make a similar observation (e.g., Kuchler et al. 2020). At the same time, social networks not only can potentially explain patterns of disease contagion, but they can also help account for spillovers in ideas and behavior. Controlling for the country-specific dynamics of COVID-19 cases, people's risk perceptions may respond differently and also be affected by the experience and perceptions of individuals in their networks of social connections, including those residing abroad. The same is true for responses in terms of social distancing: individuals who had large connections to countries where the virus outbreak and the social distancing responses were already happening may have learned from their early experiences, taken the epidemic more seriously, and responded similarly.

To measure the actual social distancing response in each country, I exploit a novel dataset made available by Google through its country-specific Social Mobility reports. Finally, I use Internet data from Google Trends to measure coronavirus risk perceptions and to have a real-time, daily indicator of unemployment.

I estimate a global VAR model to study the transmission of pandemic health shocks both domestically and globally.[2] In my global framework, for each country, COVID-19 cases can affect risk perceptions about the virus, which can trigger a social distancing response. As a result of social distancing or general uncertainty, unemployment may increase. The model allows me to treat all these variables as endogenous. This is necessary since social distancing, for example, is likely implemented in response to rising numbers of COVID-19 cases, but it also itself has an impact on the future number of cases. Moreover, domestic variables in the model are also allowed to respond to foreign aggregates. The foreign variables enter each domestic model with weights that depend on the matrix of social connections. The relevant foreign aggregate for each country is different, since the patterns of connections are unique to the country. In the GVAR literature, the domestic models can be estimated separately as conditional VARs. All endogenous variables can then be stacked together to form a large-scale global VAR; it is then possible to track the responses of all variables to each shock in each country. Through the use of a connectivity matrix (my Social Connection matrix), the Global VAR model offers a relatively simple and parsimonious way to deal with potentially complex interactions across different variables and countries.

Main results My estimates highlight the importance of interdependencies and social networks in the transmission of coronavirus cases, in the increase of risk perceptions, and in social distancing behavior. Domestic variables, for the vast majority of countries, are significantly affected by foreign aggregates, constructed with weights based on the strength of social connections across countries.

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[1]For example, as documented in Brynildsrud and Eldholm (2020), the first cases in Nordic countries (in their case, Norway, but likely similar in neighboring countries) were due to travelers returning from vacations in Lombardy. To the extent that some of these tourism patterns increase the probability of Facebook links as well, which I believe reasonable, my measure will allow me to track likely routes for the spread of the disease.

[2]The GVAR model has been proposed by Pesaran et al. (2004) and is surveyed in Chudik and Pesaran (2016).

Given the role played by Italy and the USA as centers of the outbreak in different phases of the epidemic, I study how variables in the rest of the world respond to coronavirus shocks originating in these countries. I document strong and significant responses of risk perceptions and social distancing to the Italy COVID shock almost everywhere in the world. Countries also respond to the subsequent US shock, although with a smaller magnitude. Spillovers from Spain and the UK also play a sizable role.

The countries' responses to foreign and their own domestic coronavirus shocks are heterogeneous. I can, however, reveal some common patterns. The countries that respond with social distancing do so with a delayed and sluggish adjustment. They seem to learn from the experience of other countries, but they display an adaptive behavior: they do not adjust their habits instantly; instead, they gradually reduce their social mobility, which reaches a negative peak almost a week after the shock. In the opposite direction of causality, changes in social distancing lead to a decline in the growth rate of COVID-19 cases.

The implications of the pandemic for unemployment also vary significantly by country. Labor markets in the USA and Spain are the most negatively affected, with large expected increases in unemployment rates. But large spikes in unemployment are not inevitable since most other countries seem to experience much more contained fluctuations. The results suggest that different institutional features can partly insulate the corresponding populations from the worse effects of large exogenous shocks.

Related literatures Due to the historical importance of the COVID-19 pandemic, research related to the disease and its effects has been growing swiftly. Many papers use the leading model in epidemiology, the SIR (or, alternatively, the extended SEIR) model based on Kermack and McKendrick (1927), to simulate the evolution of the disease (e.g., Ferguson N and et al (2020)). In economics, a number of recent papers have adopted a similar framework and developed the theory further by adding relevant trade-offs between health and economic costs (e.g., Eichenbaum et al. (2020), Alvarez et al. (2020), Jones et al. (2020)). This paper, instead, takes a different route by providing empirical evidence related to the social response to the outbreak, and using an alternative framework. In contrast to studies using the SIR model, I do not aim to predict the evolution of the number of infected individuals in a population; my focus lies more on explaining the social responses to the original health shocks around the world.

Other recent works investigate the determinants of different approaches to social distancing. Gupta and et al. (2020) find that social distancing responses do not necessarily correspond to policies mandated by State and local governments. Painter and Qiu (2020) and Adolph et al. (2020) find that political beliefs affect compliance with social distancing indications in the USA. Andersen (2020) finds evidence of substantial voluntary social distancing, and he also shows that it is affected by partisanship and media exposure. In light of these results, my approach does not use data on mandates, but it exploits, instead, the actual decline in mobility, as measured using location tracking technologies.

Qiu et al. (2020) focus on the early months of the pandemic. They provide empirical evidence on the transmission of coronavirus cases across cities in China between January and February. They estimate how the number of new daily cases in a city is affected by the number of cases that occurred in nearby cities and in Wuhan, over the previous 2 weeks. They show that social distancing measures reduced the spread of the virus, whereas population flows out of Wuhan increased the risk of transmission.

My paper stresses the importance of modeling cross-country interrelationships to understand the evolution of the next phase of the pandemic. A recent work by Zimmermann et al. (2020) shares a similar goal. They find that countries that are more globalized are affected by the pandemic earlier and to a larger extent. Therefore, they discuss how early measures that temporarily reduce inter-country mobility would be beneficial.

Outside of the recent COVID-19 literature, my paper also provides a contribution to the literature on GVAR models (see Chudik and Pesaran 2011, for a survey). Most papers in the literature consider macroeconomic applications and study the global spillovers of policy and other shocks (e.g., Pesaran et al. 2004; Chudik and Fratzscher 2011; Dees et al. 2007). Others have studied interdependencies in housing markets (Holly et al. 2011), firm-level returns (Smith and Yamagata 2011), and a variety of other applications (Di Mauro and Pesaran 2013; Pesaran et al. 2009). The effect of foreign variables is usually assumed to depend on trade balances across countries. My framework, instead, introduces a different connectivity matrix, based on social networks, which can be promising for a different set of applications. Therefore, my paper is also connected to recent papers that propose the use of Facebook connections to measure social networks across locations (Bailey et al. 2018).

Finally, I measure risk perceptions and fears of unemployment using Google Trends data. This approach has become more and more popular and is now exploited in different fields to measure people's attention (Da et al. 2011), in forecasting and nowcasting economic variables (see the various examples discussed in Choi and Varian 2012), and to track the spread of diseases (e.g., Ginsberg et al. 2009; Brownstein et al. 2009) in the absence of easily observable private information. Askitas and Zimmermann (2015) discuss how Internet data can be useful for empirical research in a variety of social science applications and, in particular, for research about human resource issues (Askitas and Zimmermann (2009) and Simionescu and Zimmermann (2017) provide evidence directly related to the unemployment rate).

2 COVID-19 and social response data

The paper exploits a variety of newly available datasets to study the interrelationship between health shocks originating from the COVID-19 pandemic, people's real-time perceptions about coronavirus risk, the extent of their social distancing response, and unemployment. I investigate the connections among these variables both within countries, and across borders, by studying contagion and spillovers internationally.

The data are collected on a sample of 41 countries. Those include current OECD member countries, candidate countries that applied for membership, and the countries

that the OECD defines as key partners (Brazil, India, Indonesia, South Africa).[3] The countries account for 70% of global GDP (besides China, the main omission is Russia, which accounts for about 2%) and 41% of global population; they also account for 83% of coronavirus cases in the sample period.

Data on novel COVID-19 cases each day for each country are made available by Johns Hopkins University's Center for Systems Science and Engineering (CSSE). The estimations use either the growth rate or, as a robustness check, the number of daily cases.

The epidemiology literature stresses the importance of social distancing to contain the spread of the virus, by reducing the basic reproduction number R_0 (the expected number of secondary infections produced by a single infection in a population where everybody is susceptible) and flattening the curve of infected individuals. The response has been different across countries, either in terms of policies, enforcement, or voluntary reductions in mobility. Therefore, it is important to have accurate data on actual social distancing by different populations to track the implied health and economic effects. To this scope, I use daily time series indicators on social mobility made available by Google.[4] The indicators are obtained using aggregated, anonymized data from GPS tracking of mobile devices, for users who opted in to "Google Location History."

The data measure the change in the number of visits and length of stay at different places compared with a baseline. For each day of the week, mobility numbers are compared with an historical baseline value, given by the median value for the corresponding day of the week, calculated during the 5-week period between January 3 and February 6, 2020. The data are reported for five place categories: grocery and pharmacies, parks and beaches, transit stations, retail and recreation, and residential.

In addition to the official number of COVID-19 cases, which may be an imperfect measure of the pervasiveness of the virus in the population, I also measure the population's risk perception about coronavirus. The risk perception is measured using daily data on Web searches from Google Trends. I use the search results for the whole "Topic" category; therefore, the indicator also includes all related search terms, such as "Coronavirus symptoms," "Coronavirus treatment," "Coronavirus vs. flu," and so forth.

Finally, I similarly use an indicator of unemployment to measure the initial economic effects of the outbreak. Given that actual unemployment data are typically available only at monthly frequency and that their release is lagged by more than a

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[3]The full list of countries is as follows: Australia, Austria, Belgium, Brazil, Canada, Chile, Colombia, Costa Rica, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, India, Indonesia, Ireland, Israel, Italy, Japan, South Korea, Latvia, Lithuania, Luxembourg, Mexico, Netherlands, New Zealand, Norway, Poland, Portugal, Slovak Republic, Slovenia, South Africa, Spain, Sweden, Switzerland, Turkey, UK, the USA. The only country that has been removed from the OECD list is Iceland, since Google mobility data were not available. For non-OECD key partners, I exclude China, since for my sample the numbers of cases had already declined (Google mobility data would also be unavailable for the country).

[4]Google LLC "Google COVID-19 Community Mobility Reports." https://www.google.com/covid19/mobility/

month, I also exploit Google Trends data about unemployment as a variable that can be used to have early and real-time indications of the official variable. As before, I use Google searches about the Unemployment Topic (again, including all searches related to unemployment, such as "unemployment benefits," "unemployment insurance," "how to apply for unemployment," "losing my job," and so forth). Askitas and Zimmermann (2009) and Choi and Varian (2009), among others, show that unemployment searches can help predict initial unemployment claims and the unemployment rate. More recently, Askitas and Zimmermann (2015) and Simionescu and Zimmermann (2017) document how Internet data can be useful for nowcasting and forecasting the unemployment rate in a diverse set of countries. My unemployment variable can, therefore, be interpreted as a real-time signal for unemployment, or, alternatively, as a measure of people's perceptions, attention, or fears, about unemployment over the time period that I study.[5]

Finally, I measure international social connections using Facebook's Social Connectedness data. The index uses active Facebook users and their friendship networks to measure the intensity of connectedness between each pair of locations. The measure of Social Connectedness between two locations i and j is given by:

$$Social\ Connectedness_{i,j} = \frac{FB\ Connections_{i,j}}{FB\ Users_i \cdot FB\ Users_j}$$

where $FB\ Connections_{i,j}$ denotes the number of friendship connections between region i and j, and $FB\ Users_i$, $FB\ Users_j$ denote the number of Facebook users in i and j. The Social Connectedness index, therefore, measures the relative probability of a Facebook connection between any individual in location i and any individual in location j. The data used in this paper refer to the measure calculated for March 2020.

Bailey et al. (2018) proposed the measure to study the effects of social networks across US counties. Other current papers are uncovering the link between social networks and the diffusion of COVID-19 (e.g., Kuchler et al. 2020). The measure can be preferred to alternatives based simply on inverse geographic distance, since it can provide a more accurate account of business relations, tourism patterns, and family or friendship ties, across different areas. I argue here that the strength of social connections can also affect information about the outbreak and social distancing responses. As Bailey et al. (2018) show, Facebook friendship links between the USA and other countries, for example, are strongly correlated both with bilateral migration patterns and trade flows. They regress social connectedness on geographic distance, the number of residents with ancestry in the foreign country (as an indicator of past migration), and on the number of residents born in the foreign country (indicating current migration), and show that all three are strongly significant. Friendship connections also lead to statistically significant increases in both exports and imports between the USA and the foreign country.

[5]For both Google Trends series, I use both the time series information and the cross-section information, by also extracting the relative popularity of the searches in each country for the period of interest. I then multiply the time series by the relative popularity in country i divided by the popularity in the country with the highest search volume (fixed at 100 in Google Trends by construction).
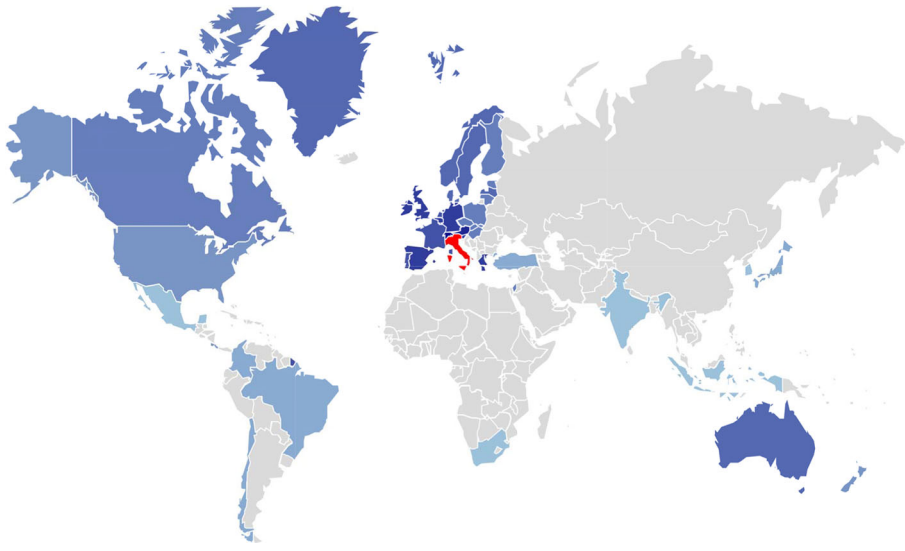
Fig. 1 Social connections between Italy and the rest of countries in the sample. The reference country (Italy) is shown in red; social connections are measured with different tonalities of blue, with darker tones denoting stronger connections; countries that are not considered in the estimation are in gray

Figures 1 and 2 show the likelihood of social connections across countries, with Italy and the USA chosen as examples (and, therefore, shown in red in their corresponding figure).
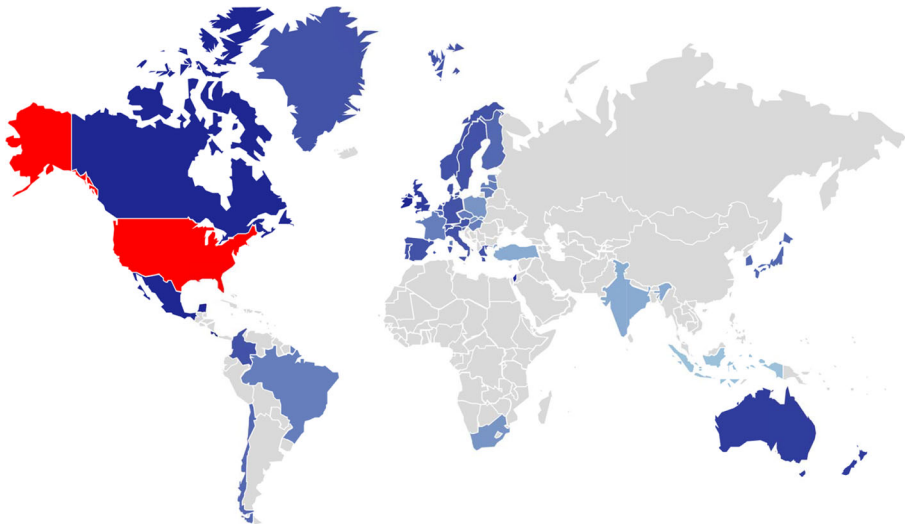
Fig. 2 Social connections between the USA and the rest of countries in the sample. The reference country (the USA) is shown in red; social connections are measured with different tonalities of blue, with darker tones denoting stronger connections; countries that are not considered in the estimation are in gray

For Italy, the strongest social connections are with Switzerland and Slovenia, followed by Austria, Germany, Spain, Belgium, and the UK. Distance is clearly a determinant of social networks, but not the only determinant. Social connections are stronger between Italy and Australia, Italy and the USA, and Italy and Canada, than between Italy and Turkey, although the latter is geographically much closer.

For the USA, as expected, the most socially connected countries are Mexico and Canada, followed, at lower levels, by Ireland and Israel. The USA have strong connections with Australia and New Zealand, which would be downplayed based on a pure measure of distance.

Figure 3 shows, instead, the social distancing response across a sample of major countries in the sample (for easiness of exposition, I show the experiences of 15 out of 41 countries in the figure). Mobility declined by 60% or more in Italy, France, Spain, and New Zealand. While in some countries, the adjustment was abrupt (e.g., New Zealand, France, Spain), it was slower and more gradual in others, such as the UK (where the response starts a few days later) and the USA; their overall declines in mobility were also more modest. Sweden is an outlier in Europe, as it maintained only small fluctuations of mobility around the historical mean. Japan and Korea observed their first cases earlier; therefore, their social distancing responses during this period appear more limited. In many European countries and in the USA, mobility returns to its historical average by the beginning of June.

3 A global VAR model

To model global interdependencies in the spread of the disease and countries' responses, I follow the GVAR approach proposed in Pesaran et al. (2004) and surveyed in Chudik and Pesaran (2011).

Assume that there are N units, representing countries in this case, and for each unit, the dynamics is captured by k_i domestic variables. For each country i, the $k_i \times 1$
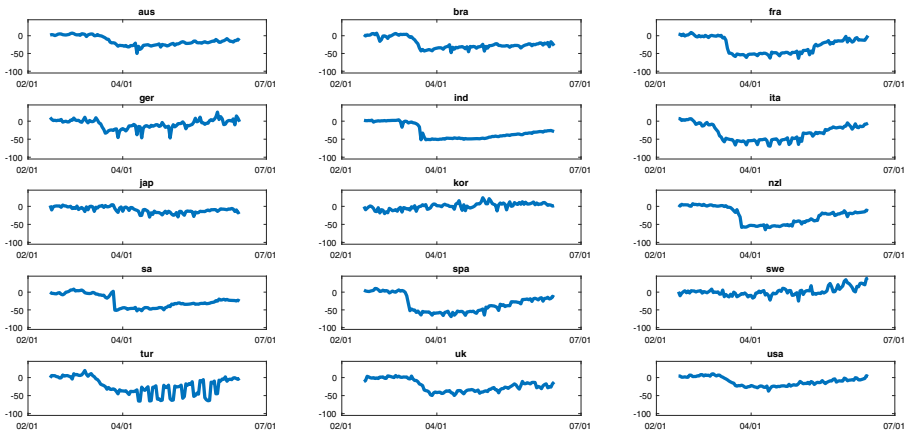

Fig. 3 Decline in social mobility across a selection of countries (Google mobility data)

vector $x_{i,t}$ of endogenous variables includes four domestic series: the growth rate of COVID-19 cases, the risk perception about COVID-19, the change in social mobility, and the perception about unemployment.[6] The vector of domestic variables is modeled as:

$$x_{i,t} = \sum_{l=1}^{p_i} \Phi_{il} x_{i,t-l} + \Lambda_{i0} x_{i,t}^* + \sum_{l=1}^{q_i} \Lambda_{il} x_{i,t-l}^* + \varepsilon_{i,t} \qquad (1)$$

for $i = 1, 2, ..., N$, and where Φ_{il}, Λ_{i0}, and Λ_{il} denote matrices of coefficients of size $k_i \times k_i$ and $k_i \times k_i^*$, where k_i^* denotes the number of "foreign" variables included in the vector $x_{i,t}^*$, and $\varepsilon_{i,t}$ is a $k_i \times 1$ vector of error terms. In the empirical analysis, I select the optimal number of lags p_i and q_i for each country using Schwartz's Bayesian Information Criterion (BIC).

For each country i, therefore, domestic variables are a function of their p_i lagged values, possibly of the contemporaneous values and q_i lagged values of foreign, or global, variables. The foreign variables $x_{i,t}^*$ are $k_i^* \times 1$ cross-section averages of foreign variables and they are country-specific:[7]

$$x_{i,t}^* = \bar{W}_i' x_t, \qquad (2)$$

for $i = 1, ..., N$, and where $x_t = (x_{1t}', ..., x_{Nt}')'$ is a $kx1$ vector that collects the unit-specific $x_{i,t}$, with $k = \sum_{i=1}^{N} k_i$. The matrix $\bar{W}_i$ has size $k \times k_i^*$ and contains country-specific weights, with diagonal elements $w_{ii} = 0$. My approach uses the extent of social connections across country borders from the Facebook Social Connectedness index dataset to measure the weights.

GVAR models assume that the variables $x_{i,t}^*$ are weakly exogenous. This corresponds to the popular assumption in open-economy macro models that the domestic country is treated as "small" in relation to the world economy, i.e, it does not affect global variables. This assumption can be easily tested for all the variables. For cases in which a domestic variable has an unduly large effect on global variables, weak exogeneity will not be invoked there and the foreign variable, instead, will not be included in that VAR.

The estimation works in two steps. First, VARX* (that is, VARs with weakly exogenous foreign variables) models can be estimated for each country separately.

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[6]Since I study the social responses to the COVID-19 outbreak, I include in the domestic VAR also the risk perception variable, in addition to the number of cases. I believe that changes in the number of confirmed coronavirus cases may lead to different risk perceptions in the different countries, which, in turn, can affect people's willingness to adhere to stay-at-home orders or to voluntarily engage in social distancing. As a measure of economic consequences, I choose an indicator of unemployment. Other options that are available at daily frequencies include stock returns, interest rates, and electricity data. Stock returns and interest rates are inferior indicators of economic activity in this period as they were largely influenced by government and central banks' emergency interventions. Electricity data would be appropriate, but they have been made available only for a small selection of European countries (McWilliams and Zachmann 2020).

[7]In the analysis, the number k_i^* is also equal to 4, as the vector $x_{i,t}^*$ contains the country-specific global counterparts for the same variables in $x_{i,t}$, i.e., the growth rate of COVID-19 cases, coronavirus risk perceptions, social mobility, and unemployment.

Second, the estimated country models are stacked to form a large GVAR system, which can be solved simultaneously.[8]

Domestic and foreign variables are stacked in the $k_i + k^*$ vector $z_{i,t} = [x'_{i,t}, x^{*'}_{i,t}]'$. The model in Eq. 1 can be rewritten as:

$$A_{i0} z_{i,t} = \sum_{l=1}^{p} A_{il} z_{i,t-l} + \varepsilon_{i,t} \tag{3}$$

where $A_{i0} = (I_{k_i} - \Lambda_{i0})$, $A_{il} = \Phi_{il} \Lambda_{il}$, for $l = 1, ..., p$, with $p = max(p_i, q_i)$. Defining the "link" matrices $W_i = (E'_i \bar{W}'_i)$, where E_i is a selection matrix that selects $x_{i,t}$ from the vector x_t, gives:

$$z_{i,t} = \begin{bmatrix} x'_{i,t} \\ x^{*'}_{i,t} \end{bmatrix} = W_i x_t. \tag{4}$$

Substituting into Eq. 3 and stacking all the unit-specific models yield:

$$G_0 x_t = \sum_{l=1}^{p} G_l x_{t-l} + \varepsilon_t, \tag{5}$$

where $G_l = [A_{1,l} W_1, A_{2,l} W_2, ..., A_{N,l} W_N]'$, for $l = 0, 1, ..., p$, and $\varepsilon_t = [\varepsilon_{1,t}^{prime}, ..., \varepsilon'_{N,t}]'$. With G_0 invertible, as it is in this case, the GVAR is given by:

$$x_t = \sum_{l=1}^{p} F_l x_{t-l} + G_0^{-1} \varepsilon_t, \tag{6}$$

with $F_l = G_0^{-1} G_l$.

The GVAR solution can be used to trace the impact of shocks on the variables of interest, both domestically and globally. To find the impulse response to shocks, I adopt the Generalized Impulse Response Function (GIRF) approach, proposed by Koop et al. (1996), Pesaran and Shin (1998), and also used in Pesaran et al. (2004). The vector of GIRFs is given by:

$$\mathbf{g}_{\varepsilon_j}(h) = E(x_{t+h}|\varepsilon_{j,t} = \sqrt{\sigma_{jj}}, \mathcal{I}_{t-1}) - E(x_{t+h}|\mathcal{I}_{t-1}) \tag{7}$$

where j indexes the different shocks, h denotes the horizon for the impulse response function, $I_t = x_t, x_{t-1}, ...$ denotes the available information set at time t, and where $\sqrt{\sigma_{jj}}$ indicates that the magnitude of the shock is set at one standard deviation of the corresponding $\varepsilon_{j,t}$.

The GVAR specification can be seen in relation to a number of econometric alternatives: spatial VARs, panel VARs, and dynamic factor models. Spatial VARs are very strongly connected. They also assume a connectivity matrix, which is usually based on geographic distance. The main difference between the two approaches lies with the structure of correlations: as discussed at length in Elhorst et al. (2018), spatial VARs may be preferred when correlations across units are extremely sparse, for example, when a unit is only affected by few bordering units ("weak," or local, cross-sectional dependence). The GVAR is meant to capture stronger interrelationships,

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[8]Additional details are provided in the Appendix.

with dense connectivity matrices, where each country unit is affected, in different ways, by several other countries, or by an aggregate measure ("strong" cross-sectional dependence). Spatial VARs can also be seen as a particularly restricted case of a GVAR model. The approach can similarly be seen as a particular form of panel VAR. The main advantage here is that, through the weight matrix W_i, this approach exploits knowledge about social networks and uses that knowledge to inform the magnitude of cross-country interdependencies. Panel VARs often impose the same coefficients for each unit, shutting down static and dynamic heterogeneity, as well as neglecting cross-country interdependencies. An exception is provided by Canova and Ciccarelli (2009): they introduce a factor structure in the coefficients to solve the curse of dimensionality. Their approach is particularly useful when there is no a priori knowledge that can be exploited about the spillovers. In this case, the extent of social networks can be, instead, exploited to provide some information about the relative strength of interdependencies. Finally, the GVAR has relations with dynamic factor models. As Chudik and Pesaran (2011) show, the GVAR specification approximates a common factor across units, and it extracts common factors using structural knowledge.

The model is particularly suited to account for potentially complex patterns of interdependencies across countries. At the same time, the GVAR specification does so while maintaining simplicity and parsimony. The dimensionality issue is resolved by decomposing a large-scale VAR into a number of smaller scale VARs for each unit, which can be estimated separately, conditional on the dynamics of weakly exogenous foreign variables. The interdependencies are not left entirely unrestricted, since it would be unfeasible to estimate all the parameters, but they are given a structure based on knowledge of the data.

In the benchmark analysis, I estimate the GVAR model using daily data from February 15 to April 11, 2020. The dates are chosen based on availability of Google social mobility data at the time the paper was written.[9] The exogeneity assumption is relaxed where it appears unlikely: for COVID cases, I do not include foreign variables in the model for the USA, Italy, and Spain, since they may be endogenous. Those countries, at different times, have accounted for a large share of global cases. I allow the COVID variable for all other countries to be affected by foreign series. I also allow risk perceptions in each country, as well as social distancing outcomes, to be affected even contemporaneously by corresponding variables in different countries. Finally, I assume that domestic unemployment perceptions are affected by foreign unemployment perceptions, but not within the same day. This assumption is not important for the results (which are robust), but it is motivated by the idea that the unemployment data are driven more by country-specific, than across-the-border, factors. I test the weak exogeneity assumptions for all foreign variables, and they are never rejected in the data.

Recently, some studies have emphasized the importance of superspreaders in the transmission of the virus (e.g., Adam et al. 2020, who study clusters in Hong

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[9]In this revised version, I add an update in Section 4.5, where I show the results for the most recent sample between April 12 and June 14.

Kong). Beldomenico (2020) discusses how SARS-CoV-2 appears to start by spreading gradually in a region, until transmission is triggered by a possible cascade of superspreader events, and cases explode. As a result, the pattern of transmission can become highly heterogeneous. Here, I focus on numbers of cases aggregated at the country level. My framework can account for heterogeneous responses across countries. However, even if the weak-exogeneity tests suggest that domestic countries do not affect global variables in a statistical sense, it is conceivable that, with superspreaders, COVID infections can transmit very quickly, and do so even between country pairs with a limited degree of social connections. My identification assumption, however, requires that the impact of a superspreader from country i on the total number of global cases remains small enough.

4 Results

4.1 Cross-country interdependencies

First, to study the magnitude of global interdependencies, Table 1 shows the contemporaneous effects of foreign variables on domestic variables, for each country. The table reports the estimated coefficients, alongside the associated standard errors. Domestic variables are significantly affected by the country-specific foreign aggregates, computed using the matrix of social connections as country-by-country weights. The results indicate that the international spread of COVID-19 cases can be, in part, explained by existing social networks across country borders. Moreover, the contagion not only relates to the number of cases and the spread of the disease, but it also affects the spread of perceptions and social behavior. Both the measure of risk perceptions about coronavirus and the social distancing responses are significantly influenced by developments in the rest of the world.

Only few countries do not show a statistically significant response to global conditions. Risk perceptions do not rise in response to increasing international distress only in Brazil, South Africa, and Turkey. It is likely that their populations initially underestimated the likelihood of the pandemic reaching them, as they were farther from the epicenters. Most countries also gradually learn from each others' social distancing responses. Among the few exceptions, Japan and Korea are not significantly affected by foreign experiences: they implemented social distancing earlier than other countries, but they already relaxed many of the restrictions before the period that I consider.

These results highlight the importance of considering global interrelationships and social connections in understanding the transmission of the virus and societal responses. My results add to those in Zimmermann et al. (2020), who investigate the role of globalization during the pandemic. Countries with a higher index of globalization had faster transmission speed and higher infection rates, although they responded better to the challenges by achieving lower fatality rates. International travel and migration play key roles in the transmission. Their paper, therefore, discusses the benefits of inter-country distancing, based on the imposition of temporary travel restrictions. My empirical results point to similar policy implications: since

Table 1 Contemporaneous effects of foreign aggregates on domestic variables

Countries	COVID	Risk Perc.	Soc. Dist.	Countries	COVID	Risk Perc.	Soc. Dist.
Australia	0.404*** (0.094)	0.726*** (0.126)	1.042*** (0.164)	Italy		1.055*** (0.389)	0.643*** (0.129)
Austria	0.631*** (0.243)	1.266*** (0.117)	0.902*** (0.098)	Japan	0.081 (0.076)	0.272*** (0.091)	0.239 (0.264)
Belgium	0.547*** (0.188)	0.881*** (0.095)	0.781*** (0.143)	Korea	−0.524* (0.294)	0.260*** (0.074)	0.010 (0.247)
Brazil	0.999*** (0.203)	0.153 (0.172)	1.068*** (0.174)	Latvia	0.036 (0.147)	0.849*** (0.095)	1.571*** (0.191)
Canada	0.326*** (0.121)	1.301*** (0.147)	0.905*** (0.179)	Lithuania	−0.008 (0.207)	0.280*** (0.076)	0.989*** (0.214)
Chile	1.041*** (0.306)	0.824*** (0.153)	0.809*** (0.113)	Luxembourg	0.032 (0.118)	0.833*** (0.163)	1.084*** (0.222)
Colombia	0.512** (0.223)	0.561** (0.229)	0.648*** (0.200)	Mexico	−0.158 (0.287)	0.463*** (0.160)	0.191 (0.190)
Costa Rica	0.316 (0.300)	0.569** (0.223)	0.755*** (0.166)	Netherlands	1.559*** (0.213)	0.830*** (0.089)	0.696*** (0.156)
Czech Republic	0.899*** (0.193)	0.613*** (0.112)	0.679*** (0.112)	New Zealand	0.257 (0.209)	0.562*** (0.160)	0.897*** (0.196)
Denmark	0.968*** (0.322)	0.686*** (0.130)	0.845*** (0.241)	Norway	0.761** (0.306)	0.952*** (0.108)	0.749*** (0.292)
Estonia	0.705*** (0.263)	0.555*** (0.113)	1.579*** (0.168)	Poland	0.387 (0.252)	1.522*** (0.202)	0.804*** (0.221)
Finland	0.493*** (0.101)	0.725*** (0.085)	0.615*** (0.095)	Portugal	0.283 (0.177)	0.431*** (0.133)	0.277** (0.131)
France	1.046*** (0.121)	0.843*** (0.150)	0.662*** (0.095)	Slovakia	0.131 (0.119)	0.694*** (0.143)	1.268*** (0.129)
Germany	1.078*** (0.115)	0.738*** (0.196)	1.640*** (0.181)	Slovenia	0.631*** (0.205)	0.823*** (0.101)	1.152*** (0.141)
Greece	1.100*** (0.274)	0.546*** (0.108)	0.361 (0.253)	South Africa	−0.104 (0.274)	0.230 (0.344)	−0.101 (0.361)
Hungary	0.281 (0.199)	0.771*** (0.190)	0.965*** (0.162)	Spain		1.560*** (0.232)	1.198*** (0.221)
India	1.439*** (0.380)	0.315* (0.167)	0.511* (0.286)	Sweden	1.050*** (0.265)	0.782*** (0.072)	0.432** (0.204)
Indonesia	0.864** (0.394)	0.381** (0.157)	0.753*** (0.116)	Switzerland	0.739** (0.296)	0.626*** (0.166)	1.090*** (0.239)
Ireland	1.784*** (0.337)	1.860*** (0.214)	0.674*** (0.194)	Turkey	0.277 (0.256)	0.071 (0.080)	0.494* (0.254)
Israel	0.943*** (0.247)	0.246*** (0.066)	0.085 (0.381)	UK	0.895*** (0.121)	1.067*** (0.186)	0.587*** (0.151)
				USA		1.622*** (0.154)	0.545*** (0.110)

The table reports the estimated GVAR coefficients with the associated standard error shown below in parentheses. Significance at the 1% level is denoted by ***, at the 5% level by **, and at the 10% level by *

border closures and travel restrictions can be effective.
coronavirus cases spread internationally as a result of existing social networks, early

4.2 Global transmission of shocks from Italy and the USA

I study the global responses to shocks from Italy and the USA since these countries played outsized roles in different phases of the pandemic.

Figures 4 and 5 show the impulse response functions for all countries in the sample for the risk perception and social distancing variables to a one-standard-deviation COVID shock originating in Italy. Risk perceptions increase, with some sluggish
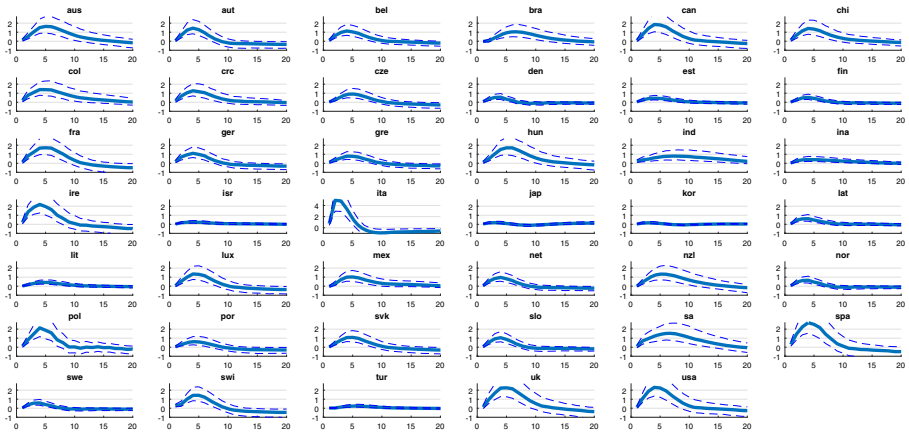
Fig. 4 Impulse responses across countries of coronavirus risk perception to a COVID-19 growth rate shock originating in Italy

adjustment, almost everywhere in the world in response to the initial shock from Italy. The responses typically reach their peak about 4–6 days after the original shock. The response is more delayed in Brazil, India, and South Africa. As seen in the previous section, these countries are less influenced by global variables in this period. Populations in neighboring European countries, as well as in the USA, Australia, and Canada, instead significantly update their perceptions. The overall effect is much smaller in Sweden, Finland, Turkey, Israel, and Lithuania. Again, Japan and South Korea do not seem to significantly respond, as they experienced their outbreaks earlier than the rest of countries.

Similarly, most countries respond with reductions in social mobility. The social distancing response, however, is already delayed and sluggish in Italy, with a negative
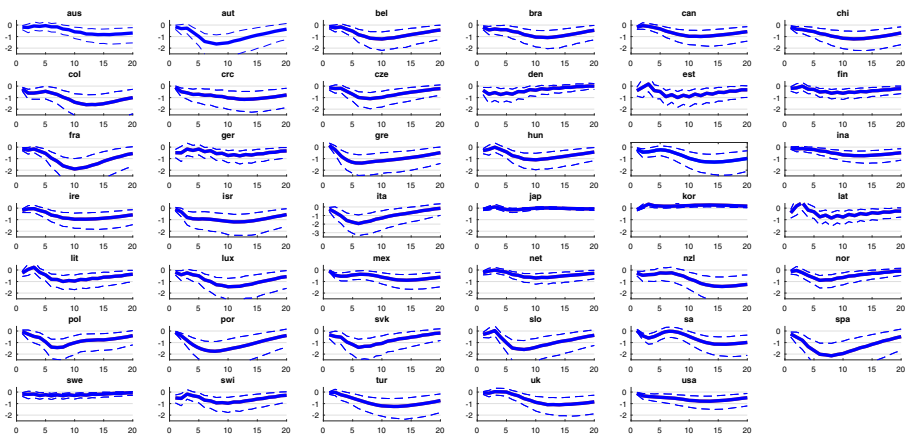

Fig. 5 Impulse responses across countries of social mobility to a COVID-19 growth rate shock originating in Italy

peak in mobility occurring 6 days after the shock. Other European countries, such as France, Switzerland, and the UK, do not seem to adjust at all for the initial 3–5 days, after which they gradually reduce their social mobility as well. The patterns are similar everywhere: after the situations worsen in one country, the others do not immediately learn from its experience and change their behavior. Instead, they appear to behave more adaptively, by only gradually altering their habits in response to the evolving situation.

One issue to consider is whether the joint declines in social mobility are driven by policies that happened at the same time. My measure of actual mobility captures both the effects of mandates and those of voluntary distancing. I use data on the Government Response index made available for different countries through the Oxford COVID-19 Government Response Tracker (OxCGRT)'s website and discussed in Thomas Hale et al. (2020). I regress the Google mobility indicator on a constant and on the Government Response index for each country. Figure 6 shows the estimated coefficients for the sensitivity of mobility to the government response, and the resulting R^2 for each country's regression. The results clarify that measures based on actual mobility carry additional information that goes beyond what can be captured by looking only at the implemented policies. For many countries, mobility responds negatively to policy restrictions, with R^2 coefficients falling in the 0.7–0.9 range. The explanatory power is particularly strong in Mexico and New Zealand. But simply using policy responses would miss the extent of social responses in many other countries, where the explanatory power is closer to 0 (as in Korea, Netherlands, and Scandinavian and Baltic countries).

The focal point of the pandemic later moved to the USA, at least starting from mid-March. Figure 7 displays the effects on coronavirus risk perceptions in the rest of the world to a US coronavirus risk shock. I consider the risk perception shock for the USA, rather than the one based on the number of cases, since testing was initially
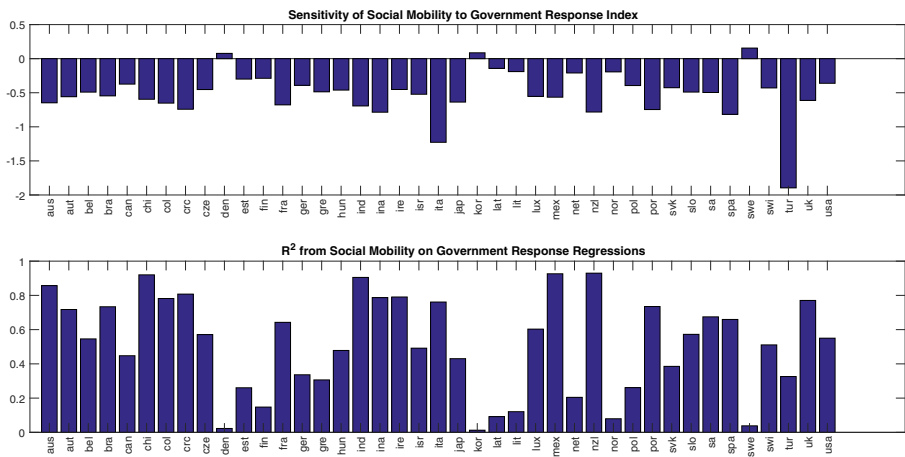
Fig. 6 Relation between voluntary social distancing and government lockdown policies. The results are based on the regression $Social\ Mobility_t = \beta_0 + \beta_1 Govt.\ Response_t + \varepsilon_t$ for each country. The top panel shows the estimated coefficient β_1, the second the regression R^2
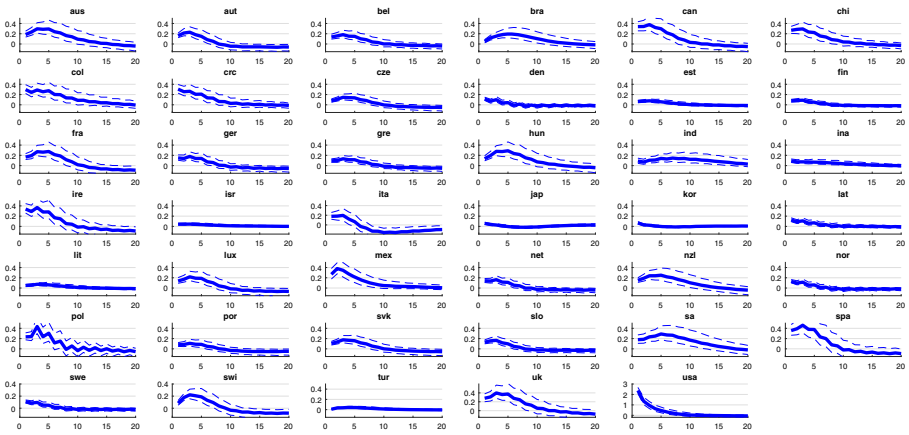
Fig. 7 Impulse responses across countries of coronavirus risk perception to a coronavirus risk perception shock originating in the USA

very limited and the shock may not correctly identify the spread of the pandemic. The spillovers in risk perceptions are again statistically significant, but much smaller in magnitude than those observed in response to the corresponding Italian shock. The same is true for responses of social mobility to a US coronavirus risk shock, shown in Fig. 8. For many countries, I observe a slight increase in social distancing, including for the USA themselves.

In terms of policy implications, the results highlight the importance of rapid inter-changes of information: the rest of the world can learn from policies and behaviors that seemed to work in the countries that were reached early by the virus. The results show that perceptions about the pandemic spread to different countries. The resulting
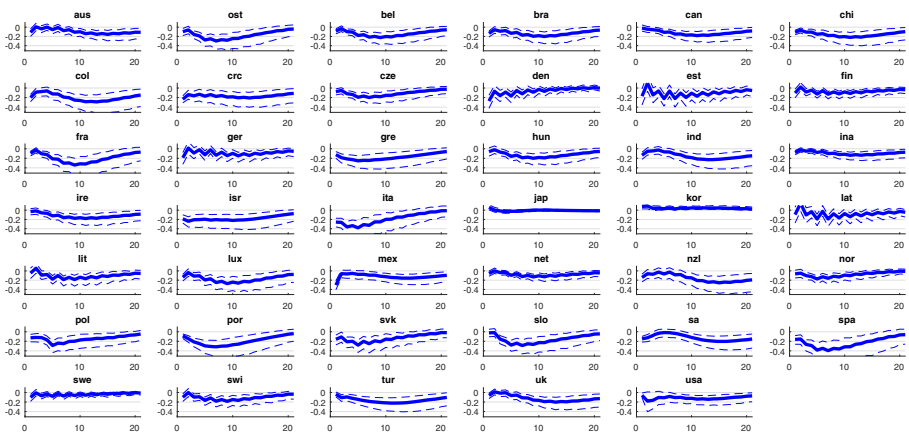
Fig. 8 Impulse responses across countries of social mobility to a coronavirus risk perception shock originating in the USA

adjustments, however, both in terms of policies and distancing behavior, have been quite sluggish.

4.3 Heterogeneity in country responses

The responses to the pandemic have been heterogeneous across countries. Figure 9 overlaps, for a selection of countries, the impulse responses of social distancing and unemployment to the country's own coronavirus risk shock. I single out the responses for Italy, Spain, the UK, the USA, Sweden, and Japan, since they characterize somewhat different approaches to the crisis.

The populations of Italy and Spain sharply decreased their social mobility after the domestic coronavirus shock. The responses reach their maximum effects after 5–6 days, and they last for weeks. Their behavior suggests that even in the countries that were most affected by the virus, their social distancing responses, while substantial, have been unnecessarily delayed. Japan displays a smaller, and more sluggish, response. The USA and the UK are also characterized by negative and statistically significant adjustments in mobility, but their responses are many order of magnitudes smaller than the ones observed in Italy and Spain. Finally, it is well documented that Sweden adopted a more permissive approach, by letting its citizens adjust their
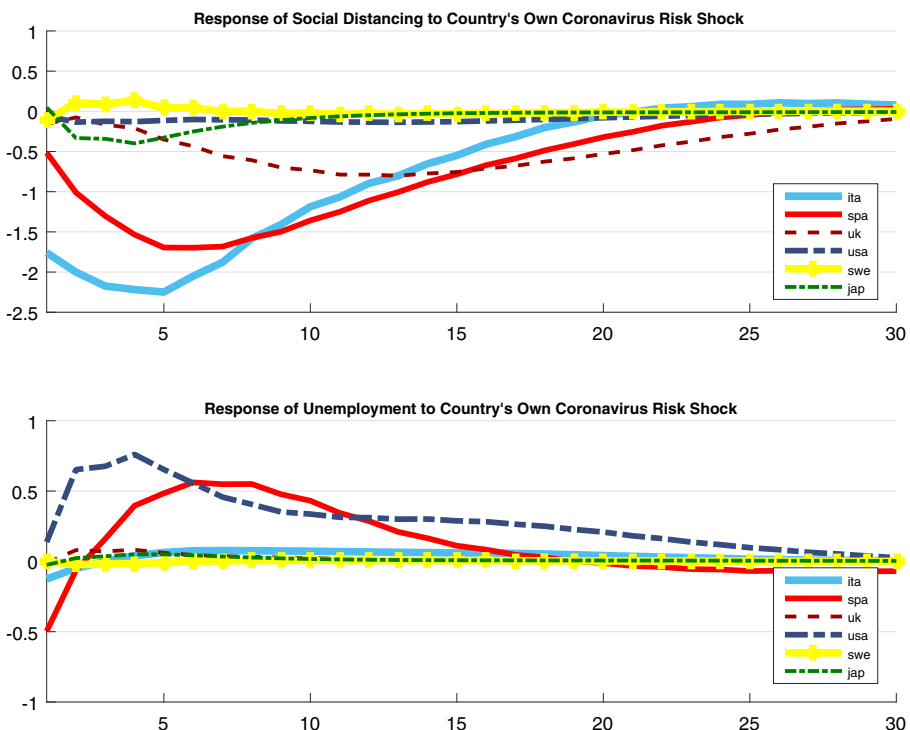
Fig. 9 Impulse response functions of coronavirus risk perceptions and unemployment to the country's own coronavirus risk shock

behavior without the same strict enforcement that was observed in other countries. The response for Sweden, accordingly, does not show any significant decrease in mobility to the country-specific risk shock.

Turning to the early estimates about potential economic effects, I show the responses of the real-time unemployment indicator to each country-specific coronavirus shock. The figure shows that unemployment does not necessarily need to skyrocket in response to health shocks. Unemployment insurance claims have reached record levels in the weeks after the outbreak in the USA. The impulse responses are consistent with the behavior of unemployment claims, revealing an extremely large response of the Google unemployment indicator. Unemployment is also set to considerably increase in Spain. The country has a large share of workers on temporary contracts, who are more likely to become unemployed due to the uncertainty generated by the pandemic. Other countries in the sample, however, as well as the vast majority of countries not shown in the figure, appear more successful in insulating their labor forces from the crisis. Even if the recessionary effects on output are likely to be large almost everywhere, for most countries, early indicators of unemployment suggest that local labor markets are not going to experience the same turbulence as those in the USA.

4.4 The benefits of social distancing

So far, the analysis has focused on the direction of causality that goes from COVID cases to social and economic responses. Here, I provide evidence on the opposite direction: the effects of social distancing on new COVID cases.

Figure 10 shows the impulse responses of the growth rate of COVID-19 cases in different countries to a social distancing shock, measured as a one-standard-deviation decline in social mobility. Social distancing leads to declines in the growth rate of coronavirus cases in the days after the shock. The only country in the figure that does not show a negative response is the UK, for which social distancing has, in fact, been much slower to start.

The results reaffirm the importance of social distancing, whether through mandatory policy or voluntary behavior, in reducing the spread of the virus. While in epidemiology, the benefits of social distancing are usually modeled as changes in the parameters of a SIR model, here I show that the effects can be uncovered also in a simpler linear framework.

Moreover, the results regarding unemployment, presented in the previous section, suggest that social distancing does not necessarily have to translate into high unemployment rates. A prompt social distancing response, coupled with labor institutions that attenuate the impact of business cycles, can successfully limit the health shocks from the pandemic, without causing extensive economic damage.

4.5 Data update: second phase with cases surging in Latin America and India

The empirical analysis, so far, has been based on data up to mid-April. I now update the dataset to include the most recent months. After April, the social distancing efforts were successful in most of Europe: the number of daily cases in Italy, Spain,
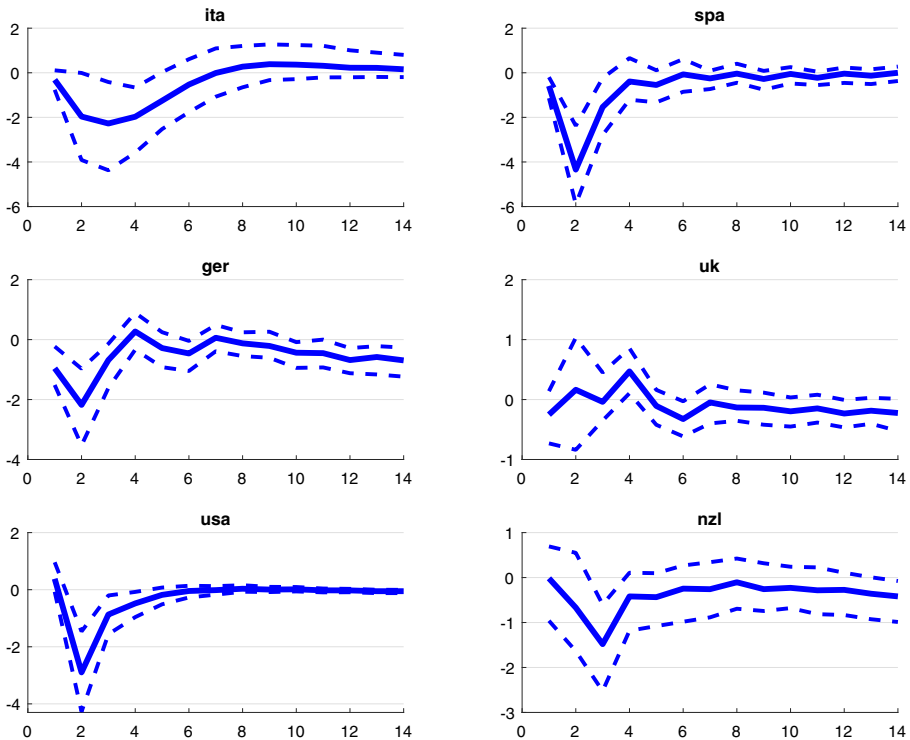
Fig. 10 Impulse responses of COVID-19 growth rates to a social distancing shock

Germany, France, and most neighboring countries, declined; as a result, the countries started to relax most restrictions on mobility.

The global centers of the virus moved instead to the Americas, with US cases still remaining high, and with Brazil's situation rapidly deteriorating. The situation also worsened considerably in India.

To incorporate data for this second phase, I re-estimate the GVAR model for the more recent sample between April 12 and June 14 (the last day of availability of Google Mobility data at the time of writing). The results are reported in Tables 2 and 3.

Table 2 shows the values of the peak responses for the impulse response functions of coronavirus risk perceptions in each country in the sample to corresponding coronavirus risk shocks from seven countries: Italy, the USA, Spain, UK, Brazil, Chile, and India. These countries are selected as they had large number of cases at different times, during the sample. Table 3 reports similar information (in this case, the size of the largest negative responses across horizons) for the social distancing responses, instead. To compare the role played by the different countries, I show the results for both the first phase, starting in mid-February and ending in mid-April, and for the second phase, from mid-April to mid-June.

Table 2 Peak effects of coronavirus risk shocks from Italy, the USA, Spain, UK, Brazil, Chile, and India on risk perceptions about coronavirus in the rest of the countries

Countries	Italy		U.S.		Spain		U.K.		Brazil		Chile		India	
	Feb–Apr	Apr–Jun	Feb–Apr	Apr–Jun	Feb–Apr	Apr–Jun	Feb–Apr	Apr–Jun	Feb–Apr	Apr–Jun	Feb–Apr	Apr–Jun	Feb–Apr	Apr–Jun
Australia	2.16	0.15	0.30	0.50	1.03	0.88	1.37	1.54	0.40	0.16	0.23	0.26	0.10	0.16
Austria	2.00	0.04	0.23	0.11	0.85	0.39	1.12	0.28	0.27	0.05	0.19	0.07	0.07	0.02
Belgium	1.52	0.10	0.18	0.23	0.69	0.67	0.82	0.68	0.23	0.09	0.15	0.13	0.05	0.06
Brazil	1.36	0.17	0.19	0.60	0.73	1.02	0.74	1.41	2.67	1.06	0.16	0.39	0.06	0.15
Canada	2.67	0.09	0.38	0.35	1.21	0.52	1.47	0.87	0.40	0.11	0.28	0.17	0.12	0.11
Chile	2.11	0.20	0.29	0.80	1.19	1.40	1.18	1.64	0.37	0.28	2.65	1.06	0.08	0.18
Colombia	2.01	0.31	0.30	1.30	1.24	2.27	1.19	2.54	0.41	0.45	0.72	1.07	0.09	0.28
Costa Rica	1.79	0.24	0.31	1.07	0.92	1.69	0.98	1.98	0.30	0.34	0.37	0.70	0.07	0.22
Czech Rep.	1.21	0.03	0.15	0.07	0.53	0.24	0.68	0.18	0.18	0.03	0.12	0.04	0.04	0.02
Denmark	0.83	0.06	0.11	0.18	0.40	0.48	0.58	0.54	0.11	0.07	0.10	0.10	0.03	0.05
Estonia	0.62	0.03	0.08	0.06	0.29	0.23	0.35	0.19	0.09	0.03	0.07	0.04	0.02	0.02
Finland	0.75	0.02	0.09	0.06	0.33	0.13	0.45	0.17	0.10	0.02	0.07	0.03	0.03	0.02
France	2.27	0.12	0.28	0.31	1.05	1.07	1.28	0.72	0.38	0.13	0.23	0.18	0.09	0.06
Germany	1.46	0.07	0.18	0.20	0.69	0.60	0.85	0.55	0.22	0.09	0.14	0.12	0.05	0.05
Greece	1.11	0.03	0.13	0.07	0.49	0.24	0.62	0.18	0.16	0.03	0.10	0.04	0.04	0.02
Hungary	2.29	0.12	0.29	0.30	1.08	1.04	1.32	0.72	0.39	0.12	0.23	0.18	0.09	0.06
India	1.00	0.19	0.15	0.69	0.61	1.16	0.64	1.84	0.26	0.23	0.12	0.36	2.46	1.78
Indonesia	0.55	0.06	0.09	0.23	0.29	0.34	0.34	0.58	0.12	0.08	0.09	0.13	0.06	0.10
Ireland	2.84	0.14	0.37	0.36	1.33	1.01	2.18	1.14	0.45	0.15	0.29	0.20	0.11	0.09
Israel	0.34	0.29	0.04	0.31	0.15	0.43	0.19	0.76	0.05	0.09	0.04	0.15	0.01	0.08
Italy	7.71	0.26	0.20	0.05	0.75	0.19	0.98	0.12	0.24	0.02	0.17	0.03	0.06	0.01

Table 2 (continued)

Countries	Italy		U.S.		Spain		U.K.		Brazil		Chile		India	
	Feb–Apr	Apr–Jun	Feb–Apr	Apr–Jun	Feb–Apr	Apr–Jun	Feb–Apr	Apr–Jun	Feb–Apr	Apr–Jun	Feb–Apr	Apr–Jun	Feb–Apr	Apr–Jun
Japan	0.30	0.06	0.06	0.22	0.14	0.31	0.20	0.58	0.05	0.08	0.04	0.11	0.01	0.06
Korea	0.33	0.06	0.07	0.19	0.16	0.29	0.22	0.49	0.04	0.05	0.05	0.08	0.01	0.05
Latvia	0.93	0.04	0.12	0.09	0.45	0.31	0.78	0.21	0.13	0.04	0.11	0.05	0.03	0.02
Lithuania	0.58	0.03	0.07	0.07	0.28	0.24	0.35	0.18	0.09	0.03	0.06	0.04	0.02	0.02
Luxembourg	1.90	0.08	0.22	0.18	0.85	0.54	1.01	0.48	0.28	0.07	0.18	0.11	0.06	0.05
Mexico	1.48	0.22	0.38	1.16	0.82	1.50	0.80	1.81	0.26	0.032	0.25	0.66	0.06	0.20
Netherlands	1.32	0.11	1.16	0.32	0.60	0.64	0.76	0.97	0.19	0.10	0.13	0.16	0.05	0.09
New Zealand	1.70	0.14	0.25	0.50	0.87	0.88	1.09	1.56	0.33	0.16	0.19	0.26	0.09	0.17
Norway	0.93	0.12	0.13	0.38	0.47	0.84	0.71	1.17	0.13	0.14	0.19	0.20	0.03	0.10
Poland	3.49	0.09	0.44	0.22	1.59	0.64	1.97	0.76	0.45	0.08	0.11	0.12	0.12	0.06
Portugal	0.91	0.02	0.12	0.04	0.43	0.15	0.50	0.10	0.15	0.02	0.37	0.02	0.03	0.01
Slovakia	1.49	0.04	0.18	0.09	0.64	0.29	0.82	0.23	0.22	0.04	0.09	0.05	0.05	0.02
Slovenia	1.47	0.03	0.17	0.08	0.62	0.29	0.81	0.20	0.20	0.03	0.14	0.05	0.05	0.02
South Africa	1.95	0.23	0.29	0.80	1.09	1.95	1.22	2.27	0.43	0.27	0.22	0.42	0.10	0.26
Spain	3.75	0.13	0.46	0.33	4.47	1.27	2.08	0.76	0.57	0.13	0.49	0.20	0.13	0.07
Sweden	0.78	0.05	0.11	0.14	0.38	0.40	0.59	0.39	0.11	0.06	0.09	0.08	0.03	0.04
Switzerland	2.02	0.07	0.22	0.18	0.85	0.62	1.06	0.45	0.27	0.08	0.19	0.11	0.06	0.04
Turkey	0.34	0.01	0.04	0.02	0.16	0.06	0.18	0.05	0.06	0.01	0.03	0.01	0.01	0.004
UK	3.14	0.14	0.40	0.43	1.48	1.16	3.98	2.25	0.53	0.17	0.32	0.24	0.13	0.11
USA	3.22	0.11	2.38	1.30	1.49	0.91	1.79	0.76	0.49	0.13	0.38	0.20	0.13	0.07

The table reports the largest value, across horizons, of the impulse responses of each country's coronavirus risk perceptions to shocks originating in Italy, the USA, Spain, UK, Brazil, Chile, and India, for two phases: the period between February 15 and April 11, 2020, and the period between April 12 and June 14, 2020

Table 3 Peak effects of coronavirus risk shocks from Italy, the USA, Spain, UK, Brazil, Chile, and India on social mobility in the rest of the countries

Countries	Italy		U.S.		Spain		U.K.		Brazil		Chile		India	
	Feb–Apr	Apr–Jun	Feb–Apr	Apr–Jun	Feb–Apr	Apr–Jun	Feb–Apr	Apr–Jun	Feb–Apr	Apr–Jun	Feb–Apr	Apr–Jun	Feb–Apr	Apr–Jun
Australia	−1.09	−0.16	−0.16	−0.56	−0.67	−1.66	−0.66	−1.55	−0.30	−0.24	−0.13	−0.32	−0.05	−0.16
Austria	−2.14	−0.44	−0.30	−1.63	−1.20	−3.02	−1.28	−3.66	−0.49	−0.60	−0.24	−0.94	−0.10	−0.43
Belgium	−1.59	−0.34	−0.23	−1.03	−0.91	−3.72	−0.91	−2.42	−0.39	−0.38	−0.18	−0.60	−0.08	−0.23
Brazil	−1.41	−0.23	−0.20	−0.84	−0.83	−1.47	−0.84	−1.95	−0.90	−0.45	−0.16	−0.52	−0.07	−0.22
Canada	−1.25	−0.37	−0.18	−1.36	−0.76	−3.87	−0.75	−3.27	−0.34	−0.55	−0.14	−0.78	−0.06	−0.31
Chile	−1.51	−0.21	−0.22	−0.81	−0.94	−1.25	−0.91	−1.80	−0.42	−0.30	−0.52	−0.57	−0.08	−0.21
Colombia	−2.03	−0.36	−0.29	−1.04	−1.25	−2.16	−1.20	−2.25	−0.56	−0.37	−0.40	−0.70	−0.10	−0.25
Costa Rica	−1.43	−0.34	−0.24	−1.48	−0.90	−2.35	−0.87	−2.90	−0.41	−0.50	−0.27	−0.94	−0.08	−0.33
Czech Rep.	−1.50	−0.22	−0.20	−0.82	−0.81	−2.32	−0.89	−1.88	−0.32	−0.31	−0.16	−0.49	−0.07	−0.22
Denmark	−2.00	−0.42	−0.27	−1.23	−1.00	−4.71	−1.16	−3.25	−0.25	−0.52	−0.27	−0.74	−0.06	−0.29
Estonia	−1.65	−0.43	−0.22	−1.30	−0.90	−4.63	−1.14	−3.70	−0.32	−0.57	−0.20	−0.76	−0.07	−0.30
Finland	−0.92	−0.44	−0.13	−1.64	−0.54	−4.74	−0.62	−4.09	−0.21	−0.66	−0.12	−0.94	−0.04	−0.43
France	−2.41	−0.45	−0.34	−1.38	−1.37	−4.98	−1.43	−3.17	−0.58	−0.50	−0.27	−0.81	−0.11	−0.30
Germany	−1.42	−0.31	−0.19	−0.96	−0.71	−3.38	−0.67	−2.25	−0.25	−0.33	−0.21	−0.56	−0.05	−0.21
Greece	−1.80	−0.38	−0.25	−0.98	−1.02	−3.49	−1.04	−2.39	−0.43	−0.37	−0.20	−0.59	−0.08	−0.22
Hungary	−1.42	−0.31	−0.20	−0.96	−0.83	−3.45	−0.84	2.31	−0.35	−0.36	−0.16	−0.57	−0.07	−0.22
India	−1.61	−0.14	−0.23	−0.34	−0.97	−1.27	−0.97	−0.79	−0.45	−0.15	−0.18	−0.21	−0.51	−0.10
Indonesia	−0.95	−0.13	−0.14	−0.42	−0.58	−1.47	−0.58	−0.96	−0.26	−0.15	−0.11	−0.24	−0.05	−0.12
Ireland	−1.22	−0.16	−0.18	−0.47	−0.77	−1.71	−0.75	−1.20	−0.34	−0.18	−0.14	−0.28	−0.06	−0.11
Israel	−1.80	−0.24	−0.24	−0.63	−0.93	−1.95	−1.06	−1.42	−0.42	−0.24	−0.22	−0.38	−0.08	−0.13
Italy	−2.56	−0.52	−0.38	−1.44	−1.49	−4.82	−1.67	−3.63	−0.56	−0.59	−0.31	−0.82	−0.12	−0.38

Table 3 (continued)

Countries	Italy Feb–Apr	Italy Apr–Jun	U.S. Feb–Apr	U.S. Apr–Jun	Spain Feb–Apr	Spain Apr–Jun	U.K. Feb–Apr	U.K. Apr–Jun	Brazil Feb–Apr	Brazil Apr–Jun	Chile Feb–Apr	Chile Apr–Jun	India Feb–Apr	India Apr–Jun
Japan	−0.31	−0.11	−0.03	−0.33	−0.12	−1.19	−1.18	−0.82	−0.04	−0.12	−0.03	−0.20	−0.01	−0.08
Korea	0.14	−0.01	0.02	−0.002	0.10	0.06	−0.02	−0.04	−0.05	0.01	−0.02	0.005	−0.01	−0.004
Latvia	−1.47	−0.35	−0.19	−1.04	−0.76	−3.78	−1.05	−3.11	−0.26	−0.44	−0.17	−0.64	−0.05	−0.26
Lithuania	−1.43	−0.35	−0.19	−1.00	−0.78	−3.56	−0.93	−2.86	−0.31	−0.40	−0.17	−0.61	−0.06	−0.24
Luxembourg	−1.91	−0.39	−0.28	−1.17	−1.10	−4.19	−1.15	−2.73	−0.47	−0.43	−0.21	−0.69	−0.09	−0.27
Mexico	−1.09	−0.15	−0.31	−0.60	−0.67	−1.14	−0.65	−1.27	−0.30	−0.21	−0.26	−0.37	−0.06	−0.14
Netherlands	−0.93	−0.31	−0.13	−0.91	−0.54	−3.40	−0.56	−2.36	−0.22	−0.37	−0.10	−0.55	−0.04	−0.21
New Zealand	−1.79	−0.41	−0.26	−1.22	−1.11	−3.92	−1.06	−3.20	−0.51	−0.51	−0.20	−0.73	−0.09	−0.28
Norway	−1.34	−0.76	−0.17	−2.65	−0.69	−4.84	−0.84	−6.91	−0.25	−0.92	−0.15	−1.48	−0.05	−0.71
Poland	−2.23	−0.42	−0.29	−1.24	−1.14	−4.55	−1.29	−3.37	−0.41	−0.49	−0.25	−0.75	−0.08	−0.30
Portugal	−2.19	−0.28	−0.32	−0.77	−1.24	−2.92	−1.26	−1.85	−0.54	−0.30	−0.24	−0.48	−0.11	−0.17
Slovakia	−2.04	−0.49	−0.28	−1.81	−1.10	−3.30	−1.23	−4.29	−0.41	−0.67	−0.22	−1.06	−0.09	−0.48
Slovenia	−2.22	−0.40	−0.29	−1.11	−1.16	−4.09	−1.31	−2.85	−0.47	−0.45	−0.25	−0.69	−0.09	−0.25
South Africa	−1.41	−0.20	−0.20	−0.49	−0.86	−1.68	−0.84	−1.20	−0.39	−0.19	−0.16	−0.29	−0.07	−0.11
Spain	−2.79	−0.39	−0.40	−1.42	−1.86	−3.85	−1.68	−3.26	−0.66	−0.52	−0.33	−0.88	−0.14	−0.36
Sweden	−0.75	−0.48	−0.10	−1.50	−0.38	−5.53	−0.38	−4.14	−0.12	−0.69	−0.11	−0.89	−0.02	−0.38
Switzerland	−1.32	−0.20	−0.19	−0.60	−0.74	−2.10	−0.80	−1.39	−0.31	−0.23	−0.15	−0.36	−0.06	−0.16
Turkey	−1.51	−0.90	−0.22	−2.83	−0.93	−4.57	−0.90	−7.63	−0.43	−1.00	−0.17	−1.57	−0.08	−0.82
UK	−1.38	−0.23	−0.20	−0.67	−0.86	−2.50	−0.85	−1.64	−0.38	−0.27	−0.16	−0.40	−0.07	−0.15
USA	−0.98	−0.22	−0.18	−0.98	−0.60	−2.18	−0.60	−2.04	−0.28	−0.36	−0.11	−0.48	−0.05	−0.18

The table reports the lowest value, across horizons, of the impulse responses of each country's social mobility indicator to shocks originating in Italy, the USA, Spain, UK, Brazil, Chile, and India, for two phases: the period between February 15 and April 11, 2020, and the period between April 12 and June 14, 2020

Most countries were significantly affected by Italy's shocks during the first phase. Risk perceptions particularly increased in Spain, the UK, and the USA. Higher risk perceptions led to a much larger decline in social mobility in Spain (-2.79), though, than in the other two countries (-1.38 and -0.98, respectively). In the second phase, Italy's role diminished, and many countries reacted instead to shocks from the USA, Spain, and the UK. Although cases exploded in Brazil, Chile, and India, between April and June, the spillovers from these countries to the rest of the world have remained more limited. The largest effects may be detected in neighboring countries: for example, the largest increase in risk perceptions in response to shocks in Brazil and Chile is observed in Colombia. The effects on social mobility are somewhat larger, but far from the values obtained in response to shocks from Spain and the UK, for example.

The results suggest that, in most countries, public perceptions and behavior respond to global, not only to domestic, variables. The impact of individual countries, instead, varies over different phases of the pandemic and depending on the extent of social connections.

4.6 Discussion and limitations

Overall, this paper's results highlight the importance of interconnections to understand not only the spread of the virus, but also adaptation and gradual learning in importing ideas and behavior from other countries. Risk perceptions and the willingness to engage in social distancing by the populations of most countries significantly respond to the corresponding variables in socially connected countries. I stress the role of existing social networks across borders in the transmission of health shocks, perceptions about the risk of the disease, and ideas regarding the merit of social distancing.

The results reveal heterogeneous responses across countries to their own domestic coronavirus shocks. A common feature in all responses is that individuals responded with a lag and only gradually reduced their social mobility. This observation is consistent with epidemiological models that include adaptive human behavior, such as the model presented in Fenichel and et al (2011). That research stresses the role of public policies based on informing and motivating people to reduce person-to-person contacts. This may be particularly important for countries in which citizens have weaker social connections to the rest of the world, and in which, policymakers may delay in implementing mitigation policies.

Institutional differences among the countries' labor markets are likely responsible for substantially different increases in unemployment. The lower degree of employee protections in the USA and the large share of temporary workers in the Spanish economy are likely to account for the far worse outcomes in these countries. Everywhere else, fluctuations in unemployment have remained more subdued.

There are some possible limitations related to the data series used in the analysis. Unemployment indicators based on Internet data may be more or less accurate depending on the country: as discussed in Simionescu and Zimmermann (2017), their predictive power for actual unemployment may depend on the Internet penetration in the country, and on demographic variables, such as the age composition of Internet

users. Internet use may also vary across the income distribution, particularly in less economically developed countries. Perceptions about coronavirus risk may not be captured equally well in all countries in the sample. The matrix of social connections based on Facebook friendships may be subject to similar problems: Facebook users may have different average income and age than the population as a whole, and such friendships may capture to a larger extent personal, rather than business, links. My sample of countries necessarily excludes others (for example, China), which may be important in terms of social connections. Their omission may potentially lead to an omitted variable bias in the VAR regressions.

4.7 Sensitivity analysis

This section assesses the sensitivity of our estimates to alternative data and econometric choices.

The benchmark estimation used data on COVID-19 cases transformed into daily growth rates. I can examine the sensitivity of the results to using the number of new daily cases instead. Table 4 reports the estimated interdependencies corresponding to those previously shown in Table 1. To save space, the results are shown for a subset of six countries. The estimates remain similar, with the exception of a smaller spillover of global risk into the domestic Italian risk perception variable.

Also, in the benchmark estimation, the conditional country-specific models corresponded to VARs with the addition of weighted foreign aggregates. Another option

Table 4 Sensitivity analysis: contemporaneous effects of foreign aggregates

Countries	COVID	Risk Perc.	Social Dist.	Countries	COVID	Risk Perc.	Social Dist.
i) COVID-19 # of new cases instead of growth rate							
Italy		0.559 (0.442)	0.611*** (0.139)	USA		1.617*** (0.157)	0.545*** (0.117)
France	3.818*** (1.080)	0.792*** (0.152)	0.519*** (0.102)	Germany	5.242*** (0.996)	0.785*** (0.194)	1.655*** (0.175)
Spain		1.677*** (0.232)	1.103*** (0.222)	UK	5.965*** (1.225)	1.154*** (0.184)	0.267* (0.156)
ii) VECMX* instead of VARX*							
Italy		0.994** (0.389)	0.671*** (0.140)	USA		1.619*** (0.150)	0.527*** (0.108)
France	1.052*** (0.131)	0.863*** (0.157)	0.702*** (0.095)	Germany	1.041*** (0.108)	1.111*** (0.207)	1.703*** (0.189)
Spain		1.528*** (0.234)	1.200*** (0.241)	UK	0.887*** (0.119)	1.035*** (0.183)	0.575*** (0.162)
iii) Exclude Google Residential Mobility							
Italy		1.061*** (0.384)	0.652*** (0.154)	USA		1.580*** (0.154)	0.552*** (0.112)
France	1.002*** (0.123)	0.835*** (0.148)	0.408*** (0.146)	Germany	1.078*** (0.114)	0.755*** (0.203)	1.963*** (0.235)
Spain		1.596*** (0.234)	1.360*** (0.234)	UK	0.924*** (0.121)	1.085*** (0.185)	0.500*** (0.151)

Sensitivity check i) repeats the estimation using the level of new daily COVID-19 cases rather than their growth rate; case ii) estimates conditional vector-error-correction models rather than a VAR for each country; case iii) computes changes in social mobility excluding the series related to residential mobility

often used in the GVAR literature is to allow for long-run relationships and estimate Vector Error Correction (VECM) models instead.[10] The results shown in Table 4, as well as all the main findings, remain in line with those discussed so far.

Finally, the Google mobility indicator was computed by taking the average of mobility changes across all available categories. It can be argued that the relevant social distancing measure that matters for health outcomes should exclude Residential mobility. Therefore, I repeat the analysis by constructing social mobility, but now excluding the residential component. Again, the results remain substantially unchanged.

5 Conclusions

I estimated a global model of 41 countries to examine the interconnections in coronavirus cases and in social and economic responses during the first months of the COVID-19 pandemic.

The results suggest that social connections across borders are helpful to understand not only the spread of the disease, but also the spread in perceptions and social behavior across countries.

Initial shocks from Italy affected risk perceptions about coronavirus in most countries in the world. Many of them responded by significantly reducing their mobility. Populations in most countries, however, displayed a degree of behavioral adaption: they did not change their habits instantly, but only gradually over time. Shocks from the USA, Spain, and the UK also had significant effects later on. A subset of countries did not respond much through social distancing to global or domestic shocks. As a result, they do not show the same reduction in the growth rate of COVID-19 cases in response to social distancing that is observed in other countries.

The original health shocks, either directly, or through increased uncertainty and social distancing, have economic effects. While I do not have data at high frequency on realizations of the unemployment rate, I exploit daily data on an indicator that has been shown to predict actual unemployment quite accurately: unemployment from Google searches. The response of unemployment across countries is very heterogeneous. In the USA, unemployment skyrockets. This is consistent with the response of initial unemployment claims in the country. The same happens in Spain, with a large increase of unemployment in response to health shocks. In other countries, the responses are more muted, as public programs intervened to provide subsidies to employers and employees to protect existing employment relationships.

Compliance with ethical standards

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[10]I preferred to refrain from cointegration relationships in our benchmark estimation, since it may be difficult to put confidence on long-run relationships estimated from 2 months of daily data.

Appendix : Estimation details

I outline here the steps for the estimation of the GVAR model (see also Smith and Galesi 2014):

1. First, the connectivity matrix W (of size 41×41 in this case) is constructed using Facebook's Social Connectedness Index data. For each country i, I fix $w_{i,i} = 0$ (the domestic country is not used for the construction of the foreign variable) and I calculate the weights $w_{i,j}$, $i \neq j$, as the social connectedness between countries i and j as a fraction of the sum of connectedness between country i and each country in the sample, $SCI_{i,j} / \sum_{j=1}^{N} SCI_{i,j}$. Therefore, the resulting connectivity matrix has columns that sum to 1.

2. Country-specific foreign variables are then constructed as $x_{i,t}^* = \sum_{j=0}^{N} w_{i,j} x_{j,t}$, using the weights $w_{i,j}$, for each reference country i.

3. I estimate conditional VARX* (that is, a VAR with a foreign, weakly exogenous, variable) models, as specified in expression Eq. 1. The models can be estimated separately for each country by OLS. I choose lag length also separately for each of them based on Schwartz's Bayesian Information Criterion (BIC). In most cases, the data select short lag lengths (p and q equal to 1 or 2) as optimal. I did not find consistent patterns of seasonality in the data. Therefore, we do not perform any seasonal adjustment before the estimation.

    The benchmark estimation considers VARX* models. The robustness section experiments with VECMX* specifications, which allow for cointegrating relationships both within the variables in $x_{i,t}$ and between variables $x_{i,t}$ and $x_{i,t}^*$. In that case, for each domestic VECMX*, the cointegration rank is selected based on Johansen's trace statistics.

4. After being estimated independently, the domestic VARs are stacked together as shown in Eq. 3. The Global VAR is "solved" for all the $k = \sum_{i=0}^{N} k_i$ endogenous variables, as shown in (4)–(6).

5. I check the moduli for the system eigenvalues and confirm that they are all within the unit circle.

6. I compute Generalized Impulse Response Functions following Koop et al. (1996), as shown in expression (7) as $\mathbf{g}_{\varepsilon_j}(h) = E(x_{t+h} | \varepsilon_{j,t} = \sqrt{\sigma_{jj}}, \mathcal{I}_{t-1}) - E(x_{t+h} | \mathcal{I}_{t-1})$. The response to a one standard-deviation shock is given, for each horizon h, by $\mathbf{g}_{\varepsilon_j}(h) = \frac{R_h G_0^{-1} \Sigma_\varepsilon e_j}{\sqrt{e_j' \Sigma_\varepsilon e_j}}$, where e_j is a selection vector, composed of zeros, except for an element equal to 1 to select the shock of choice. The matrix R_h is the matrix of coefficients in the GVAR's moving average representation: $x_t = \varepsilon_t + R_1 \varepsilon_{t-1} + R_2 \varepsilon_{t-2} + \ldots$ I use bootstrapping to compute the impulse response error bands.

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