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Latent social distancing: Identification, causes and consequences☆

M. Aykut Attar a, *, Ayça Tekin-Koru b

a Dept. of Economics, FEAS, Hacettepe University, Beytepe Campus, 06800, Cankaya, Ankara, Turkey
b Dept. of Economics, TED University, Ziya Gökalp Caddesi, No.47, 06420, Cankaya, Ankara, Turkey

ARTICLE INFO

JEL classifications:
C02
D91
I18

Keywords:
SEIRD
Social distancing
COVID-19
Output loss

ABSTRACT

It is not directly observable how effectively a society practices social distancing during the COVID-19 pandemic. This paper proposes a novel and robust methodology to identify latent social distancing at the country level. We extend the Susceptible-Exposed-Infectious-Recovered-Deceased (SEIRD) model with a time-varying, country-specific distancing term, and derive the Model-Inferred DIsncancing index (MIDIS) for 120 countries using readily available epidemiological data. The index is not sensitive to measurement errors in epidemiological data and to the values assigned to model parameters. The evolution of MIDIS shows that countries exhibit diverse patterns of distancing during the first wave of the COVID-19 pandemic—a persistent increase, a trendless fluctuation, and an inverted U are among these patterns. We then implement regression analyses using MIDIS and obtain the following results: First, MIDIS is strongly correlated with available mobility statistics, at least for high income countries. Second, MIDIS is also strongly associated with (i) the stringency of lockdown measures (governmental response), (ii) the cumulative number of deceased persons (behavioral response), and (iii) the time that passed since the first confirmed case (temporal response). Third, there is statistically significant regional variation in MIDIS, and more developed societies achieve higher distancing levels. Finally, MIDIS is used to explain output losses experienced during the pandemic, and it is shown that there is a robust positive relationship between the two, with sizable economic effects.

1. Introduction

The COVID-19 pandemic, the biggest epidemic shock since the Spanish Flu, has enveloped the planet in its entirety and triggered a wide range of containment or distancing measures in all parts of the world. These measures have resulted in a serious economic downturn with the potential to dwarf the Great Depression. As of November 17, 2021, the disease claimed over 5 million lives, and the case numbers reached over 250 million worldwide.

Until vaccination rates reach a certain threshold, the only available instrument to slow down the rate of infection was and continues to be social distancing, which can be loosely defined as a set of non-pharmaceutical interventions (NPIs) to reduce person-to-person contact. These interventions can be taken by governments or individuals and serve the objective of “flattening the epidemiological curve,” a plot of the number of new cases per day. Theoretical reasoning suggests that the social return to distancing exceeds its private

☆ The first version of this paper appeared in the 26th issue of Covid Economics: Vetted and Real-Time Papers in June 2020 as a working paper. The present paper is a substantially revised version with methodological improvements, an extended sample with 120 countries, and additional robustness checks for measurement errors.

* Corresponding author.
E-mail addresses: maattar@hacettepe.edu.tr (M.A. Attar), ayca.tekinkoru@tedu.edu.tr (A. Tekin-Koru).
return, thereby necessitating policy interventions (e.g., Bethune and Korinek, 2020; Farboodi et al., 2020).

Social distancing to “flatten the curve” unequivocally creates a plethora of economic shocks. But which countries have experienced the highest rates of increase in social distancing, and what is the extent of social distancing? These questions are imperative to understanding what triggers the economic tremors felt all over the world, and yet we know remarkably little about social distancing that has the power of creating major economic downturns. Why? It belongs to a set of intrinsically latent variables that are typically well understood but rarely rigorously defined (Kmenta, 1991). Unlike a proxy variable, an intrinsically latent variable is unobserved and never characterized by just one measurable factor. Hence, it can only be inferred from other observable variables using formal (mathematical) theory that provides identification restrictions.

This paper sheds light on these issues by developing a way of identifying unobserved social distancing and aims to contribute to the vivid debate on “flattening the curve,” cross-country heterogeneity in the effectiveness of governmental and behavioral responses, and economic costs of the pandemic.

In the first part of the paper, we derive a Model-Inferred DISTancing (MIDIS) measure using an extended version of the workhorse Susceptible-Exposed-Infectious-Recovered-Deceased (SEIRD) framework. In the typical SEIRD model, there is a nonlinear dynamical system that explains the spread and eventual containment of an infection over time. In this paper, we extend the simple SEIRD model with a time-varying and country-dependent social distancing term. The core idea of our paper is to identify this distancing term for each country and each day by exploiting the fact that the average incubation period is constant and common across countries. The resulting solution expresses the distancing term as a function of observable epidemiological data and thus provides a model-inferred measure of a latent variable that can be tracked over time. An important advantage of our identification strategy is that it is easy to put into practice by other researchers because it employs a relatively simple epidemiological model and readily available data.

To the best of our knowledge, Fernández-Villaverde and Jones’s (2020) paper is the closest to ours with respect to identification. The authors also use a compartmental model (the SIRD version) and daily epidemiological data, and their identification strategy of recovering the time-varying transmission rate using observables is similar to our identification of distancing. However, there are three substantial differences. First and foremost, our model has the exposed compartment between the susceptible and infectious compartments, whereas Fernández-Villaverde and Jones (2020) implicitly assume that exposed individuals are in the susceptible compartment. Second, while both papers use daily epidemiological data on the numbers of deceased and recovered individuals, we use observed data of country-dependent and time-varying recovery and fatality rates in the identification. In contrast, Fernández-Villaverde and Jones (2020) assign fixed and country-independent values to several model parameters (but of course do so rigorously). Finally, our paper focuses on the identification, causes, and economic consequences of distancing, but Fernández-Villaverde and Jones (2020) use their model and the recovered sequences of time-varying transmission rates to understand the evolution of death rates and the progression of the pandemic in the near future. We believe that it is necessary to explicitly account for the exposed compartment since COVID-19 has a strictly positive average incubation period. Besides, our approach of utilizing observed changes in recovery and fatality rates allows us to understand the evolution of distancing during the pandemic.

One advantage of our identification strategy is that MIDIS captures a wide range of social distancing components. These include not only policy interventions (school/work closures, bans on traveling and mass gatherings or stay-at-home orders) but also behavioral responses such as fear, trust, or reciprocity, which cannot be measured in a straightforward way. As underlined by Toxvaerd (2020), modeling how people behave during a pandemic (under the presence of distancing interventions) by exogenously given diffusion parameters is not sufficient for the analysis of disease control. There exists an endogenous response of human behavior to a highly contagious disease—embodied in every day social interactions—that needs to be accounted for in epidemiological models.

While it would be best to collect direct data on different components of social distancing, this is hardly possible in practice due to severe data limitations. Data on policy measures taken to curb the spread of the disease may not always be readily available for a number of countries on a daily basis, let alone daily data for behavioral responses. The MIDIS measure derived in this paper eschews this problem by providing researchers with a measure that is easy to construct. It can be useful not only for studying economic cost but also for other applications that require a time-varying measure of social distancing for a wide range of countries.

Naturally, our analysis encompasses some of the caveats of SEIRD models as well as measurement errors in the observed data. For the latter problem, it is known that countries are not equally successful at testing and tracking, and data manipulation by official bodies in some countries could cause quantitative results to be misleading to some extent. However, we demonstrate that measurement errors in epidemiological data do not significantly alter our construction of latent social distancing.

For the former issue, one of the most serious problems of SEIRD models is the weak identification of parameters (Avery et al., 2020). As Fernández-Villaverde and Jones (2020) have also underlined, different constellations of model parameters that have similar fits in the short run—days to weeks—may imply significantly diverse outcomes in the longer run—months to years. Our imperfect remedy for this problem is to check the sensitivity of our results. We show that the evolution of MIDIS is considerably robust under alternative values of the average incubation period. Another issue is parameter stability under the presence of policy changes, as shown by Chang and Velasco (2020) with reference to the Lucas critique. Since we do not pursue counterfactual policy analyses, parameter stability is not a central concern for us. Last but not least, the simple models with homogeneous individuals inhabiting a single society may be misleading because of (i) population heterogeneity in age structure, exposure risk, and health status; (ii) the regional differences within a country; and (iii) spatial linkages among the localities. However, currently available data do not allow us to pursue such intriguing dimensions.

1 The model was originally proposed as a SIR model by Kermack and McKendrick (1927) and later various extensions with stochastic specifications and more compartments were produced. We briefly review that literature below.
In the second part of the paper, we take MIDIS to the data compiled by Johns Hopkins University (JHU, 2021) and compute it for 120 countries. These are the countries for which we have mobility data available for an “initial” reference day. As in Dandekar and Barbastathis (2020) and Dreher et al. (2020), this initial date is taken to be the day after the 500th case is confirmed for each country. For the immediate 30 days after this “initial” day, our results show that countries exhibit considerable variation with respect to distancing. More specifically, we are able to identify at least three distinct patterns for three groups of countries—a persistent increase, a trendless fluctuation, and an inverted U shape. Hong Kong, New Zealand, Luxembourg, South Korea, and Australia are the countries that sustain the highest average levels of distancing.\(^2\)

We then compare MIDIS values to the mobility data supplied by Apple and Google that have been used in the burgeoning COVID-19 literature—sometimes as a proxy for social distancing.\(^3\) Our results indicate a highly significant negative correlation between MIDIS values and different components of mobility. The advantage of MIDIS over the mobility data is its wide coverage at country-day detail as long as the epidemiological data are available.

In the third part of the paper, we try to identify the cross-country heterogeneity in MIDIS that might be a result of differences in governmental response, behavioral response, and a plethora of country-specific factors. We argue that behavioral response to a pandemic is at least as important—if not more—as governmental response in explaining the variation in MIDIS across countries and time. As expected, our results show that our social distancing measure varies positively with containment measures taken by governments and people’s reaction to the pandemic in a robust manner. Indeed, the impact of the behavioral response measured by the number of the deceased on the previous day is stronger than the impact of containment measures.

In the final part of the paper, we use our model-inferred social distancing measure to study the economic costs of social distancing during a pandemic. While doing so, we stay oblivious to supply- or demand-side dynamics of these economic costs and focus on their outcome in terms of output loss only. Our daily measure of output loss is derived from the peak-hour electricity consumption data, generously provided by McWilliams and Zachmann (2020). Our results indicate a significant negative output response to social distancing during the COVID-19 pandemic. In other words, in countries with higher levels of MIDIS, there is a higher level of output loss in the 30 days following the 500th case. Indeed, a 10 point increase in social distancing causes up to a 2.3 percent increase in output loss.

The paper is structured as follows: Section 2 reviews the related literature. Section 3 introduces the model and our identification strategy. Section 4 summarizes the main patterns of distancing for selected countries and validates our MIDIS measure through mobility data from Apple and Google. Section 5 studies the robustness of MIDIS under the presence of measurement errors. Section 6 investigates the cross-country differences in MIDIS using various explanatory variables. Section 7 then investigates whether and to what extent distancing during the pandemic is related with output loss. Section 8 concludes the paper with some final remarks. We present the results of further sensitivity analyses in Appendix A, and variable definitions, data sources, and statistical summaries in Appendix B. Computer codes and MIDIS data can be accessed on the MIDIS website.

2. Related literature

There is now a large and growing literature studying various economic aspects of the COVID-19 pandemic. As of November 17, 2021, there are around 500 COVID-19-related research papers documented by the National Bureau of Economic Research.\(^4\) There also exist other outlets where researchers share their recent works on the COVID-19 pandemic. Covid Economics: VETTED and REAL-TIME PAPERS, published by the Centre for Economic Policy Research since March 2020, now comprise 83 completed issues containing hundreds of papers on the COVID-19 pandemic.

Our purpose in this section is to present a discussion of the related literature by focusing on the papers that are most directly related to ours. Compartmental models such as SIR, SEIR, or SEIRD are useful tools in the mathematical study of infectious diseases. Originally developed by Kermack and McKendrick (1927) in the form of SIR, the (stochastic versions of) models with more compartments (e.g., quarantined or hospitalized ones) have been proposed to make the analysis more realistic (e.g., Chowell et al., 2003; Zhou et al., 2004; Lekone and Finkenstädt, 2006; Feng, 2007). Most recently, researchers estimated such realistic versions with the Chinese COVID-19 data (Tang et al., 2020; He et al., 2020). In this paper, we focus on the simplest version of a compartmental model that fits our purposes. Hence, we build on a deterministic version that explicitly accounts for the exposed compartment and extend it with time-varying and country-dependent (unobservable) distancing.

Recent works by economists are related to our paper in two respects. First, several papers embed a compartmental epidemiological model within a dynamic equilibrium framework to tackle a diversity of research questions. Second, another set of papers empirically investigate the causes and consequences of social distancing, identified or measured/proxied in one way or another.

In the first strand, where researchers use a version of a compartmental model, they generally focus on how governmental and behavioral responses affect the progression of the pandemic through distancing. Other than Fernández-Villaverde and Jones (2020), which we discussed above, there are several papers in this category. We choose to discuss only some of them for space considerations. Building on the SIR model, Toxvaerd (2020) designs an optimal control problem at the individual level to solve for daily equilibrium dynamics of social distancing. The model implies that there exists an episode during which the number of infections does not increase as a result of optimal behavioral responses. In a similar fashion, Cochrane (2020) shows simulations of an SIR model where

\(^2\) We show that MIDIS is not very sensitive to our benchmark case count of 500 cases and our construction of a 30-day sample for each country.

\(^3\) See Alfaro et al. (2020); Coven and Gupta (2020); Durante et al. (2020), and Doganoglu and Ozdenoren (2020) and the references therein.

\(^4\) These papers can be accessed at https://www.nber.org/topics/covid-19.
distancing behavior depends on the infection rate or an increase in the death toll as people decrease their exposure under the presence of increasing infection rates or deaths. Acemoglu et al. (2020) extend the SIR model with three age groups that face different levels of mortality risk and show that targeted policies are more effective than uniform policies in terms of both economic cost and health outcomes. The authors also emphasize the sizable positive effects of group distancing isolating the most vulnerable from the rest of the society. Alvarez et al. (2020) also use the SIR model and study the optimal control problem of lockdown policies. The optimal policy they find depends on the fractions of susceptible and infected individuals, and prescribes a severe initial lockdown and a gradual withdrawal from it over months. The SIR-based results presented by Cakmakli et al. (2021) also confirm that an early and strict lockdown is optimal from both economic and public health perspectives. Berger et al. (2020) extend a SEIR model with incomplete information, testing, and quarantine policies. They find that targeted quarantine policies with higher testing rates are effective in mitigating adverse economic and epidemiological effects. Eichenbaum et al. (2020) embed the SIR model within a typical dynamic macroeconomic model to study the effects of various policy responses. In their SIR-macro model, individuals’ distancing decisions, which decrease their consumption and labor supply, have positive health impacts but increase the size of the economic downturn. Another modeling exercise pursued by Kaplan et al. (2020) incorporates the SIR model within a New Keynesian model with heterogeneous agents. The authors underline the differential impact of the pandemic across different types of consumer goods and occupations, and show that the ownership structure of liquid versus illiquid assets matters because the group of individuals that are most exposed to economic risks have the lowest liquidity.

Our paper benefits from this literature in motivating the roles of governmental and behavioral responses to the pandemic; our empirical results—confirming that governmental and behavioral responses drive effective distancing—have a strong theoretical basis. However, our approach differs from all these papers in two respects: First, a vast majority of the papers ignore the role of the exposed compartment while realistic epidemiological studies of the COVID-19 pandemic necessitate a SEIRD framework (He et al., 2020; Tang et al., 2020). Second, instead of investigating whether a particular policy or behavior is optimal, we remain agnostic about this counterfactual question and assume that the observed epidemiological data reflect the decentralized equilibrium of distancing. The presumption that the observed data must be consistent with a SEIRD model then allows for the identification of distancing during the pandemic.

The second strand of literature we discuss here focuses more on the empirics of distancing and disease progression, and more specifically on whether governmental and/or behavioral responses are statistically associated with increased distancing and decreased mobility.

Chen and Qiu (2020) and Castex et al. (2020) investigate the role of governmental responses on infection rates by recovering the daily infection rates from a SIR model. The former paper designs different scenarios using NPIs for nine countries and shows that school closures, mask wearing, and centralized quarantine measures are effective in reducing transmission rates. The authors also show that these three measures have quantitatively similar effects when compared to a strict lockdown. The latter paper implements the analysis for a large number of countries and finds that GDP per capita, population density, and surface area decrease policy effectiveness. Doganoglu and Ozdenoren (2020) investigate the role of trust and social norms on behavioral responses to the pandemic. They first isolate the effects of (i) policy measures using the Stringency Index of Hale et al. (2021), (ii) the number of infections, and (iii) the temperature on people’s mobility using Google (2021) data. They then estimate the role of trust on the country fixed effects that cannot be explained by policies, infections, and temperature. Their results indicate that, while policies and infections decrease mobility levels, trust has a positive impact on mobility. Alfaro et al. (2020) also focus on behavioral responses motivated by fear, altruism, and reciprocity, and investigate the effects of both policy measures and these traits. Their empirical results utilizing Apple (2021) mobility data show that the effects of policy measures are less pronounced if people are more patient and more altruistic and exhibit a lesser degree of negative reciprocity.

The empirical literature also shows that partisanship may be an important dimension in guiding people’s distancing behavior. Painter and Qiu (2020) use geolocation data for the United States to show that people in Democratic counties are more responsive to policy interventions. Engle et al. (2020) estimate that an official stay-at-home restriction decreases mobility by more than 7 percent in the United States. In a separate study, Brzezinski et al. (2020) confirm that the effect is indeed close to 8 percent. In another interesting paper related to partisanship effects, Argentieri Mariani et al. (2020), using an event-study approach and regional variation of vote shares in Brazil, demonstrate that the president’s public disrespect for the recommendations of health authorities has increased the infection rates.

Empirical studies demonstrate that policies are effective in reducing infection rates and the number of deaths through distancing (Deb et al., 2020; Askitas et al., 2020). However, estimates also show that people respond to the pandemic by decreasing their mobility to some extent even in the absence of policy interventions (Brzezinski et al., 2020). This result (for the United States) has also been supported by Maloney and Taskin (2020) with mobility data from Google (2021). These authors also estimate that the effect of voluntary distancing is larger than that of policy interventions for a large number of countries.

Our empirical results are consistent with the main lessons of this literature, namely that both governmental and behavioral responses are significantly associated with distancing and mobility. We should also note that our approach is closer to those of Chen and Qiu (2020); Castex et al. (2020), and Alfaro et al. (2020). In contrast to the latter paper, we use a distancing measure originating from an epidemiological model, and, contrary to the two former, we explicitly account for exposed individuals in identifying our distancing measure, MIDIS.

3. A SEIRD model with distancing

We consider \( J \) countries indexed by \( j \in \{1, 2, \ldots, J\} \). The model time, denoted by \( t \), is discrete, and the length of a period is a day. For
all countries, the model horizon is the first 30 days after the 500th COVID-19 case is confirmed. Hence, time periods are not synchronized across countries with respect to the calendar time.

For each country, we focus on the episode after the 500th case, as in Dandekar and Barbastathis (2020) and Dreher et al. (2020). This cutoff is early enough to capture the beginning of the first wave and late enough to disregard the erratic movements in epidemiological data observed during the first days of the outbreak. We restrict the analysis to the first 30 days after the 500th case to disregard the effects of partial removal of NPIs, the diffusion of newer strains of the virus, and the role of vaccinations. In other words, we focus on the first wave of the COVID-19 pandemic. However, we also present alternative constructions for a 60-day sample and for a benchmark of 100 cases in Appendix A. The results do not exhibit much sensitivity under these alternatives.

### 3.1. Compartments and the laws of motion

Following Degue and Le Ny (2018), we study a deterministic version of the SEIRD model where the size of each compartment is expressed as a fraction of the population in each country. In this model, susceptible (S) individuals transit to the exposed (E) compartment after being infected, but they stay in the exposed compartment until they become infectious. Individuals in the infectious (I) compartment transmit the virus to susceptible individuals, and they either recover (R) or die (D).

Importantly, we extend the basic model with a time-varying transmission rate that is determined by distancing behavior of the susceptible and infectious populations. Formally, we have

\[
S_{t+1} = S_t - \zeta_t \left[(1 - d_t)S_t \right] \left[(1 - d_t)E'_t \right] 
\]

\[
E'_{t+1} = E'_t + \zeta_t \left[(1 - d_t)S_t \right] \left[(1 - d_t)E'_t \right] - \alpha E'_t 
\]

\[
I'_{t+1} = I'_t + \alpha E'_t - \gamma R_t I'_t - \gamma_{\alpha} I'_t 
\]

\[
R'_{t+1} = R'_t + \gamma_t R'_t I'_t 
\]

\[
D'_{t+1} = D'_t + \gamma_{D_t} I'_t 
\]

where $S'_t$, $E'_t$, $I'_t$, $R'_t$, and $D'_t$ denote the fractions of susceptible, exposed (but not infectious), infected (and infectious), recovered, and deceased individuals in country $j$ on day $t$. By the law of large numbers, each denotes the probability that any given individual is in the associated compartment. Hence, we have

\[
S_t' + E'_t + I'_t + R'_t + D'_t = 1 
\]

for all $j$ and $t$.

Here, $\zeta_t > 0$ is a fixed and country-specific transmission parameter calibrated using Google (2021) mobility trends for each country. Conditional on $\zeta_t > 0$, the probability of contact depends on effective (or de facto) distancing, denoted by $d_t \in [0, 1]$. If both susceptible and infectious individuals utilize social distancing instructions, then the probability that a susceptible individual and an infectious individual get into contact is equal to

\[
\zeta_t (1 - d_t)^2 S'_t I'_t 
\]

If a country can completely isolate susceptible and infected individuals with $d_t = 1$, then no individuals migrate from the susceptible to the exposed compartment. This is the one-parameter ($\zeta_t$), one-variable ($d_t$) formulation that is now familiar in the related literature (Acemoglu et al., 2020; Alvarez et al., 2020). However, the present formulation is slightly different from those of Acemoglu et al. (2020) and Alvarez et al. (2020) since our model features the exposed compartment as well.\(^5\)

A fixed parameter that is common across countries is $\alpha \in (0, 1)$, which denotes the inverse of the average incubation period of the virus in days. This parameter determines the fraction of exposed individuals that migrate to the infectious compartment on any day.

\(^{5}\) In both Acemoglu et al. (2020) and Alvarez et al. (2020), the effect of distancing is introduced via $(1 - \theta L_c)^2$ where $L_c \in [0, 1]$ is the lockdown variable, and $\theta \in (0, 1]$ governs the effectiveness of the lockdown.
Finally, time-varying fractions of individuals in the infectious compartment move to the recovered and deceased compartments on any day. These fractions are denoted by $\gamma^j_{xt} \in (0, 1)$ and $\gamma^j_{dx} \in (0, 1)$, respectively. Fig. 1 shows the compartments and transition rates in the SEIRD model.

3.2. Identification

Our purpose is to use the above model and observed epidemiological data to achieve a numerical identification of $d^j_t$ for all $(j, t)$. The strategy builds on the notion that, while the inverse of the average incubation period ($\alpha$) is fixed and common across countries, there is daily variation in $(\ell^j_t, R^j_t, D^j_t)$. Hence, the observed data and the model must be consistent with each other for some realization of $d^j_t$. In other words, we use the model and data to recover $d^j_t$ for any $(j, t)$.

Since whether an infectious individual recovers or dies does not matter for $d^j_t$, we define the compartment $X^j_t$ as the sum of $R^j_t$ and $D^j_t$ as in

$$X^j_t = R^j_t + D^j_t,$$

and we also define $\gamma^j_{xt} = \gamma^j_{xt} + \gamma^j_{dx}$. The SEIX model is then characterized by

$$S^j_{t+1} = S^j_t - \zeta^j (1 - d^j_t) \gamma^j S^j_t,$$

$$E^j_{t+1} = E^j_t + \zeta^j (1 - d^j_t) \gamma^j S^j_t - \alpha E^j_t,$$

$$I^j_{t+1} = I^j_t + \alpha E^j_t - \gamma^j S^j_t,$$

$$X^j_{t+1} = X^j_t + \gamma^j S^j_t.$$

The unobserved state variable that is central to our identification strategy is the ratio of exposed to infectious individuals, defined as in $e^j_t = E^j_t / I^j_t$. Notice that (10) and (11) allow us to write the law of motion of $e^j_t$ as in

$$\frac{e^j_{t+1}}{e^j_t} = \frac{\zeta^j (1 - d^j_t) \gamma^j S^j_t e^j_t (1 - \alpha)}{\alpha e^j_t + (1 - \gamma^j S^j_t)}.$$ (13)

The distancing term $d^j_t$ for country $j$ on day $t$ can then be written as a function of $(e^j_{t+1}, e^j_t, S^j_t, \gamma^j, \alpha, \zeta^j)$:

$$d^j_t = 1 - \left[\frac{\alpha e^j_t + e^j_{t+1}(1 - \gamma^j S^j_t) - (1 - \alpha) e^j_t}{\zeta^j S^j_t}\right]^{1/2}.$$ (14)

Under the assumption that $\alpha$ is known, calculating $d^j_t$ requires

- the values of $(e^j_{t+1}, e^j_t, S^j_t, \gamma^j)_t$ for all $(j, t)$, and
- the values of $\zeta^j$ for all $j$.

The model allows us to uniquely identify $(e^j_{t+1}, e^j_t, S^j_t, \gamma^j)$ inputs: (12) identifies $\gamma^j_S$ for all $(j, t)$ as a function of observed variables $(X^j_{t+1}, X^j_t, \ell^j_t)$. Then, (11) identifies $e^j_t$ for all $(j, t)$ as a function of observed variables $(I^j_t, \ell^j_t)$ and $\gamma^j_S$. Finally, (6) and (8) identify $S^j_t$ as a function of observed variables $(\ell^j_t, X^j_t)$ and $e^j_t$.

To assign a value to the country-specific transmission parameter $\zeta^j$, we use both the model and the country-specific, daily mobility statistics provided by Google (2021). Specifically, we take residential mobility from the Google mobility trends, in percentage terms, as a proxy for distancing in public spaces. The idea here is to benchmark the rate of transmission from S to E in the model to some externally valid mobility term in the data given the model equations and parameters. Formally, our algorithm uses (14), given data and the model parameter $\alpha$, and equates the “initial” $d^j_0$ level in the model to the residential mobility from Google (2021) for country $j$:

$$\zeta^j = \frac{e^j_0 \alpha e^j_0 + e^j_1(1 - \gamma^j_{0,0}) - (1 - \alpha) e^j_0}{S^j_0(1 - d^j_0 \text{Google})^2}.$$ (15)

Hence, for each country, the “initial” value of the distancing term, $d^j_0$, is equal to the level of the country-wide distancing measure provided by Google (2021).

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5 JHU (2021) shares daily data of cumulative confirmed cases ($C^j$) and the cumulative numbers of recovered ($R^j$) and deceased ($D^j$) individuals. We calculate the daily number of actively infectious individuals as $I^j_t = C^j - R^j_t - D^j_t$. 

3.3. Indexing

Computing $d_{jt}$ for all $(j,t)$ using the identification strategy described above returns a daily panel of latent social distancing. This distancing term, expressed as a percentage in the SEIRD model, is relative to the theoretical benchmark of $d = 0$. When it takes negative (positive) values, the society is more (less) mobile relative to this benchmark.

To allow for a clearer interpretation of cross-country comparisons, we generate the MIDIS index of latent social distancing by using the following indexing formula:

$$MIDIS_{jt} = \left( \frac{d_{jt} - d^\text{min}}{\max_j \max_t \{d_{jt} - d^\text{min}\}} \right) \times 100 \quad (16)$$

where $d^\text{min}$ is the minimum level of $d_{jt}$ over $j$ and $t$.

This formula ensures that the MIDIS index, for any $(j,t)$, lies in the $[0, 100]$ interval, and whether country $j$ is more or less mobile on some day $t$ can be interpreted relative to the “initial” value MIDIS$_{j0}$.

4. MIDIS in selected countries

We apply our identification strategy to a sample of countries for which Google (2021) residential mobility statistics are available and complete. This is for the purpose of later comparisons. The sample includes $J = 120$ countries listed in Table B1 of Appendix B.

After obtaining daily epidemiological data from the Johns Hopkins University’s COVID-19 data repository (JHU, 2021) for these 120 countries, we apply the Gaussian filter to smooth the original epidemiological data and residential mobility statistics. Smoothing is necessary since the model we use is deterministic; it is not feasible to capture the daily fluctuations in the actual data sequences.

For $\alpha$, we borrow the benchmark value from He et al. (2020) and Tang et al. (2020). Both of these papers estimate stochastic versions of a multi-compartment epidemiological model with Bayesian methods using China’s COVID-19 data. In both papers, $\alpha = 1/7$ is taken as a benchmark value that corresponds to an average incubation period of 7 days.

Fig. 2 pictures the evolution of MIDIS by highlighting eight selected countries. The gray lines, for all countries in the sample, show that there is wide variation in the movement of MIDIS during the sample period. But there also exist different patterns shared by various groups of countries, as shown in the figure. We identify four different groups:

- **Group 1.** Some countries, represented in the figure by New Zealand and South Korea (red color), record a fast increase during the first 15 days and a rather stable evolution afterwards. With slight differences in terms of the stabilization dates, Australia, Hong Kong, Thailand, and Vietnam are in this group as well. The evolution of MIDIS in Austria, Canada, Czechia, Greece, Luxembourg, and Philippines seems to follow a similar pattern with varying degrees of success in the initial increase.

- **Group 2.** Some countries in the sample exhibit a persistent increase in MIDIS indexes after about the first week of the 30-day period. The United States and Italy (black color) represent this group in Fig. 2. Many European countries seem to be part of this
Table 1
Summary Statistics on MIDIS.

Panel A. Highest Average Distancing

| Country      | \(t(C_t > 500)\) | “Initial” | Average | Minimum | AutoCorr |
|--------------|-------------------|-----------|---------|---------|----------|
| Hong Kong    | 3/27/2020         | 59.15     | 85.11   | 58.73   | 0.919    |
| New Zealand  | 3/29/2020         | 65.71     | 84.38   | 64.99   | 0.924    |
| Luxembourg   | 3/21/2020         | 67.04     | 80.68   | 66.37   | 0.931    |
| South Korea  | 2/23/2020         | 55.55     | 80.21   | 55.55   | 0.924    |
| Australia    | 3/18/2020         | 54.80     | 78.58   | 54.29   | 0.937    |
| Philippines  | 3/24/2020         | 67.22     | 78.38   | 66.67   | 0.923    |
| Israel       | 3/20/2020         | 62.90     | 77.33   | 62.08   | 0.928    |
| Vietnam      | 7/30/2020         | 54.79     | 77.11   | 54.06   | 0.930    |
| Portugal     | 3/19/2020         | 65.68     | 77.06   | 64.30   | 0.935    |
| Mongolia     | 11/18/2020        | 67.19     | 76.94   | 66.75   | 0.901    |

Panel B. Lowest Average Distancing

| Country     | \(t(C_t > 500)\) | “Initial” | Average | Minimum | AutoCorr |
|-------------|-------------------|-----------|---------|---------|----------|
| Guatemala   | 4/26/2020         | 61.60     | 43.67   | 34.99   | 0.853    |
| Niger       | 4/12/2020         | 56.99     | 43.13   | 19.42   | 0.944    |
| Mali        | 5/1/2020          | 57.05     | 43.06   | 36.39   | 0.835    |
| Taiwan      | 9/16/2020         | 50.87     | 39.79   | 31.31   | 0.789    |
| Kyrgyzstan  | 4/18/2020         | 59.86     | 38.95   | 29.46   | 0.873    |
| Cameroon    | 4/3/2020          | 54.48     | 36.59   | 22.94   | 0.888    |
| Togo        | 6/9/2020          | 57.24     | 36.22   | 15.49   | 0.891    |
| Singapore   | 3/23/2020         | 57.98     | 33.40   | 14.97   | 0.886    |
| Japan       | 3/9/2020          | 53.05     | 22.20   | 3.37    | 0.917    |
| Zimbabwe    | 6/22/2020         | 61.31     | 19.63   | 0.00    | 0.882    |

Notes: \(t(C_t > 500)\) refers to the day on which confirmed cases exceed 500. The “Initial” level of MIDIS is the index level on \((C_t > 500)\). AutoCorr denotes the auto-correlation function in MIDIS for one lag.

Table 2
Validating MIDIS with Mobility Indicators from Apple and Google.

Panel A. Full Sample

| Independent Var. | Parameter | Robust S.E. | # of Countries | # of Obs. | R-squared |
|------------------|-----------|-------------|----------------|-----------|-----------|
| A-Driving        | -0.068    | 0.061       | 59             | 1,767     | 0.113     |
| A-Walking        | -0.061    | 0.056       | 59             | 1,767     | 0.101     |
| G-RetailRecreation | -0.082** | 0.037       | 120            | 3,594     | 0.146     |
| G-GroceryPharmacy | -0.035    | 0.026       | 120            | 3,590     | 0.042     |
| G-Parks          | 0.026     | 0.028       | 120            | 3,594     | 0.025     |
| G-TransitStations | -0.112** | 0.044       | 120            | 3,582     | 0.109     |
| G-Workplace      | -0.105*** | 0.032       | 120            | 3,594     | 0.132     |
| G-Residential    | 0.160*    | 0.085       | 120            | 3,592     | 0.067     |

Panel B. High Income Sample

| Independent Var. | Parameter | Robust S.E. | # of Countries | # of Obs. | R-squared |
|------------------|-----------|-------------|----------------|-----------|-----------|
| A-Driving        | -0.106*   | 0.061       | 42             | 1,260     | 0.204     |
| A-Walking        | -0.090*   | 0.053       | 42             | 1,260     | 0.188     |
| G-RetailRecreation | -0.149*** | 0.044       | 53             | 1,590     | 0.166     |
| G-GroceryPharmacy | -0.080**  | 0.037       | 53             | 1,586     | 0.060     |
| G-Parks          | 0.020     | 0.034       | 53             | 1,590     | 0.019     |
| G-TransitStations | -0.203*** | 0.049       | 53             | 1,578     | 0.115     |
| G-Workplace      | -0.173*** | 0.048       | 53             | 1,590     | 0.123     |
| G-Residential    | 0.278**   | 0.117       | 53             | 1,588     | 0.087     |

Notes: Each row corresponds to a separate regression where MIDIS (in percentage terms) is the dependent variable. The high income sample includes countries whose 2019 GDP per capita level in purchasing power parity terms is larger than 25,000 USD. The reported R-squared is the overall R-squared measure. Superscripts ***, **, and * indicate statistical significance at 1 %, 5 %, and 10 %, respectively. See Table B.2 for variable definitions and data sources.
group, including Belgium, Croatia, Estonia, France, Germany, Netherlands, Norway, Portugal, Romania, Slovenia, Spain, Switzerland, and the United Kingdom. For other countries such as Belarus, Haiti, India, Moldova, and Turkey the MIDIS indexes exhibit a similarly persistent increase with differing success.

- **Group 3.** The third group seems to be formed by a large number of countries that record a trendless evolution in latent social distancing. In Fig. 2, Cote d’Ivoire and Yemen (pink color) represent this third group. Most of the countries in this group in the sample are developing or least developed countries. Several countries from Latin America & Caribbean and the Middle East as well as from Sub-Saharan Africa are in this group. Bahrain, Barbados, Bolivia, Bosnia & Herzegovina, Botswana, Brazil, Cambodia, Colombia, Costa Rica, Honduras, Iraq, Jordan, Latvia, Lebanon, Mauritius, Mozambique, Oman, Pakistan, Qatar, Rwanda, Saudi Arabia, Togo, Uruguay, and Zambia are the ones that follow the typical trendless pattern of the third group.

- **Group 4.** Finally, the MIDIS indexes of some countries exhibit a rather unique inverted U shape during the 30-day episode under consideration. Japan and Sweden (blue color) are representatives of this group in the figure. With differing days on which the MIDIS index hits its minimum, Bulgaria, Denmark, and Singapore are other members of this small group of countries.

Table 1 presents the summary statistics for countries that achieve the highest and lowest MIDIS values on average. We see from Panel A that many countries from Group 1 described above are among those with the largest 30-day average MIDIS values. Similarly, Singapore and Japan from Group 4 are among the countries that have the lowest averages.

A comparison of the countries with the highest and lowest MIDIS averages reveals that the 30-day minimum MIDIS levels are much higher in the former. This is consistent with large levels of positive auto-correlation observed in MIDIS for virtually all the countries in the sample. In terms of “initial” levels, there does not appear to be a significant difference between the best- and worst-performing countries.

Before concluding this section, we investigate whether the daily mobility data from Apple (2021) and Google (2021) validate our latent social distancing index MIDIS. In Table 2, we document various regression results where MIDIS is the dependent variable and a mobility indicator from Apple (2021) or Google (2021) is the independent variable. In these regressions, we match the calendar dates for each country, and each row presents the results of a separate regression. Clearly, the results we document here cannot be interpreted as a sign of a causal mechanism because both the mobility indicators and MIDIS quantify the very same phenomenon—de facto distancing success of a society.

The results show that the mobility indicators are strongly correlated with MIDIS, at least for the high income sample, and support the validity of our identification strategy. Here, restricting the sample to high income countries has a major effect since data coverage of Apple and Google services is arguably much more satisfactory in high income countries.

As expected, increased mobility in residential places is positively associated with MIDIS (the last rows in both panels), and all other mobility indicators that represent mobility in public places have a strong, inverse relationship with MIDIS. In absolute value terms and for the eight indicators we consider, we estimate that the largest effect originates from the mobility in residential areas. We also estimate an insignificant effect for parks in both samples.

### 5. Measurement errors and underestimation

One of the most challenging problems in epidemiological research is the underestimation of infected, deceased, and recovered individuals, i.e., the measurement errors in epidemiological data. Underestimation is either due to underascertainment problems or underreporting problems (or both). The latter is either intentional or unintentional (or both) (Millimet and Parmeter, 2021a).

Our benchmark results presented above assume away such underestimation problems. The purpose of this section is to demonstrate that our benchmark MIDIS values do not exhibit much sensitivity against epidemiological underestimation.

To extend the SEIRD model with non-classical measurement errors as in Millimet and Parmeter (2021b), we introduce (possibly time-varying) multiplication factors for cases ($C_z$), deaths ($D_z$), and recovered individuals ($R_z$). Suppose that the variables with asterisks denote the observed values and those without asterisks denote the true values.⁸ Then, we have

$$C_t^* = \left( \frac{1}{\phi^C_t} \right) C_t, D_t^* = \left( \frac{1}{\phi^D_t} \right) D_t, R_t^* = \left( \frac{1}{\phi^R_t} \right) R_t.$$  \hfill (17)

The multiplication factors $\phi^C_t, \phi^D_t, \phi^R_t > 1$ can further be described as stochastic variables satisfying

$$\phi^z_t \equiv \exp(u^z_t) \sim F^z_t,$$ \hfill (18)

for $z \in \{C, D, R\}$ where $F^z_t$ terms represent cumulative distribution functions with strictly positive supports ($u^z_t > 0$).

Using the identification scheme introduced above and after some algebraic operations, the observed distancing term can be written as

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⁸ We suppress the country superscript $j$ in this section for notational ease.
The general formulation of the distancing term in (19) shows that the observed \( d_t^* \) would deviate from the true \( d_t \) if multiplication factors are not all equal to unity for all \( t \). However, this formulation also suggests that the presence of measurement errors would not significantly alter the benchmark results if the moments of the error distributions \( F_z \) are sufficiently similar; \( \phi_{zt} \) terms appear in (19) generally as a fraction of two underestimation terms, or two \( \phi_{zt} \) terms enter the formula with alternative signs as in the second bracketed term in the denominator.
It turns out that there is almost no difference between the observed and true MIDIS values when multiplication factors are fixed in time. Fig. 3 presents various alternative results for two selected countries, i.e., South Korea and the United States. We follow Millimet and Parmeter (2021a) and Chudik et al. (2021) in choosing the alternative values of multiplication factors for COVID-19. Ranging from 1.6–7 in different settings, these multiplication factors imply almost no visible difference in the resulting MIDIS constructions.

How would the above result change when the multiplication factors are time-varying? Clearly, the first 30 days after the 500th case is an early episode of an epidemic outbreak to achieve sizable decreases in multiplication factors. But it turns out that our results would remain qualitatively the same even if there were changes in the severity of underestimation problems. Fig. 4 pictures the benchmark MIDIS values and alternative identifications obtained under four different characterizations of time-varying multiplication factors. Specifically, we experiment with four scenarios:

- Different initial values, but an equal rate of decrease (circle): \( \phi_1^C = 2.9(0.985)^t, \phi_1^R = 1.6(0.985)^t, \phi_1^D = 2.2(0.985)^t \)
- Equal initial values, but different rates of decrease (square): \( \phi_1^C = 2.9(0.995)^t, \phi_1^R = 2.9(0.975)^t, \phi_1^D = 2.9(0.985)^t \)
- Different initial values and different rates of decrease (diamond): \( \phi_1^C = 2.9(0.995)^t, \phi_1^R = 1.6(0.975)^t, \phi_1^D = 2.2(0.985)^t \)
- Different initial values and faster decreases (cross): \( \phi_1^C = 2.9(0.975)^t, \phi_1^R = 2.9(0.925)^t, \phi_1^D = 2.9(0.950)^t \)

Here, we assume that, if the rates of decrease differ across the confirmed, recovered, and deceased compartments, then it is highest for the recovered and lowest for the confirmed compartment, as the very nature of the COVID-19 pandemic suggests.

Fig. 4 demonstrates that the direction of MIDIS is not affected by epidemiological underestimation when multiplication factors keep decreasing throughout the pandemic. Since, again, there should not be much variation in epidemiological underestimation for the period we focus on, it is fair to conclude that the identification of MIDIS is quite robust to measurement errors, whether they are fixed or time-varying.

6. Cross-country heterogeneity in MIDIS

To examine how our social distancing measure varies with a number of country characteristics along governmental, behavioral, and developmental dimensions, we estimate the following regression at the country-day level, \( (j,t) \), with each country being \( j \) and each day being \( t \):

\[
\text{MIDIS}_{jt} = \phi_0 + \phi_1 G_{jt-1} + \phi_2 B_{jt-1} + \phi_3 T_{jt} + D_j \phi_4 + e_{jt}
\]

Here, \( \text{MIDIS}_{jt} \), in percent, is the social distancing measure we construct in this paper at \( (j,t) \) level. The next two variables are to control for the effect of NPIs: \( G_{jt-1} \) is the governmental response to the pandemic, and \( B_{jt-1} \) is the behavioral response to the pandemic by individuals. We use the daily lagged values of these variables to account for the time lapse in social distancing as a response to various NPIs. The independent variable \( T_{jt} \) denotes the number of calendar days that passed since the confirmation of the first COVID-19 case, starting with January 22, 2020. This variable controls for the temporal response in distancing—whether being hit by the COVID-19 pandemic later in the calendar has an effect. \( D_j \) is a vector of country-specific comparative development indicators (see below).

The data for governmental responses are from the Oxford COVID-19 Government Response Tracker (OxCGRT) (Hale et al., 2021). This initiative collects information on a multitude of containment measures taken by more than 180 countries and territories around the globe. Four indices are constructed to classify the data collected in different domains: (i) the Overall Government Response Index (OGRI), which documents the response of governments to the pandemic using all indicators; (ii) the Containment and Health Index (CHI), which uses ‘lockdown’ restrictions and closures along with measures such as testing policy and contact tracing, short-term investment in healthcare as well as investments in vaccines; (iii) the Stringency Index (SI), which keeps record of the strictness of lockdown style’ policies that principally restrict people’s movements; and (iv) the Economic Support Index (ESI), which combines measures such as income support and debt relief. These indices, which vary between 0 and 100, can be interpreted as de jure measures and contain no information on whether all the measures taken have been implemented effectively. We use the lagged values of \( SL_{jt-1} \) as our main variable of interest in (20) to proxy for the governmental response to the COVID-19 pandemic, \( G_{jt-1} \). In addition, we employ \( OGRI_{jt-1}, CHI_{jt-1} \) and \( ESI_{jt-1} \) for further analyses.

Second, we use JHU (2021) epidemiological data components as proxies for the behavioral response to the pandemic. It would not be hard for anyone who consciously experienced the COVID-19 pandemic to recall that they had to drop everything to get the news of the numbers of infected, deceased, and recovered for the COVID-19 cases in their cities, countries, and the world every day to prepare for the next day. In other words, people use daily epidemiological data, particularly the numbers of deceased individuals, which headlined all types of news outlets, to inform their behavior on the next day. Therefore, we utilize the lagged values of the total number of

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9 The full set of results are available upon request.

10 If the algorithm chooses \( \zeta_j = 0 \) for some \( j \), then we set \( \zeta_j \) to \( \min(\zeta_j) \), since this parameter has a strictly positive support. This correction is needed only for a few countries and the case of time-varying multiplication factors.

11 The results are not sensitive to the use of lagged values.

12 A detailed description of the data is provided by Hale et al. (2021), and the dataset is available at https://github.com/OxCGRT/covid-policy-tracker.
of deceased persons to explore the effect of behavioral response on social distancing. This variable is expressed in thousands in (20).

We construct the temporal response variable $T_{jt}$ by using the JHU (2021) data on confirmed cases. Starting the calendar on January 22, 2020, i.e., the first day in the JHU (2021) sample, $T_{jt}$ is the number of calendar days that passed since the confirmation of the first case. Hence, $T_{jt}$ increases over time by one day for country $j$ but starts at a higher value at $t = 0$ if the first case in country $j$ is confirmed later in the calendar.

Finally, we investigate how latent social distancing varies with a range of country characteristics borrowed from the comparative development literature. This aids in understanding the importance of cross-country heterogeneity in geography as well as economic, social, and cultural development (e.g., Easterly and Levine, 1997; Acemoglu et al., 2001; Alesina et al., 2003; Ashraf and Galor, 2013). In particular, we use $\ln(GDP \text{ per capita})$, human capital index, social progress index, ethnolinguistic fractionalization, and region dummies. The definitions and data sources of all the variables used in the regressions are compactly presented in Table B2, with Table B3 reporting the summary statistics.

Table 3 displays the regression results of different specifications of (20) by progressively adding variables. Column (1) explores the impact of the governmental response to the pandemic. The variable $SI$ has a significant positive impact on the level of social distancing. As governments adopt more stringent containment measures, social distancing proliferates. Indeed, a 1-point increase in stringency increases MIDIS by about 0.18–0.24 points.

Column (2) explores governmental and behavioral responses together. The number of deceased individuals due to the COVID-19 one day prior has a positive and significant impact on the level of social distancing. Indeed, a 1-point increase in stringency increases MIDIS by about 0.18–0.24 points.

In columns (3)-(6), we add the variables $\ln(GDP \text{ per capita})$, human capital index, social progress index, and ethnolinguistic fractionalization one by one since these are highly correlated with each other. All of these variables exert a significant effect in explaining MIDIS. The signs of the four parameters indicate that more developed countries practice more effective social distancing on average (after controlling for governmental, behavioral, and temporal responses). In other words, as the development level rises, social

Table 3
Cross-Country Heterogeneity in MIDIS.

| Variables                              | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|----------------------------------------|-----|-----|-----|-----|-----|-----|-----|-----|
| Stringency ($SI$)                      | 0.239*** | 0.189*** | 0.185*** | 0.188*** | 0.189*** | 0.182*** | 0.184*** | 0.180*** |
|                                        | (0.053) | (0.055) | (0.054) | (0.055) | (0.054) | (0.059) | (0.055) | (0.022) |
| # of deceased persons                  | 2.080*** | 1.981*** | 2.015*** | 2.004*** | 2.176*** | 1.998*** | 1.903*** | 1.901*** |
|                                        | (0.387) | (0.377) | (0.383) | (0.381) | (0.416) | (0.381) | (0.182) |          |
| # of calendar days since the 1st case  | 0.416*** | 0.388*** | 0.412*** | 0.401*** | 0.400*** | 0.380*** | 0.408*** | 0.434*** |
|                                        | (0.062) | (0.063) | (0.064) | (0.066) | (0.065) | (0.066) | (0.064) | (0.020) |
| $\ln(GDP \text{ per capita})$         | 7.542*** |          |          |          |          |          |          |          |
|                                        | (1.339) |          |          |          |          |          |          |          |
| human capital index                    |          |          |          |          |          |          |          |          |
|                                        |          |          |          |          |          |          |          |          |
| social progress index                  | 9.916*** |          |          |          |          |          |          |          |
|                                        | (2.088) |          |          |          |          |          |          |          |
| ethnolinguistic frac.                  | 0.587*** |          |          |          |          |          |          |          |
|                                        | (0.095) |          |          |          |          |          |          |          |
| East Asia & Pacific                    |          |          |          |          |          |          |          |          |
|                                        |          |          |          |          |          |          |          |          |
| Europe & Central Asia                  |          |          |          |          |          |          |          |          |
|                                        |          |          |          |          |          |          |          |          |
| Latin America & Caribbean              |          |          |          |          |          |          |          |          |
|                                        |          |          |          |          |          |          |          |          |
| Middle East & North Africa             |          |          |          |          |          |          |          |          |
|                                        |          |          |          |          |          |          |          |          |
| South Asia                             |          |          |          |          |          |          |          |          |
|                                        |          |          |          |          |          |          |          |          |
| Sub-Saharan Africa                     |          |          |          |          |          |          |          |          |
|                                        |          |          |          |          |          |          |          |          |
| R-squared                              | 0.012 | 0.015 | 0.102 | 0.073 | 0.124 | 0.040 | 0.147 | 0.746 |
| # of Countries                         | 119 | 119 | 116 | 114 | 114 | 109 | 119 | 119 |
| # of Observations                      | 3,451 | 3,446 | 3,359 | 3,301 | 3,301 | 3,156 | 3,446 | 3,446 |
| Notes: The dependent variable is MIDIS (in percentage terms). Robust standard errors are in parentheses. The reported R-squared is the overall R-squared measure. Superscripts ***, **, and * indicate statistical significance at 1 %, 5 %, and 10 %, respectively. For region dummies, the excluded category is North America. See Appendix B for the list of countries, variable definitions, data sources, and summary statistics.
In all specifications reported in Table 3, the coefficient estimates in regards to development indicators and region dummies— which are qualitatively very similar to the ones in Table 3—are suppressed for brevity in Table 4. The impacts of # of deceased persons and # of calendar days since the 1st case continue to be significant and positive with similar coefficient sizes.

What is more noteworthy in Table 4 is that, among all government response indicators, ESI has the lowest impact on social distancing. While a 1-point increase in CHI and OGRI causes from 1/4 to 1/3 point rise in MIDIS, the same amount of increase in the economic support index moves MIDIS upwards by only about 1/10 point. Put differently, on average, the economic support measures taken by different governments across the globe have not achieved much in terms of social distancing practices. This might be a result of the heterogeneity in the generosity of these support measures as well as the relative levels of sheer necessity to work to survive in different countries.
This section presents an application for the use of the MIDIS index constructed in this paper. We focus on the economic cost of social distancing triggered by the COVID-19 pandemic. Baldwin and Weder di Mauro (2020) clearly explain the types of economic shocks created by the COVID-19 pandemic that cause reduced economic activity. Among these, we concentrate on output loss.

### 7.1. Proxying for output loss

Unlike epidemiological data, it is impossible to obtain daily data for output. This necessitates the use of a proxy. Therefore, we use the Bruegel Electricity Tracker (BET) of COVID-19 Lockdown Effects compiled and calculated by McWilliams and Zachmann (2020) to approximate output losses experienced during the pandemic. This is based on the premise that a lot of economic activity relies heavily on the use of electricity. The BET reports the temperature-adjusted daily sums of peak-hour electricity consumption (08:00-18:00) as a measure of economic activity owing to the intensity of economic activity within these hours.

Let relative output be the ratio of daily peak-hour electricity consumption in 2020 to that in 2019. Stated in percentage terms, we have

$$\text{relative output}_j, t = \left(\frac{\text{output}_2020^j, t}{\text{output}_2019^j, t}\right) \times 100.$$  \hfill (21)

Here, we calculate relative output for country $j$ on day $t$ by aligning each week in 2020 with the corresponding week in 2019. In our analysis, we include only working days (ignoring weekends and public holidays from our sample of 30 days for which MIDIS is calculated). This leaves us with 20–22 days for each country.

### 7.2. Estimation results

To explore the relationship between social distancing and output loss, we estimate a very basic regression specification at the country-day level, $(j, t)$, with each country being $j$ and each day being $t$:

$$\text{output loss}_j, t = \phi \text{MIDIS}_j, t + \eta_j + \delta_t + \epsilon_j,$$  \hfill (22)

where output loss$_j, t = 100 – \text{relative output}_j, t$, and $\eta_j$ and $\delta_t$ denote country and day fixed effects, respectively. Here, $\phi$ can be interpreted as the social distancing elasticity of output loss given that both MIDIS and output loss are expressed in percentages.

Table 5 reports the estimation results for (22) using different fixed effects structures. The left panel is for the sample excluding weekends and the right panel for the sample excluding both weekends and public holidays. The results indicate a robust positive impact of MIDIS on output loss. In other words, an escalation in social distancing increases output loss. Indeed, the social distancing elasticity of output loss varies between 0.105 and 0.230, depending on the specification. Put differently, a 10 percent increase in social distancing causes a 1.05–2.30 percent increase in output loss. This is clearly a sizable effect on real economic activity.

In short, the social distancing measure MIDIS—implied by the SEIRD model and daily epidemiological data—explains output loss

| Weekends Excluded | Weekends & Holidays Excluded |
|-------------------|-----------------------------|
| MIDIS             |                             |
|                   | 0.208***                    |
|                   | (0.025)                     |
| Country FE        | No                          |
|                   | Yes                         |
| Time FE           | No                          |
| R-squared         | 0.097                       |
| # of Countries    | 30                          |
| # of Obs.         | 642                         |
|                   |                             |
|                   | 0.160***                    |
|                   | (0.034)                     |
|                   | 0.105**                     |
|                   | (0.042)                     |
|                   | 0.230***                    |
|                   | (0.024)                     |
|                   | 0.183***                    |
|                   | (0.031)                     |
|                   | 0.113***                    |
|                   | (0.036)                     |
| Country FE        | No                          |
|                   | Yes                         |
| Time FE           | No                          |
| R-squared         | 0.369                       |
| # of Countries    | 30                          |
| # of Obs.         | 642                         |
|                   | 0.410                       |
|                   | 0.136                       |
|                   | 0.482                       |
|                   | 0.533                       |
|                   | 0.410                       |
|                   | 0.482                       |
|                   | 0.533                       |

Notes: The dependent variable is output loss (in percentage terms). The reported R-squared is the adjusted R-squared measure. Superscripts ***, **, and * indicate statistical significance at 1 %, 5 %, and 10 %, respectively. See Appendix B for the list of countries, variable definitions, data sources, and summary statistics.
experienced during the COVID-19 pandemic in a meaningful way. Clearly, the effects of MIDIS on output loss that we document in Table 5 do not identify the structural mechanisms, but the regression serves as a reduced-form device that allows us to see the quantifiable output impact of distancing.  

8. Concluding remarks

The COVID-19 pandemic has made social distancing a central aspect of our lives. At the personal level, it has directly affected our daily routines. At the professional level, researchers have started asking new research questions concerning the causes and consequences of social distancing.

In this paper, we propose a novel methodology that identifies latent social distancing for a large number of countries and for the first wave of the pandemic within the framework of the SEIRD model. With minimum data requirements, our methodology allows the construction of an index, MIDIS, for a key unobserved variable that has economic, social, psychological, and political significance. Existing mobility statistics implies that our index is a valid indicator of latent social distancing. Perhaps most importantly, it is not sensitive to measurement errors that severely contaminate official epidemiological statistics.

The paper contributes to the literature both empirically and methodologically. Empirically, we present original evidence on the evolution, causes, and consequences of social distancing by using our MIDIS index. We are able to identify at least four groups of countries where each group exhibits a unique pattern of social distancing during the first wave. Our empirical results also confirm the significance of governmental, behavioral, and temporal effects on de facto social distancing. These remain significant when we add region dummies and control for cross-country differences in economic and social development. Furthermore, when we use MIDIS to explain output loss experienced during the pandemic, we are able to show robust and sizable effects.

Our methodological contribution lies in the usefulness and simplicity of our quantitative algorithm, which identifies and computes the MIDIS index. Even after several waves and the development of various effective vaccines, the COVID-19 pandemic is not under control. New strains of the virus, low vaccination rates, premature relaxations of lockdowns and mobility restrictions, and pandemic fatigue imply that social distancing is likely to be a critical component of our lives in the near future. Since both policymakers and individuals will be in the midst of the tension between the necessity and tolerability of social distancing, our robust methodology could be used to inform decision-making processes, especially if it is applied to other waves of the pandemic and to newer strains of the virus that have different epidemiological parameters.

Acknowledgments

We are grateful to two anonymous reviewers for their helpful comments and suggestions on an earlier version of this paper. We wish to thank Ben McWilliams and Georg Zachmann for sharing their daily electricity data with us. We also wish to thank the participants of the Science Academy’s COVID-19 Modeling Workshop, the 19th International Conference of the Middle East Economic Association, and the 47th Annual Conference of the Eastern Economic Association for their helpful comments and suggestions on an earlier version of this paper. Finally, we thank Joe Spearin, who has pointed out to us that our results are robust under the presence of measurement errors; his blog post was the original inspiration for Section 5 of this version. Any remaining errors are our own.

Appendix A. Robustness

In this appendix, we investigate the robustness of MIDIS with respect to three aspects of our research design. First, we change the fixed and common parameter \( \alpha \), i.e., the inverse of the average incubation period. Second, we implement the analysis by looking at the period after the confirmation of the 100th COVID-19 case in a country (benchmark: the 500th case). Finally, we extend the sample for each country to 60 days after the confirmation of the 500th case (benchmark: 30 days). For all three experiments, we present new results for South Korea and the United States for space considerations. The full set of sensitivity results is available upon request.

The benchmark value of \( \alpha \) is set to \( \alpha = 1/7 \); this corresponds to an average incubation period of 7 days. Fig. A1 shows that the evolution of MIDIS is not significantly altered if the average incubation period is 5 or 9 days.

The benchmark analysis focuses on the period after the confirmation of the 500th case in each country. The 500th case allows us to disregard the erratic movements of epidemiological data in the first few days of the pandemic in a country. Fig. A2 presents the evolution of MIDIS when we set this cutoff to 100 cases and confirms that the evolution of MIDIS remains qualitatively the same.

While the benchmark analysis in this paper studies the evolution of MIDIS during the 30 days following the confirmation of the 500th case in a country, the sample can easily be extended to longer episodes. To demonstrate the robustness of the results, we implement the analysis with 60-day samples for each country. Fig. A3 shows that the benchmark and experimented values closely follow each other during the first 30 days of the sample.

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16 The strong relationship between distancing and output loss is expected to hold in the very short run, e.g., a month, and it may weaken and be reversed in the longer run. This is because both the centralized/optimal distancing policies and decentralized/individual distancing practices are time-dependent—changing daily—as demonstrated in the related literature (Bethune and Korinek, 2020; Farboodi et al., 2020).
Fig. A1. MIDIS under Alternative $\alpha$ Values.
Notes: This figure shows the evolution of MIDIS for South Korea and the United States under alternative values of $\alpha$; the lower and higher values are $1/9$ and $1/5$ and correspond to 9 and 5 days of incubation, respectively.

Fig. A2. Samples starting with the 500th case versus the 100th case.
Notes: This figure shows the evolution of MIDIS for South Korea and the United States, where the 30-day sample for each country starts at the confirmation of the 100th COVID-19 case.
Appendix B. Statistical Appendix

Table B1
Countries in the MIDIS Sample.

| Angola       | Haiti        | Norway  |
|--------------|--------------|---------|
| Angola       | Haiti        | Norway  |
| Argentina    | Honduras     | Oman    |
| Australia    | Hong Kong    | Pakistan|
| Austria      | Hungary      | Panama  |
| Bahamas      | Indonesia    | Peru    |
| Bahrain      | Iraq         | Philippines|
| Barbados     | Ireland      | Poland  |
| Belarus      | Israel       | Portugal|
| Belgium      | Italy        | Qatar   |
| Benin        | Jamaica      | Romania |
| Bolivia      | Jordan       | Rwanda  |
| Bosnia and Herzegovina | Kazakhstan | Saudi Arabia |
| Brazil       | Kenya        | Senegal |
| Bulgaria     | Kuwait       | Singapore|
| Burkina Faso | Kyrgyzstan   | Slovakia|
| Cambodia     | Laos         | Slovenia|
| Cameroon     | Latvia       | South Africa|
| Canada       | Lebanon      | South Korea|
| Chile        | Lithuania    | Spain   |
| Colombia     | Luxembourg   | Sri Lanka|
| Costa Rica   | Malaysia     | Sweden  |
| Cote d’Ivoire| Mali         | Switzerland|
| Croatia      | Malta        | Taiwan  |
| Czechia      | Mauritius    | Tajikistan|
| Denmark      | Mexico       | Thailand|
| Dominican Republic | Moldova | Togo |
| Ecuador     | Mongolia     | Trinidad and Tobago|
| Egypt        | Morocco      | Turkey  |
| El Salvador  | Mozambique   | Ukraine |
| Estonia      | Myanmar      | United Arab Emirates|
| Fiji         | Namibia      | United Kingdom|
| Finland      | Nepal        | United States|
| France       | Netherlands  | Uruguay |
| Gabon        | New Zealand  | Venezuela|
| Germany      | Nicaragua    | Vietnam |
| Ghana        | Niger        | Yemen   |
| Greece       | Nigeria      | Zambia  |
| Guatemala    | North Macedonia| Zimbabwe|
### Table B2
Variable Definitions and Data Sources.

| Variable | Definition | Source |
|----------|------------|--------|
| Stringency | SI, score, (0-100) strictness of lockdown measures | Source: Hale et al. (2021) |
| Government Response | OGRI, score, (0-100) a composite of various government responses | |
| Containment & Health | CHI, score, (0-100) combining mobility restrictions with contact tracing, testing policy, healthcare investments, etc. | |
| Economic Support | ESI, score, (0-100) strength of income support and debt relief | |
| # of deceased persons | Total number of individuals deceased because of COVID-19 in 1,000 s | Source: JHU (2021) |
| Human capital index | Human capital per person, indexed, 2019 values based on years of schooling and returns to education | Source: Feenstra et al. (2015) |
| Social progress index | Social Progress Index, score, (0-100), 2019 values based on more than 50 development indicators | Source: SPI (2021) |
| GDP per capita | GDP per capita, 2019 values purchasing power parity, constant 2017 international dollars | Source: World Bank (2021) |
| Ethnolinguistic frac. | Ethnolinguistic fractionalization, score, (0-100), 2013 values probability that two randomly drawn individuals within a country are not from the same ethnic group | Source: Drazanova (2019) |
| A-Driving | Map requests for driving route directions (relative to Jan 13, 2020, %) | Source: Apple (2021) |
| A-Walking | Map requests for walking route directions (relative to Jan 13, 2020, %) | |
| G-RetailRecreation | Mobility trends for places like restaurants, cafes, shopping centers, theme parks, museums, libraries, and movie theaters (relative to Jan 3-Feb 6, 2020, %) | |
| G-GroceryPharmacy | Mobility trends for places like grocery markets, food warehouses, farmers markets, specialty food shops, drug stores, and pharmacies (relative to Jan 3-Feb 6, 2020, %) | |
| G-Parks | Mobility trends for places like local parks, national parks, public beaches, marinas, dog parks, plazas, and public gardens (relative to Jan 3-Feb 6, 2020, %) | |
| G-TransitStations | Mobility trends for places like public transport hubs such as subway, bus, and train stations (relative to Jan 3-Feb 6, 2020, %) | |
| G-Workplace | Mobility trends for places of work (relative to Jan 3-Feb 6, 2020, %) | |
| G-Residential | Mobility trends for places of residence (relative to Jan 3-Feb 6, 2020, %) | |
| Relative Output | Peak hour daily electricity consumption in 2020 (relative to 2019 values, %, excluding weekends and holidays) | Source: McWilliams and Zachmann (2020) |
Table B3
Summary Statistics.

| Variable                        | # of Obs. | mean   | std. dev. | min.     | max.     |
|---------------------------------|-----------|--------|-----------|----------|----------|
| MIDIS (%)                       | 3,600     | 61.20  | 14.92     | 0.00     | 100.00   |
| SI (%)                          | 3,570     | 75.50  | 18.10     | 0.00     | 100.00   |
| OGR1 (%)                        | 3,570     | 61.44  | 13.69     | 8.33     | 89.84    |
| CHI (%)                         | 3,570     | 63.61  | 13.66     | 9.52     | 91.96    |
| ESI (%)                         | 3,570     | 46.26  | 29.97     | 0.00     | 100.00   |
| # of deceased persons           | 3,594     | 198.28 | 885.30    | 0.00     | 14,553.00|
| # of days since the 1st case    | 3,600     | 52.27  | 21.44     | 1.00     | 129.00   |
| Human capital index             | 3,420     | 2.81   | 0.68      | 1.22     | 4.35     |
| Social progress index (%)       | 3,450     | 72.58  | 13.24     | 42.54    | 93.08    |
| GDP per capita                  | 3,510     | 25,949.34 | 22,588.00 | 1,224.51 | 113,940.20|
| Ethnolinguistic frac. (%)       | 3,270     | 44.29  | 23.69     | 1.90     | 88.00    |
| East Asia & Pacific             | 3,600     | 0.15   | 0.36      | 0.00     | 1.00     |
| Europe & Central Asia           | 3,600     | 0.32   | 0.46      | 0.00     | 1.00     |
| Latin America & Caribbean       | 3,600     | 0.18   | 0.39      | 0.00     | 1.00     |
| Middle East & North Africa      | 3,600     | 0.12   | 0.32      | 0.00     | 1.00     |
| South Asia                      | 3,600     | 0.04   | 0.20      | 0.00     | 1.00     |
| Sub-Saharan Africa              | 3,600     | 0.17   | 0.38      | 0.00     | 1.00     |
| A-Walking (%)                   | 1,767     | 48.27  | 24.81     | 9.82     | 161.59   |
| G-RetailRecreation (%)          | 1,767     | 43.96  | 24.62     | 5.82     | 161.76   |
| G-GroceryPharmacy (%)           | 3,594     | 51.34  | 25.02     | 4.00     | 159.00   |
| G-Parks (%)                     | 3,590     | 74.96  | 22.71     | 5.00     | 176.00   |
| G-TransitStations (%)           | 3,594     | 72.21  | 32.53     | 5.00     | 288.00   |
| G-Workplace (%)                 | 3,594     | 48.29  | 21.06     | 5.00     | 115.00   |
| G-Residential (%)               | 3,592     | 48.29  | 21.06     | 5.00     | 115.00   |
| Relative Output (%)             | 642       | 89.81  | 10.49     | 0.00     | 129.99   |

References

Acemoglu, D., Johnson, S., Robinson, J.A., 2001. The colonial origins of comparative development: an empirical investigation. Am. Econ. Rev. 91 (5), 1369–1401.

Acemoglu, D., Chernozhukov, V., Werning, L., Whinston, M.D., 2020. Op-Timal Targeted Lockdowns in a Multi-group SIR Model. Working Paper 27102. National Bureau of Economic Research. https://doi.org/10.3386/w27102.

Alesina, A., Devleeschauwer, A., Easterly, W., Kurlat, S., Wacziarg, R., 2003. Fractionalization. J. Econ. Growth 8 (2), 155–194.

Alfaro, L., Faia, E., Lammersdorf, N., Saidi, F., 2020. Social Interactions in Pandemics: Fear, Altruism, and Reciprocity. Working Paper 27134. National Bureau of Economic Research. https://doi.org/10.3386/w27134.

Alvarez, F.E., Argentesi, D., Lippi, F., 2020. A simple planning problem for COVID-19 lockdown. In: Covid Economics: Vetted and Real-Time Papers, 14.

Apple, 2021. Mobility Trends Reports. https://www.apple.com/covid19/mobility.

Argentieri Mariani, L., Gagete-Miranda, J., Rettil, P., 2020. Words can hurt: how political communication can change the pace of an epidemic. In: Covid Economics: Vetted and Real-Time Papers, 1, 12.

Askitas, N., Tatsiramos, K., Verheyden, B., 2020. Lockdown strategies, mobility patterns and Covid-19. In: Covid Economics: Vetted and Real-Time Papers, 1, 23.

Ashraf, Q., Galor, O., 2013. The Out of Africa hypothesis, human genetic diversity, and comparative economic development. Am. Econ. Rev. 103 (1), 1–46.

Axtsas, N., Tatsiramos, K., Verheyden, B., 2020. Lockdown strategies, mobility patterns and Covid-19. In: Covid Economics: Vetted and Real-Time Papers, 1, 23.

Avery, C., Bosert, W., Clark, A.T., Ellison, G., Ellison, S.F., 2020. Policy implications of models of the spread of coronavirus: perspectives and opportunities for economists. In: Covid Economics: Vetted Papers, 1, 12.

Baldwin, R., Weder di Mauro, B., 2020. Economics in the Time of COVID-19, VoxEU.org Book. Centre for Economic Policy Research, London.

Berger, D.W., Herkenhoff, K.F., Mongey, S., 2020. An SEIR Infectious Disease Model with Testing and Conditional Quarantine. Working Paper 26901. National Bureau of Economic Research. https://doi.org/10.3386/w26901.

Bethune, Z., Korinek, A., 2020. COVID-19 infection externalities: pursuing herd immunity or containment?. In: Covid Economics: Vetted and Real-Time Papers, 1, 11.

Brzezinski, A., Deiana, G., Kecht, V., Dijckie, D.V., 2020. Governor versus community action across the United States. In: Covid Economics: Vetted and Real-Time Papers, 1, 7.

Cakmakli, C., Demiralp, S., Kalemi-Ozcan, S., Yesiltas, S., Yildirim, M.A., 2021. COVID-19 and Emerging Markets: A SIR Model, Demand Shocks and Capital Flows. Working Paper 27191. National Bureau of Economic Research. http://www.nber.org/papers/w27191.

Casagrande, L., Drazanova, L., 2019. Historical Index of Ethnic Fractionalization Dataset (HIEF). https://doi.org/10.7910/DVN/4JQRCL.

Coven, J., Gupta, A., 2020. Disparities in Mobility Responses to COVID-19. Technical Report. National Bureau of Economic Research.

Degue, K.H., Le Ny, J., 2018. An interval observer for discrete-time SEIR epidemic models. 2018 Annual American Control Conference (ACC) 5934.

Dreher, N., Spiera, Z., McAuley, F., Koshin, L., Darbin, J., Moratin, N., Ali, M., Lira, A., Hannah, T., Genetz, A., Koshin, J., Choudhri, T., 2020. Impact of Policy Interventions and Social Distancing on SARS-CoV-2 Transmission in the United States. Technical report, medRxiv.

Drazanova, L., 2019. Historical Index of Ethnic Fractionalization Dataset (HIEF). https://doi.org/10.7910/DVN/4JQRCL.

Dreher, N., Spiera, Z., McAuley, F., Koshin, L., Darbin, J., Moratin, N., Ali, M., Lira, A., Hannah, T., Genetz, A., Koshin, J., Choudhri, T., 2020. Impact of Policy Interventions and Social Distancing on SARS-CoV-2 Transmission in the United States. Technical report, medRxiv.
Durante, R., Guiso, L., Gulino, G., 2020. Civic Capital and Social Distancing: Evidence from Italians' Response to COVID-19. VoxEU Column.

Easterly, W., Levine, R., 1997. Africa's growth tragedy: policies and ethnic divisions. Q. J. Econ. 112 (4), 1203–1250.

Eichenbaum, M.S., Rebelo, S., Trabandt, M., 2020. The Macroeconometrics of Epidemics. Working Paper 26882. National Bureau of Economic Research. https://doi.org/10.3386/w26882.

Engle, S., Stromme, J., Zhou, A., 2020. Staying at home: mobility effects of Covid-19. In: Covid Economics: Vetted and Real-Time Papers, 1, 4.

Easterly, W., Levine, R., 1997. Africa’s growth tragedy: policies and ethnic divisions. Q. J. Econ. 112 (4), 1203–1250.

Farkoodi, M., Jarosch, G., Shimer, R., 2020. Internal and external effects of social distancing in a pandemic. In: Covid Economics: Vetted and Real-Time Papers, 1, 9.

Falk, A., Becker, A., Dohmen, T.J., Huffman, D., Sunde, U., 2016. The Preference Survey Module: a Validated Instrument for Measuring Risk, Time, and Social Preferences. IZA Discussion Paper No. 9674. https://github.com/CSSEGISandData/COVID-19.

Falk, A., Becker, A., Dohmen, T., Enke, B., Huffman, D., Sunde, U., 2018. Global evidence on economic preferences. Q. J. Econ. 133 (4), 1645–1692.

Farboodi, M., Jarosch, G., Shimer, R., 2020. Internal and external effects of social distancing in a pandemic. In: Covid Economics: Vetted and Real-Time Papers, 1, 9.

Feenstra, R.C., Inklaar, R., Timmer, M.P., 2015. The next generation of the penn world table. Am. Econ. Rev. 105 (10), 3150–3182. https://doi.org/10.1257/aer.20130954.

Feng, Z., 2007. Final and peak epidemic sizes for SEIR models with quarantine and isolation. Math. Biosci. Eng. 4 (4), 675–686.

Fernandez-Villaverde, J., Jones, C.I., 2020. Estimating and Simulating a SIRD Model of COVID-19 for Many Countries, States, and Cities. Technical report. National Bureau of Economic Research.

Google, 2021. COVID-19 Community Mobility Results. https://www.google.com/covid19/mobility/.

Hale, T., Angrist, N., Kira, B., Petherick, A., Phillips, T., Webster, S., 2021. Variation in Government Responses to COVID-19. BSG Working Paper Series 2020/032, June 2021. https://www.bsg.ox.ac.uk/research/research-projects/coronavirus-government-response-tracker.

Kermack, W.O., McKendrick, A.G., 1927. A Contribution to the mathematical theory of epidemics. Proc. R. Soc. Lond. Series A 115 (772), 700–721.

Kmenta, J., 1991. Latent variables in econometrics. Stat. Neerl. 45 (2), 73–84.

Kaplan, G., Moll, B., Violante, G., 2020. Pandemics According to HANK. https://benjaminmoll.com/wp-content/uploads/2020/03/HANK_pandemic.pdf.

Khan, Z., 2007. Final and peak epidemic sizes for SEIR models with quarantine and isolation. Math. Biosci. Eng. 4 (4), 675–686.

Lele, P.E., Finklesthal, B.F., 2006. Statistical inference in a stochastic epidemic SEIR model with control intervention: ebola as a case study. Biometrics 62 (4), 1170–1177. http://dx.doi.org/10.1111/j.1541-0420.2005.00995.x.

Maloney, W., Taskin, T., 2020. Determinants of social distancing and economic activity during COVID-19: a global view. In: Covid Economics: Vetted and Real-Time Papers, 1, 13.

McWilliams, B., Zachmann, G., 2020. Bruegel Electricity Tracker of COVID-19 Lockdown Effects. https://www.bruegel.org/publications/datasets/bruegel-electricity-tracker-of-covid-19-lockdown-effects/.

Millimet, D.L., Parmeter, C.F., 2021a. COVID-19 Severity: A New Approach to Quantifying Global Cases and Deaths. IZA Discussion Paper No. 14116. https://www.iza.org/publications/dp/14116/covid-19-severity-a-new-approach-to-quantifying-global-cases-and-deaths.

Millimet and Parmeter, 2021b. Accounting for skewed or one-sided measurement error in the dependent variable. Political Anal. 1–23. https://doi.org/10.1017/pan.2020.45.

Painter, M.O., Qiu, T., 2020. Political beliefs affect compliance with Covid-19 social distancing orders. In: Covid Economics: Vetted and Real-Time Papers, 1, 4.

SPI, 2021. Social Progress Index. Social Progress Imperative. https://www.socialprogress.org/.

Tang, B., Wang, X., Li, Q., Bragazzi, N.L., Tang, S., Xiao, Y., Wu, J., 2020. Estimation of the transmission risk of the 2019-nCoV and its implication for public health interventions. J. Clin. Med. 92, 1–13, 462.

Toxvaerd, P., 2020. Equilibrium social distancing. In: Covid Economics: Vetted and Real-Time Papers, 1, 15.

World Bank, 2021. World Development Indicators. https://databank.worldbank.org/source/world-development-indicators.