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Abstract

This study documents how the demographics of new infections and mortality changed over time across US counties. We find that counties with a larger population share aged above 60 were hit harder initially in terms of both cases and mortality in March and April while counties with a larger population share aged below 20 were hit harder in June and July. At the same time, how counties that voted Democratic in 2016 are affected does not change over time. Subsequently, we simulate an alternative evolution of the pandemic, assuming that states extended the lockdown measures until daily new cases reach the levels of European countries after their lockdown measures were relaxed. In the baseline simulation, we find that cases and deaths would have increased by around 50% less by the end of June, but it would have led to a 2 percentage point larger drop in Q2 GDP.

JEL-Codes: C530, H120, I180, R110.

Keywords: spatial population distribution, pandemic, Covid-19, lockdown, stay-at-home order, economic impact, non-pharmaceutical interventions.

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1 Introduction

The spread of the corona virus has spurred quick and significant responses around the globe in order to slow down the spread or to stop it completely. To this end, many countries initially introduced social distancing measures to reduce the number of interactions between people. In most European countries, these social distancing measures were kept in place until new cases were at a low level which was sustained throughout the summer. In the US however, social distancing became a political issue and many governors lifted measures well before the low and sustainable levels were reached. This caused new cases to increase again and reach new high levels. This raises two important questions. First, are the variables that drive which counties were affected most initially the same as the ones that drive the summer peak? Second, what would have been the experience of a "hypothetical US" that followed the approach taken by most European countries in terms of cases and deaths and what would have been the economic cost of implementing such an approach in terms of GDP?

There are several key variables that can help explain the spread of a disease like COVID-19 or the Spanish Flu which had a similar global impact. One of the most important factors is how many interactions people have with each other. As there are limited data on this directly, researchers often resort to approximate measures like the population density.[1] Bürgi and Gorgulu (2019) recently introduced the newly developed measure of Spatial Population Concentration (SPC), which measures how many people live on average within a given radius of every person. This measure might be a better approximation of how close people live together, as it does not include deserts or lakes and is not bounded, unlike urbanization. Other researchers have utilized cell phone data as well: we do not use these data, as they are not available at the county level.[2]

Other factors that might influence the number of interactions people have can be related

[1] e.g. see Lall and Wahba (2020), Maroko et al. (2020), Pedrosa (2020), Rocklöv and Sjödin (2020) or Tarwater and Martin (2001)

[2] e.g. see Atkinson et al. (2020), Goolsbee and Syverson (2020) and Maloney and Taskin (2020)

to the nature of the occupation people have and what they do in their free time. For example, taxi drivers and some other service industries might have more interactions with a variety of people than someone working in an office. In turn, demographic factors like education have an influence on the type of jobs people have. As the US turned the lockdown into a political issue, it might also be the case that the voting behavior influences the spread. In order to find out which if any of these factors are important and whether their importance changed over time, we regress them on the new cases per 100,000 and the new deaths per 100,000 attributed to COVID-19 in the US at the county level for each month from March to July.[3]

The second important question addressed here is to simulate what consequences in terms of cases, deaths and the drop in GDP a longer shutdown would have had up to the end of the second quarter in 2020. There have already been several projections about the path that deaths and new cases are going to take.[4] Also, there are several projections on the potential economic impact available including the impact of social distancing, but to our knowledge no simulation that looks at the hypothetical alternative scenario where the US followed the policy of the European experience.[5] Specifically, the scenarios we simulate are an extended shutdown followed by a sustained low number of daily new cases. Our simulation assumes that the daily new cases follow an exponential decay after implementing the shutdown and that states keep the shutdown in place until a low threshold of weekly new cases is reached. After the shutdown is lifted, it is assumed that the daily new cases remain at the low level until the end of the simulation, similar to the experience in many European countries and several US states like New York or Massachusetts for example. This allows to estimate how long a shutdown is necessary for each state, which in turn can be utilized to estimate the economic impact of the scenario assumptions.

[3]We use the official data throughout and don't make any adjustments for under counts or testing difficulties. Potentially more accurate measures like excess deaths are not available in a timely manner and high frequency at the county level.

[4]For example Acemoglu et al. (2020), Buckman et al. (2020) or Sebastiani et al. (2020)

[5]For example Ivanov (2020) projected the impact on the supply chain and Barua (2020) and Maloney and Taskin (2020) assessed the impact of social distancing on the economy.

We estimate the state level impact of the shutdown and the new cases based on the first quarter 2020 GDP growth and use these estimates in the simulation for the second quarter. As a robustness check, we repeat this regression across European countries for both the first and second quarter, which yields broadly similar relationships. These estimates allow us to then compare the actual decline in GDP as well as the actual new cases and deaths to the simulated ones to see how effective the extended shutdown could have been at reducing the number of cases and deaths and what economic cost this shutdown would have had in terms of GDP. This allows a comparison to Aum et al. (2020) who find no clear trade-off between the health and the economy.

The remainder of the paper is structured as follows: The next section provides a short overview of the Spanish flu and how it relates to the current analysis, followed by the data and empirical model section. Next, we present the results of how the drivers of the pandemic changed over time followed by the simulation. The last section concludes.

2 Economic and Social Background of the 1918 Pandemic

The 1918 influenza is probably the most comparable pandemic to the COVID-19 pandemic in the recent past. In the US, the influenza caused 675,000 deaths and many million deaths worldwide (Brainerd et al., 2003) and has been extensively studied.

In terms of demographic indicators during the 1918 pandemic, Grantz et al. (2016) find that areas with lower education, higher unemployment and a higher population density saw higher numbers of deaths. In addition, Tuckel et al. (2006) found that ethnicity played an important role for the spread of the virus. In terms of the economic impact, Barro et al. (2020) estimate that the 1918 pandemic lead to a decline in annual GDP and consumption of 6 and 8%, respectively. However, Velde (2020) found that this impact appears to be shortlived based on high-frequency US coal industry data. In addition, Garrett (2009) found that a higher mortality rate was associated with a faster wage growth during 1914-1919 and areas with non-pharmaceutical interventions saw faster recoveries and fewer deaths (Correia and Verner, 2020).

At the same time, there were also many longer term impacts both with respect to the health and the economy. For example, Brainerd et al. (2003) found that economic growth 1919-1930 was faster in areas more affected by the pandemic. They argue that the higher capital-labor ratio caused substantial increases in productivity. Cohorts born during the 1918 pandemic displayed worse education (lower literacy), health (higher rates of physical disability), and socioeconomic outcomes (lower income) compared with other birth cohorts both in the United States and Brazil (Almond (2006), Guimbeau et al. (2020)).

3 Data and Empirical Model

Since the daily data on COVID-19 cases and deaths are available at the county level, this is our level of analysis. We mainly use three data sources: The Global Human Settlement (GHS) data for 2014 from Freire et al. (2000), which includes population data for a raster with cell sizes of 1km squared; USA facts data for county level corona virus cases (usafacts.org); and the stay home order announcements for each state from general news sources. Our control variables include county level demographics (mainly race and age components), the median income, the unemployment rate, and the education level from the Census Bureau, plus political data from the MIT Election Data and Science Lab.

The daily data set covers the period from January 22, 2020 (first official COVID-19 reported in the United States) to August 20, 2020 and most other indicators use the year 2014 to match the GHS data.[6] In order to see what demographic variables best explain

[6]The political data uses 2016 and we repeated the regressions for the 2019 data and the results remain qualitatively the same.

new cases and COVID-19 related deaths over time, we take the log of new cases (or deaths) per 100,000 for each month separately and check, which variables become significant. Our explanatory variables at the county level include the natural log of the Spatial Population Concentration (SPC) measure introduced by Bürgi and Gorgulu (2019) who find this to be a better measure to predict the economic activity than urbanization or population density. This indicator measures how close people live together as shown in Equation 1.

$$SPC_d = \frac{\sum_{i=1}^{N} x_i * n_{di}}{\sum_{i=1}^{N} x_i} - 1 \tag{1}$$

where SPC_d is the distribution measure for distance d, measuring how many people live within distance d of every person averaged across all individuals in a given county. x_i is the number of people at raster cell i and n_{di} is the number of people within distance d of cell i. We use d=50km for our analysis.[7] We also include the log of the population density at the county level, the log of the county area and the urban population share. Our main demographic indicators include the share of the African American, Hispanic and Asian populations separately, the population share aged 60 and above, the population share aged 20 and below, the log of the median income in the county, the share of the population with less than high school and the share of the population with a high school degree. Last but not least, we include what share of the county voted for the Republican Party in the 2016 presidential election to test, whether the political affiliation matters.

Our regression equation for each month and the overall sample is

$$LNewCases_c = \rho \sum_{c \neq j} w_{c,j} LNewCases_j + \alpha + \beta X_c + \psi_s + \mu_c \tag{2}$$

where $LNewCases_c$ is either the log of new cases per 100,000 in county c over the period of interest or the log of new deaths per 100,000 attributed to COVID-19, $\rho \sum_{c \neq j} w_{c,j} LNewCases_j$

[7] The results for the entire sample period and for other distances (10km-200km) are presented in the appendix.

is the spatial auto-correlation, X_c are our our indicators listed above, ψ_s are the state fixed effects and μ_c is the error term. We estimate it using General Methods of Moments (GMM) and $w_{c,j}$ is the weight based on the inverse centroid distances between each of the US countries. ρ thus captures whether the cases in close by counties influence the number of cases in county c.

4 Results

Our first results in Table 1 show that the closer people live together, the fewer cases there are. While this finding seems counter-intuitive at first, this result was also found by Lall and Wahba (2020) for example. They argue that this finding might be explained by more densely populated areas having larger floor space as well. Another factor could be that closely living together is not the same as having many interactions with other people. As a result, it could be the case that people living further apart have to travel further for shopping and amenities, and are thus more likely to get exposed to the virus. At the same time, we can exclude the county size as a factor because the negative sign remains when excluding counties with a population of less than 50,000 and counties with fewer than 100 new cases. The other density indicators, urban population rate, population density, and area of county, have mixed signs and are mostly insignificant. From the ethnicity variables, the Hispanic share appears positive and significant, which is in line with the data showing that this population was more affected and the ethnicity also mattered in 1918. The population age structure shows that initially, the older population was more affected in March, while the younger population was more affected in June and July. This is the only variable that shows a relatively clear pattern over time. Richer areas appear to be more affected as well throughout as are less educated areas. The less educated people were also more affected during the 1918 pandemic. Areas that voted Democratic appear to be more affected as well and this does not change over time. The spatial auto-correlation ρ suggests positive spatial dependence and hence it is important to include it in the regression.

Next, we repeat the regression for the new deaths per 100,000 and the results are shown in Table 2. The overall picture is similar to that of new cases, but the urbanization appears to be much more important. Of the demographic variables, the Hispanic population share matters less, while the Asian population appears to be less affected. Also, the older population is more affected throughout. This is in line with COVID-19 being particularly deadly for senior citizens. Counties with a higher income, a lower education and a democratic affiliation all not only have an increased number of cases but also a larger number of deaths. Lower education and the ethnicity were also important factors during the 1918 pandemic.

Overall, these results suggest that the indicators that explain the new cases or new deaths do not change much over time with the exception of the age structure of the counties. While counties with a larger share of older people were more affected initially, counties with a larger share of younger people were affected more in the summer.

5 Simulation and Counterfactual

In this section, we simulate alternative scenarios to the shutdown response in the US. Specifically, we simulate how long a shutdown would have been necessary to get into the range of several European countries that managed to stabilize the weekly increases in cases at low levels.[8] Adjusted for the US population, the weekly increase would range from around 9,500 new cases per week (Italy) to around 40,000 new cases per week (Belgium). In a first step, we reduce the sample to the states that had a shutdown.[9] We then compile the number of cases each state had on the day of the shutdown and each week after for two weeks. At the two week mark, we take the log increase from week 1 to week 2 of the shut down and assume three exponential decay scenarios for the new cases per week. We chose the two week mark,

[8]Specifically, the countries considered are Germany, Italy, Spain, the Netherlands, Belgium and Switzerland.

[9]This excludes the Dakotas, Nebraska, Arkansas and Iowa

as the time between testing and learning the results in the US took up to two weeks at that time. This means that new case numbers up to week two might still include cases from before the shutdown which could skew the analysis. In the optimistic first scenario, the log increase in cases halves every week, meaning that it has an exponent of $-log(2)$. This corresponds to the national decrease from week 2 to week 3. In the pessimistic scenario, we assume that the decay is slower at $-log(1.5)$ corresponding to a one third decrease of the log change of new cases per week. This corresponds roughly to the observed national decrease from week 3 to week 4 of the shutdown. The third (baseline) scenario assumes that the decrease starts off at the optimistic scenario and switches to the pessimistic scenario after two weeks. All three scenarios assume that the shutdowns at the state level remain effective and are continued until new cases increase by less than 60.6 per million inhabitants every week in each state (or 20,000 new cases at the national level) and then hover at that level until 13 weeks after the start of the shutdown is reached, corresponding roughly to the end of June.[10]

As Figure 1 shows, under all scenarios and the actual case level observed, the total cases do not exceed 2.5 million. In both the baseline and optimistic scenarios, there are around 1 million cases. Assuming the same mortality rate as the observed one until the end of the simulation (5%), this would imply around 50,000 deaths for the more optimistic scenarios and around 100,000 deaths for the pessimistic scenario, compared to the around 125,000 deaths that were officially recorded until the end of June.[11]

Comparing the shutdown period across states reveals that the optimistic scenario requires up to 11 weeks of shutdowns, while the baseline has up to 16 weeks of shutdowns and the pessimistic scenarios up to 19 weeks. In all cases, New Jersey, New York and Louisiana are the states that require the longest shutdowns to get below the European post shutdown equilibrium of 60.6 cases per million inhabitant. In comparison, the longest actual shutdown was in New York with almost 12 weeks which is close to the average of 10 and 14 weeks in

[10]Under the assumption that all states shut down on March 27th, the simulation ends on June 26th. Note that the simulation does not use calendar time.

[11]The mortality rate has since declined to around 3% in the US.

the optimistic and baseline scenarios. However, in reality about half the states opened earlier than even the optimistic scenario, which could be one of the reasons why the daily new cases increased soon after the shutdown was over.

5.1 Economic Implications

In order to determine the economic impact of the shutdown, it is necessary to estimate two separate effects. First, shutting down the state for an extended period of a quarter is likely to reduce output in that quarter. Second, more new cases lead to lower output as sick workers either stay home or are treated in a hospital and hence do not produce output. As a result, we run the following cross-section regression

$$GDP_i = \alpha + \beta lpos\_March_i + \gamma lockQ1_i + \delta X_i + \varepsilon_i \tag{3}$$

where GDP_i is the annualized real GDP growth rate for Q1 2020 in state i, $lpos\_March_i$ is the natural log of new cases in the first quarter, $lockQ1_i$ is the number of days that the state shut down, X_i are control variables and ε_i is the error term. Our control variables include the natural log of the population of the state (lpop), the log of our SPC measure at 10 kilometers (lspc10), the share of total output produced by sectors that were most affected by the virus at a national level (share), and the percentage decrease of people at workplaces based on Google mobility data (Q1work).[12] As the first column in Table 3 shows, the number of new cases significantly reduces the growth rate of a state, but the direct effect of the number of days the state was shut down is insignificant. As governors typically announce the shutdown ahead of time, we also include a second variable which captures the number of days a state shutdown in the first week of the second quarter (lockQ12) in the other columns of Table 3.

[12] The sectors most affected include Mining, Utilities, Transport and Warehousing, Arts, Entertainment and Recreation and Accommodation and Food Services. The Google mobility data uses smart phone location data and reports percentage changes in the number of phones in the work locations relative to January 2020. This data has been used in Atkinson et al. (2020) as well.

This additional variable is borderline significant. Of our controls, only population appears to be important. Overall, we find that the lockdown and the reduction of mobility appear to be less important in explaining the cross-sectional differences than the number of cases in line with what Correia and Verner (2020) found for the 1918 pandemic. All our specifications explain between a quarter and a third of the variance. As a robustness check, we run a similar regression for European countries as shown in Table 4. The first quarter results mirror the results of the US with similar magnitudes of the coefficient for the new cases and an insignificant coefficient for the shutdown length.[13] We repeat the analysis using the second quarter data as well and the new cases become insignificant as well.

The simulation of cases and the shutdown show that the scenarios leading to European levels of new infections after the shutdown is lifted typically lead to a longer shutdown period and a reduced number of cases. This implies that shutdowns become particularly costly if the coefficient on the shutdown is very negative and the coefficient on the log cases is close to zero. As a result, we opt to use the coefficients of the second column of Table 3 to obtain an upper bound of the cost of the shutdowns and new cases. As the Q2 GDP numbers at the state level have not yet been released, we simulate five separate scenarios. In the first scenario (actual), we use the actual shutdown times of the second quarter as well as the log of the actual new cases in the second quarter. The second scenario (actualsim) takes the actual number of cases after the 13 week simulation instead. The third through fifth scenarios are the optimistic, baseline and pessimistic scenarios that use the simulated number of cases in week 13 and the shutdown periods required in each scenario. The results are presented in Table 5. We find that the optimistic scenario is closest to the actual using the time line of the simulation. Both the pessimistic and the baseline scenario have a larger drop in GDP.

In term of 2012 USD, the 4 percentage point larger decline under the pessimistic scenario implies an approximately USD 190bn additional loss relative to the actualsim scenario.

[13] The results remain qualitatively the same if the first and second quarter data are pooled. Also note that the US data are annualized while the European data are not, implying that the European effect is larger. Based on for example Goto and Bürgi (2020), one would expect similar results for unemployment.

Correspondingly, the baseline scenario leads to around USD 95bn additional decline in GDP.

An important caveat of this analysis is that the projected decline in GDP is much less severe than the actual decline. The likely reason for this is that our regression estimated the variation across counties and states and not for the US as a whole. As a result, the analysis does not capture any variables related to COVID-19 that affect the US as a whole.

6 Conclusion

We document drives the spread of new infections and mortality and how it changed over time in the US. We looked at a variety of geographic, demographic and political indicators and find that counties with a larger population share aged above 60 were hit harder initially in terms of both cases and mortality in March and April while counties with a larger population share aged below 20 was hit harder in June and July. At the same time, counties that mainly voted Democratic in 2016, have a higher income, have a lower education level or whose population lives closer together have been harder hit throughout without clear changes in the relationship.

Subsequently, we simulate an alternative evolution of the pandemic, assuming that states extended the lockdown measures until daily new cases reach the levels of European countries after their lockdown measures were relaxed. In the baseline simulation, we find that cases and deaths would have increased by around 50% less by the end of June, but it would have led to a 2 percentage point larger drop in Q2 GDP. In a more pessimistic scenario, the economic decline would have been around 4 percentage points larger in Q2, while the impact on the new cases and mortality becomes more ambiguous.

Overall, this analysis provides an overview over the evolution of the COVID-19 pandemic in the US and shows that many deaths could have been prevented with a different policy response. However, a response that decreased the number of deaths might have lead to a higher economic cost.

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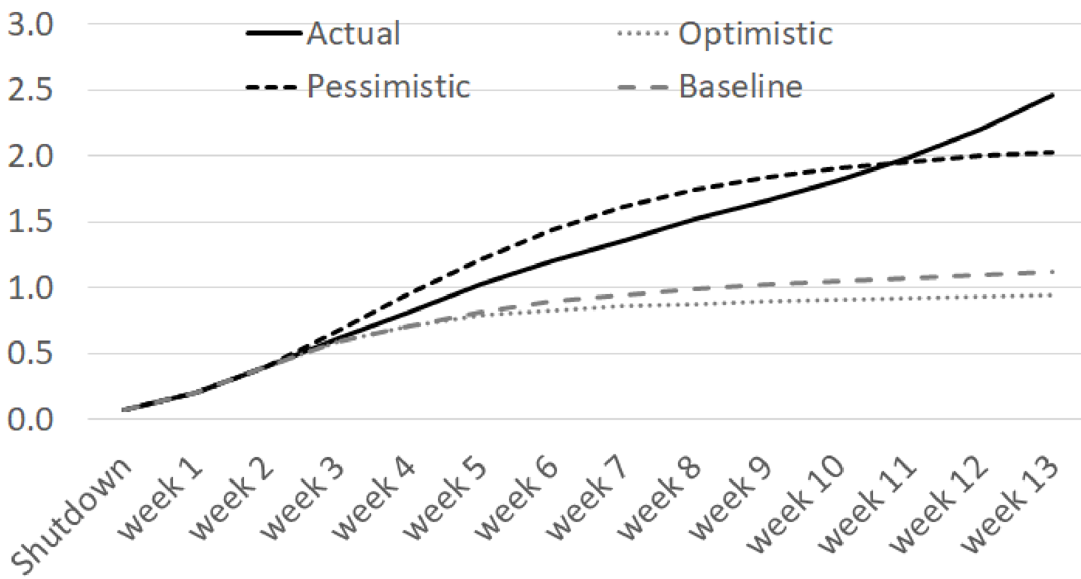
Figure 1: Simulated Total Cases



Note. This graph shows the simulated weekly total cases in millions from the aligned shutdown date. The first 2 weeks use the actual and the simulation starts with week 3. The 13 week simulation corresponds to Mar 27 to June 27. The optimistic scenario assumes an exponential decay of new cases with parameter $\lambda = log(2)$, the pessimistic assumes $\lambda = log(1.5)$ and the baseline assumes the optimal parameter for two weeks and then the pessimistic parameter.

Table 1: What Indicators Are Important in Explaining the New Cases

Dependent var.:	log cases (per 100,000)					
	All	Mar	Apr	May	Jun	Jul
ρ	0.226***	0.498***	0.400***	0.562***	0.314***	0.227***
	(0.024)	(0.097)	(0.059)	(0.060)	(0.046)	(0.027)
Density Indicators						
LSPC (50km)	-0.227***	-0.124***	-0.196***	-0.266***	-0.219***	-0.226***
	(0.019)	(0.032)	(0.031)	(0.031)	(0.026)	(0.020)
LPopDensity	-6.494	-2.716	-4.231	-12.486	-11.319	-6.975
	(8.965)	(11.459)	(12.910)	(13.972)	(11.657)	(9.554)
UrbanShare	0.313***	-0.517***	-0.124	-0.121	0.150	0.323***
	(0.082)	(0.139)	(0.130)	(0.141)	(0.112)	(0.088)
LArea	-0.002	-0.068*	-0.013	-0.026	-0.018	-0.013
	(0.025)	(0.038)	(0.037)	(0.041)	(0.033)	(0.026)
Demographic and Social Indicators						
African American	0.260	-0.160	1.161***	0.826*	0.614*	0.525*
Share	(0.255)	(0.457)	(0.425)	(0.450)	(0.353)	(0.273)
Hispanic Share	0.517**	0.361	0.628*	1.085***	0.979***	0.592***
	(0.208)	(0.335)	(0.324)	(0.352)	(0.281)	(0.222)
Asian Share	-0.469**	-0.369	-0.744*	-1.288***	-0.345	-0.354
	(0.237)	(0.438)	(0.402)	(0.425)	(0.332)	(0.254)
Share Age 60+	0.834*	5.488***	1.669**	1.593**	1.549**	1.057**
	(0.461)	(0.727)	(0.712)	(0.769)	(0.624)	(0.492)
Share Age $\leq$20	2.462***	0.815	-0.256	2.048*	4.257***	3.214***
	(0.697)	(1.209)	(1.128)	(1.221)	(0.970)	(0.745)
LIncome	1.398***	1.851***	2.231***	2.414***	1.436***	1.559***
	(0.105)	(0.165)	(0.162)	(0.174)	(0.141)	(0.112)
Share less than	5.468***	2.053***	4.960***	7.760***	5.538***	5.633***
High-school	(0.403)	(0.692)	(0.649)	(0.700)	(0.559)	(0.433)
Share High-school	-1.295***	-1.946***	-0.747	-0.595	-2.235***	-1.349***
	(0.313)	(0.526)	(0.496)	(0.533)	(0.430)	(0.335)
Political Indicators						
Share Republican	-1.531***	-2.712***	-1.898***	-1.697***	-1.475***	-1.714***
	(0.163)	(0.268)	(0.253)	(0.273)	(0.222)	(0.174)
Observations	3,101	2,106	2,736	2,749	2,896	3,087
$Pseudo R^2$	0.496	0.364	0.349	0.357	0.418	0.488
Fixed Effect	State	State	State	State	State	State

Note.This table shows the General Method of Moments (GMM) estimation results with spatial autocorrelation (ρ) for the US counties. Each column is a separate regression with the dependent variables corresponding to the log of all positive cases up to August 20 (all) and the log of new cases in the respective month. Variables with an "L" in front are logs of that variable. Robust standard errors are shown in parentheses. ***, p<0.01, ** p<0.05, * p<0.1.

Table 2: What Indicators Are Important in Explaining the Mortality

Dependent var.:	log mortality (per 100,000)					
	All	Mar	Apr	May	Jun	Jul
ρ	0.442***	3.108***	1.229***	1.044***	0.756***	0.494***
	(0.073)	(0.031)	(0.143)	(0.148)	(0.145)	(0.085)
Density Indicators						
LSPC (50km)	-0.174***	-0.195***	-0.189***	-0.256***	-0.251***	-0.172***
	(0.029)	(0.056)	(0.039)	(0.042)	(0.037)	(0.031)
LPopDensity	4.070	-23.95**	1.770	-12.05	-10.32	2.169
	(11.442)	(11.702)	(12.653)	(13.225)	(11.416)	(11.966)
UrbanShare	-0.373***	-2.593***	-0.536***	-0.802***	-0.928***	-0.373***
	(0.128)	(0.322)	(0.201)	(0.204)	(0.178)	(0.140)
LArea	-0.042	-0.189***	0.003	-0.107*	-0.119**	-0.040
	(0.036)	(0.071)	(0.052)	(0.055)	(0.047)	(0.038)
Demographic and Social Indicators						
African American	-0.270	2.133*	-0.925	-0.652	-0.957*	-0.445
Share	(0.398)	(1.128)	(0.644)	(0.658)	(0.517)	(0.444)
Hispanic Share	1.297***	-1.510**	0.186	0.291	0.635	1.109***
	(0.300)	(0.654)	(0.454)	(0.466)	(0.389)	(0.320)
Asian Share	-1.547***	1.841*	-1.266**	-0.794	-1.510***	-1.774***
	(0.384)	(1.069)	(0.632)	(0.653)	(0.504)	(0.430)
Share Age 60+	5.827***	5.774***	8.795***	7.308***	7.143***	6.184***
	(0.679)	(1.528)	(1.000)	(1.070)	(0.919)	(0.732)
Share Age $\leq$20	3.498***	1.707	2.919*	3.652**	3.269**	3.226***
	(1.088)	(2.399)	(1.645)	(1.714)	(1.438)	(1.172)
LIncome	1.146***	0.809**	1.111***	1.205***	0.857***	1.332***
	(0.156)	(0.323)	(0.223)	(0.241)	(0.203)	(0.168)
Share less than	4.256***	1.292	4.602***	6.799***	6.092***	4.924***
High-school	(0.599)	(1.589)	(0.952)	(1.002)	(0.817)	(0.647)
Share High-school	-1.112**	2.739**	-0.112	0.171	0.339	-0.998*
	(0.483)	(1.111)	(0.719)	(0.781)	(0.652)	(0.521)
Political Indicators						
Share Republican	-1.646***	-1.568***	-2.336***	-2.486***	-1.966***	-1.818***
Party	(0.244)	(0.508)	(0.364)	(0.375)	(0.319)	(0.261)
Observations	2,395	491	1,383	1,328	1,344	2,245
$PseudoR^2$	0.377	0.555	0.366	0.352	0.407	0.351
Fixed Effect	State	State	State	State	State	State

Note.This table shows the General Method of Moments (GMM) estimation results with spatial auto-correlation (ρ) for the US counties. Each column is a separate regression with the dependent variables corresponding to the log of all mortality up to August 20 (all) and the log of new mortality in the respective month. Variables with an "L" in front are logs of that variable. Robust standard errors are shown in parentheses. ***, p<0.01, ** p<0.05, * p<0.1.

Table 3: Impact of New Cases and the Shutdown for US States

	Dependent variable:		
	Q1 GDP growth Ann		
	(1)	(2)	(3)
lpop	0.779^{**}	0.752^{**}	0.573
	(0.338)	(0.331)	(0.405)
lpos_March	-0.795^{***}	-0.767^{***}	-0.800^{**}
	(0.261)	(0.256)	(0.332)
lockQ1	−0.060	−0.005	−0.002
	(0.056)	(0.063)	(0.064)
lockQ12		-0.152^{*}	−0.140
		(0.088)	(0.101)
share			−0.105
			(3.233)
lspc10			0.498
			(0.326)
Q1work			0.165
			(0.191)
Constant	-10.917^{***}	-10.048^{***}	-12.132^{**}
	(3.732)	(3.691)	(4.846)
Observations	51	51	51
R^2	0.265	0.309	0.345

Note.This table shows how new cases and the shutdown affect the cross-section of Q1 GDP growth across US states with various controls. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table 4: Impact of New Cases and the Shutdown for Europe

	Dependent variable:		
	Q1 GDP growth		Q2 GDP growth
	(1)	(2)	(3)
lpop	−0.035	−0.012	−1.034
	(0.459)	(0.473)	(1.743)
lpos_march	−0.736**	−0.739**	
	(0.273)	(0.280)	
lockQ1	−0.071	−0.058	
	(0.048)	(0.061)	
lockQ12		−0.064	
		(0.179)	
lpos_june			−0.936
			(1.149)
lockQ2			0.0002
			(0.040)
Constant	5.803	5.702	15.340
	(6.000)	(6.142)	(19.644)
Observations	24	24	17
R^2	0.587	0.590	0.371

Note.This table shows how new cases and the shutdown affect the cross-section of Q1 GDP and Q2 GDP growth across European countries with various controls.: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table 5: Simulated Growth Impact of the Shutdown and New Cases (QoQ Annualized)

	Q2 GDP QoQ Ann
Actual	-15.27
Actualsim	-13.69
Optimistic	-13.31
Pessimistic	-17.57
Baseline	-15.55

Note.This table shows the simulated decline in Q2 GDP due to the shutdown and new cases.

A Appendix

Table 6: Effect of Spatial Population Concentration on the Spread of Virus for various distances, US counties

Dependent variable:	log cases (per 100,000)					
SPC Distance (d):	(10 km)	(25 km)	(50 km)	(75 km)	(100 km)	(200 km)
ρ	0.204***	0.212***	0.223***	0.228***	0.232***	0.251***
	(0.024)	(0.024)	(0.024)	(0.024)	(0.024)	(0.024)
log SPC	-0.351***	-0.262***	-0.232***	-0.205***	-0.202***	-0.275***
	(0.035)	(0.025)	(0.021)	(0.019)	(0.019)	(0.020)
Observations	3,101	3,101	3,101	3,101	3,101	3,101
$PseudoR^2$	0.493	0.494	0.496	0.494	0.495	0.506
Fixed Effect	State	State	State	State	State	State
Controls	Yes	Yes	Yes	Yes	Yes	Yes

Note.This table shows the General Method of Moments (GMM) estimation results with spatial autocorrelation (ρ) for the US counties. Each column is a separate regression for different distances, d. Log of all positive cases up to August 20 is the dependent variable. Control variables consist (i) alternative density indicators: share of urban population, population density and area of county, (ii) demographic and social indicators: African American, Hispanic and Asian population shares, population above age 60 and below age 20, income, population with high school diploma, and population with less than high school diploma, (iii) political indicators: vote share of the Republican party in 2016 elections. Robust standard errors are shown in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 7: Effect of Spatial Population Concentration on the Spread of Virus for various distances, US counties

Dependent variable:	log mortality (per 100,000)					
SPC Distance (d):	(10 km)	(25 km)	(50 km)	(75 km)	(100 km)	(200 km)
ρ	0.377***	0.395***	0.442***	0.460***	0.477***	0.532***
	(0.072)	(0.072)	(0.072)	(0.072)	(0.072)	(0.071)
log SPC	-0.116**	-0.115***	-0.174***	-0.182***	-0.201***	-0.315***
	(0.049)	(0.034)	(0.028)	(0.026)	(0.026)	(0.029)
Observations	2,395	2,395	2,395	2,395	2,395	2,395
$Pseudo R^2$	0.370	0.371	0.377	0.380	0.382	0.396
Fixed Effect	State	State	State	State	State	State
Controls	Yes	Yes	Yes	Yes	Yes	Yes

Note.This table shows the General Method of Moments (GMM) estimation results with spatial auto-correlation (ρ) for the US counties. Each column is a separate regression for different distances, d. Log of overall mortality up to August 20 is the dependent variable. Control variables consist (i) alternative density indicators: share of urban population, population density and area of county, (ii) demographic and social indicators: African American, Hispanic and Asian population shares, population above age 60 and below age 20, income, population with high school diploma, and population with less than high school diploma, (iii) political indicators: vote share of the Republican party in 2016 elections. Robust standard errors are shown in parentheses. *** p<0.01, ** p<0.05, * p<0.1