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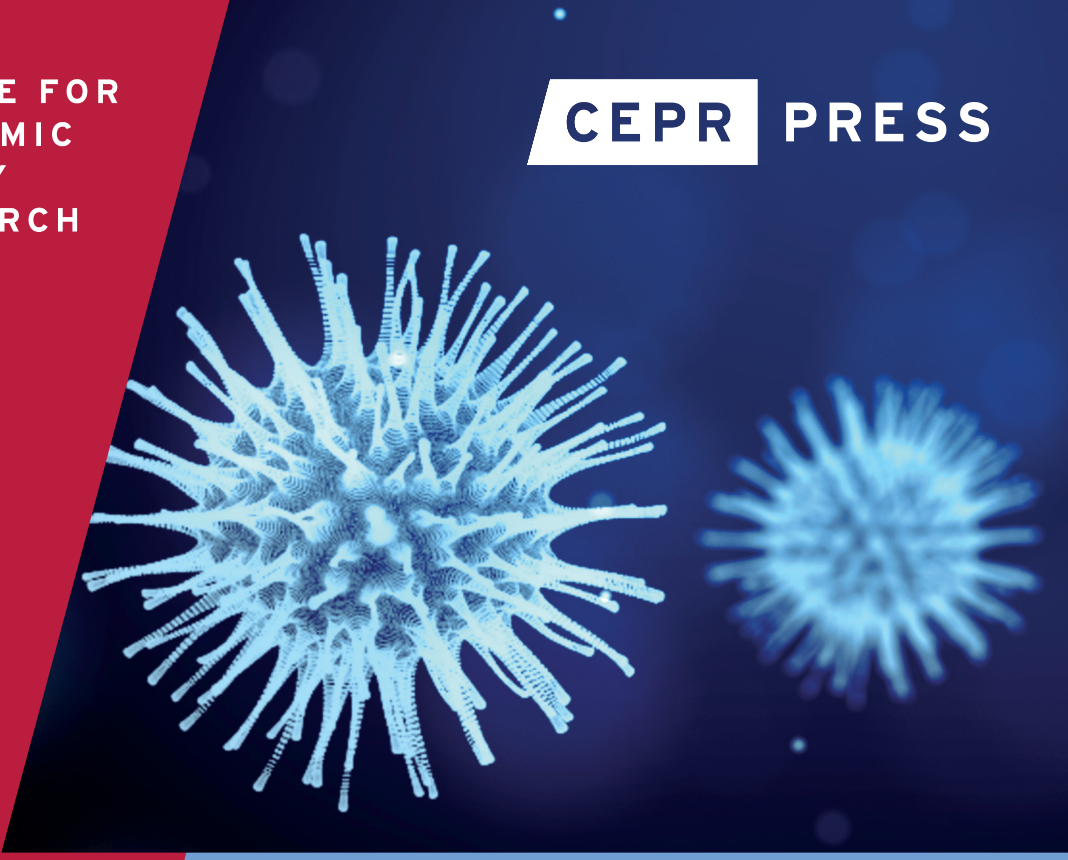

COVID ECONOMICS

VETTED AND REAL-TIME PAPERS

ISSUE 1
3 APRIL 2020

PANDEMICS: LONG-RUN EFFECTS
Óscar Jordà, Sanjay R. Singh and Alan M. Taylor

WHO CAN WORK AT HOME?
Jonathan Dingel and Brent Neiman

LOCKDOWN EFFECT
Tobias Hartl, Klaus Wälde and Enzo Weber

STOCK MARKET REACTIONS
Scott R. Baker, Nicholas Bloom, Steven J. Davis, Kyle Kost, Marco Sammon and Tasaneeya Viratyosin

COVID-19 DYNAMICS AND ASSET PRICES
Alexis Akira Toda

RESILIENCE AND GOVERNANCE
Frederic Jenny

Covid Economics
Vetted and Real-Time Papers

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Covid Economics
Vetted and Real-Time Papers

Issue 1, 3 April 2020

Contents

Longer-run economic consequences of pandemics[1]

Òscar Jordà,[2] Sanjay R. Singh[3] and Alan M. Taylor[4]

Date submitted: 27 March 2020; **Date accepted:** 30 March 2020

How do major pandemics affect economic activity in the medium to longer term? Is it consistent with what economic theory prescribes? Since these are rare events, historical evidence over many centuries is required. We study rates of return on assets using a dataset stretching back to the 14th century, focusing on 15 major pandemics where more than 100,000 people died. In addition, we include major armed conflicts that resulted in a similarly large death toll. Significant macroeconomic after-effects of the pandemics persist for about 40 years, with real rates of return substantially depressed. In contrast, we find that wars have no such effect, indeed the opposite. This is consistent with the destruction of capital that happens in wars, but not in pandemics. Using more sparse data, we find real wages somewhat elevated following pandemics. The findings are consistent with pandemics inducing labor scarcity and/or a shift to greater precautionary savings.

1. Introduction

Little is known about the medium- to long-term macroeconomic effects of global pandemics. But the recent Covid-19 outbreak places more urgency on trying to gauge the likely economic fallout. In this paper, we use a history of pandemics and rates of return since the 14th century to shed light on this problem.

1 We are grateful to Robert C. Allen, Gregory Clark, Paul Schmelzing, and the Bank of England for making their datasets publicly available. All errors are ours. The views expressed herein are solely those of the authors and do not necessarily represent the views of the Federal Reserve Bank of San Francisco or the Federal Reserve System.

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Most attention has understandably focused on short-term impacts. Even then, direct measures based on data from past episodes are not generally available (e.g., Meltzer et al., 1999 for the United States). An alternative would be to look at realised microeconomic outcomes of a given population in countries and episodes for which high-quality administrative data are available (e.g., in Sweden, Karlsson et al., 2014 for Sweden).

Absent such data, economic historians are forced to use more aggregated data at the regional or national level to study the relationship between pandemic incidence and economic outcomes (e.g., Brainerd and Siegler, 2003 for the 1918 flu epidemic across US states). But again, most historical studies have typically focused on one event in one country or region and have traced local outcomes for up to a decade at most.

Of course, the most devastating pandemic of the last millennium, the Black Death, has attracted a great deal of attention. Economists and historians debate its pivotal role in economic, social, and political change, particularly in Europe. Events such as the Peasant Rebellion in England feature centrally in a narrative of rising worker power, and the data speak to a rise in labor scarcity seen in a positive deviation in the path of real wages. This shock left England with a 25% to 40% drop in labour supply, a roughly 100% increase in real wages, and a decline in rates of return on land from about 5% to 8% (Clark, 2007; 2010). But it is an open question how representative the macroeconomic responses in the case of the Black Death are of large pandemics in general.

Here we take a more global view of the macroeconomic consequences of pandemics, and we aim to study the average effect of pandemics across all major events since the Black Death, looking at outcomes up to 40 years out. In large-scale pandemics, effects will be felt across whole economies, or across wider regions, for two reasons: either because the infection itself is widespread, or because trade and market integration – in capital and/or labour markets – eventually propagates the economic shock across the map.

To that end, our focus will be mainly on European pandemics, since macroeconomic data are only available in this region before modern times. We study rates of return on assets using a dataset stretching back to the 14th century, focusing on 15 major pandemic episodes where more than 100,000 people died. We also look at some more limited evidence on real wages. These events are listed in Table 1.

To put these historical pandemics in context, the scenarios contemplated by Ferguson et al. (2020) place Covid-19 as the most serious episode since the 1918 pandemic. Absent non-pharmaceutical interventions, these researchers estimate the death toll at 510,000 in Britain and 2.2 million in the United States.

Aggressive and recurrent suppression strategies would reduce the death toll only by a factor of 10 approximately, according to these authors.[5] Worldwide, that could still leave Covid-19 as the second most devastating event of the past 100 years. At the time of this writing, global deaths have already totalled over 20,000, with the infection peak still weeks away.

Event	Start	End	Deaths
Black Death	1347	1352	75,000,000
Italian Plague	1623	1632	280,000
Great Plague of Sevilla	1647	1652	2,000,000
Great Plague of London	1665	1666	100,000
Great Plague of Marseille	1720	1722	100,000
First Asia Europe Cholera Pandemic	1816	1826	100,000
Second Asia Europe Cholera Pandemic	1829	1851	100,000
Russia Cholera Pandemic	1852	1860	1,000,000
Global Flu Pandemic	1889	1890	1,000,000
Sixth Cholera Pandemic	1899	1923	800,000
Encephalitis Lethargica Pandemic	1915	1926	1,500,000
Spanish Flu	1918	1920	100,000,000
Asian Flu	1957	1958	2,000,000
Hong Kong Flu	1968	1969	1,000,000
H1N1 Pandemic	2009	2009	203,000

Table 1 Fifteen large pandemic events with at least 100,000 deaths

Source: Alfani and Murphy (2017), Taleb and Cirillo (2020), https://en.wikipedia.org/wiki/List_of_ epidemics and references therein.

Our main interest will be in the response of the real natural rate of interest to a pandemic shock. Introduced by Wicksell, and central to modern macroeconomic theory and empirics (Laubach and Williams, 2003; Wicksell, 1898; Woodford, 2003), the natural rate of interest is the level of real returns on safe assets which equilibrates savings supply and investment demand – while keeping prices stable – in an economy. Such an ideal equilibrium variable can therefore serve as a useful barometer of medium-term fluctuations in economic dynamism.

5 However, the uncertainty around these estimates is quite large. Also, the ability and willingness of some countries to actually implement and sustain such suppression strategies properly is open to question.

In the very long run, from century to century, this variable may drift slowly for technological, political, or institutional reasons. But over a horizon of around 10–20 years, medium-term deviations will dominate. Economic theory presumptively indicates that pandemics could be felt in transitory downward shocks to the natural rate over such horizons: investment demand is likely to wane, as labour scarcity in the economy suppresses the need for high investment. At the same time, savers may react to the shock with increased saving, either behaviorally as new precautionary motives kick in, or simply to replace lost wealth used up during the peak of the calamity.[6]

2. Data

To study the macroeconomic responses to historic pandemic events, we use data collected over many years collectively by many economic historians and pulled together gradually to form continuous time series measuring economic performance at annual frequency in cities, regions, and countries from the 14th century to the present.

Historical interest rates from 1314 to 2018 compiled by Schmelzing (2020) are available at the Bank of England's data repository. We refer the reader to this source for further details on data sources. The dataset covers France (1387–2018), Germany (1326–2018), Italy (1314– 2018), the Netherlands (1400–2018), Spain (1400–1729, 1800–2018), and the United Kingdom (1314–2018).

European real interest rates are constructed by weighting real interest rates on long-term debt in these advanced economies by GDP shares (Maddison, 2010). The underlying assets are debt contracts "which are not contracted short-term, which are not paid in-kind, which are not clearly of an involuntary nature, which are not intra-governmental, and which are made to executive political bodies". More limited data on real wages for the United Kingdom from 1311 to 2016 come from the real consumption wage series of Clark (2007) extended by Thomas and Dimsdale (2017) and available at the Bank of England data repository. For France, Germany, Italy, Netherlands, and Spain, we obtain real wages from Allen (2001) available at the IISH List of Datafiles of Historical Prices and Wages.

6 Formally, in the canonical Ramsey (1928) model of neoclassical growth, it can be shown that population slowdown or greater preference to save can each depress the natural rate (Rachel and Smith, 2017).

3. Empirical design

Pandemics, like many other natural disasters, offer a unique opportunity to study how economies work. They have much in common with a randomised control trial, but at a much larger scale. Not surprisingly, our empirical approach shares similar features with such a trial. Specifically, we use history as a guide of how the future usually unfolds, then compare that prediction to how the future unfolded following pandemics. Microbiology turns out to be a natural random assignment mechanism.

Specifically, given what we observe, and using a historical sample, one can easily construct the expected value of a future outcome of interest. Similarly, one can compute the expectation of that same outcome with the added fact that a pandemic has also taken place. This is the key idea behind the local projections estimator that we use (Jordà, 2005).

In particular, we characterise the response of the natural rate to a pandemic as

$$\hat{\tau}(h) = E(r^*_{t+h} - r^* | P_t = 1 \; ; \Omega_t) - E(r^*_{t+h} - r^*_t | P_t = 0 \; ; \Omega_t) \; , \tag{1}$$

where $r^*_{t+h} - r^*_t$ refers to the change in the natural rate from the year the pandemic ends to a future time h years later. P_t is a dummy variable that is 1 if there is a pandemic ending in year t, and is 0 otherwise, and Ω_t refers to the information set available at time t.[7]

We estimate $\hat{\tau}(h)$ using local projections, specifically, using the set of regressions:

$$r^*_{t+h} - r^*_t = \alpha^h + \beta^h P_t + \sum_{l=1}^{L} \rho^h_l r^*_{t-l} + e^h_{t+h} \; ; \; h = 1, ..., H \, , \tag{2}$$

where clearly $\hat{\tau}(h) = \hat{\beta}_h$. We choose 10 lags (L = 10) though the estimate $\hat{\beta}_h$ is unbiased whether we include these controls or not.[8]

Our estimate of the natural rate of interest, r_t^*, is based on the following simple model given the data that is available:

$$\begin{aligned} r_t &= r_t^* + u_t \, , \\ r_t^* &= r^*_{t-1} + v_t \, , \end{aligned} \tag{3}$$

7 Pandemics sometimes last for more than one year. We adopt as a timing convention the year they end.

8 Note that because pandemics are unpredictable and completely exogenous to the economy, we could omit Ω_t from the conditioning information set. $\hat{\tau}(h)$ would still be unbiased. Including right-hand side information improves the efficiency of the estimator. In other instances, when treatment is determined by observables, this will not be true. Thus $\hat{\tau}(h)$ is basically the cumulative Average Treatment Effect of the pandemic on interest rates, h periods later.

Here, the natural rate is a latent unobserved variable that follows a random walk. Such a model is flexible enough to capture any secular trends without the need to specify them directly. The observed rate of interest r fluctuates around the natural rate r^*. The error terms are assumed to be Normal and Equation 3 can be estimated using the Kalman filter and maximum likelihood methods.

4. Results

These tools deliver the estimate of the natural rate shown in Figure 1, based on an aggregate using data from France, Germany, the Netherlands, Italy, Spain and the United Kingdom. We simply call this aggregate "Europe." The figure displays the raw data on interest rates, along with our estimate of the natural rate of interest. Our estimates of the natural rate show the now well-documented pattern of a secular decline over the span of centuries, from about 10% in medieval times, to 5% at the start of the Industrial Revolution, and nowadays hovering near 0%. It is easy to see that our estimate of the natural rate goes a long way towards addressing the considerable annual noise that we observe in the raw data. In large part, these reflect wild fluctuations in harvests, armed conflict, and other events to which pre-industrial societies were exposed to a much greater degree than today. With industrialisation and modern finance, those fluctuations diminished considerably.

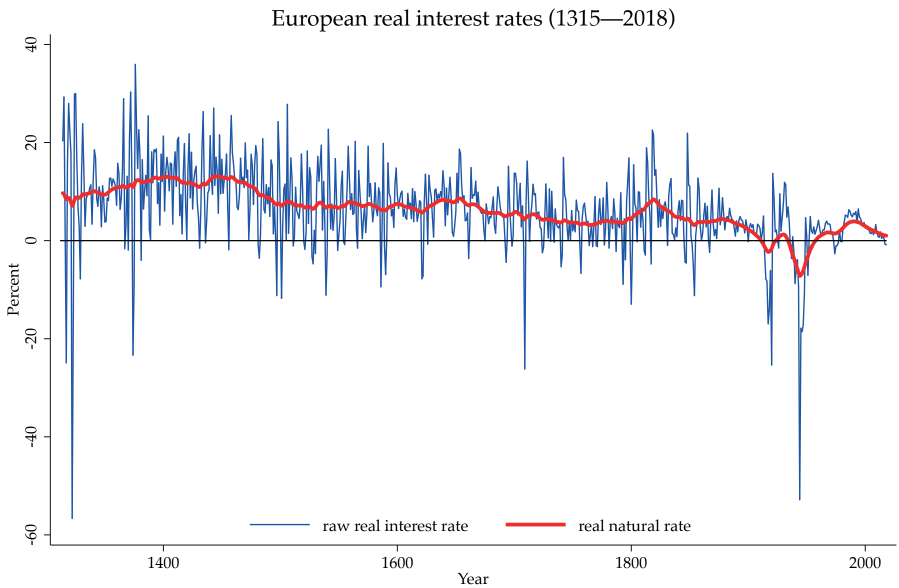

Figure 1 The European real natural rate of interest, 1315–2018

Notes: Raw interest data from Schmelzing (2020). The real rate is based on the model in Equation 3. See text.

Figure 2 contains our main result, and displays $\hat{\tau}(h)$, the response of the natural rate to a pandemic, one to 40 years into the future. Pandemics have effects that last for decades. Following a pandemic, the natural rate of interest declines for decades thereafter, reaching its nadir about 20 years later, with the natural rate about 150 basis points lower had the pandemic not taken place. At about four decades later, the natural rate returns to the level it would be expected to have had the pandemic not taken place.

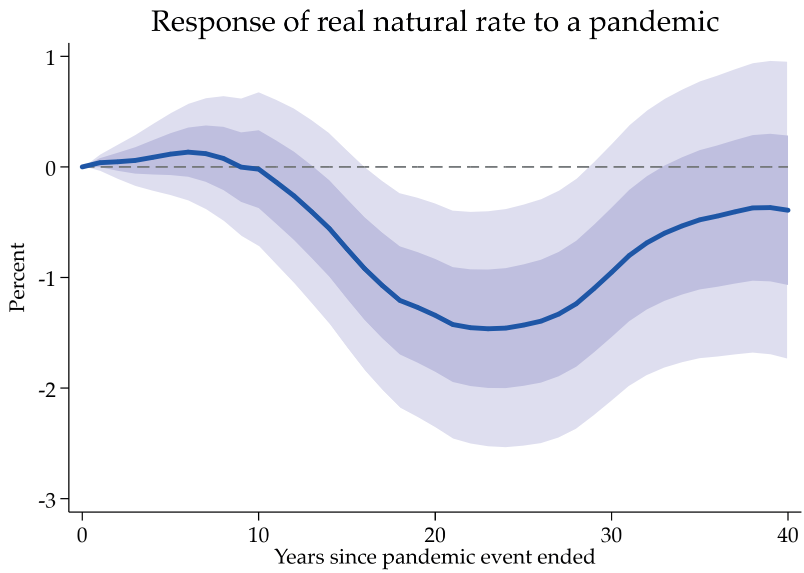

Figure 2 Response of the European real natural rate of interest following pandemics

Notes: Response calculated using Equation 2. Shaded areas are 1 and 2 s.e. bands around response estimates. See text.

These results are staggering and speak of the disproportionate effects on the labor force relative to land (and later capital) that pandemics had throughout centuries. It is well known that after major recessions cased by financial crises, history shows that real safe rates can be depressed for 5 to 10 years (Jordà et al., 2013), but the responses here display even more pronounced persistence.

However, did all countries in the Europe aggregate experience pandemics in the same manner? To answer that question, we turn to Figure 3 where we present similar responses of the natural rate for each of the component economies: France, Germany, Italy, the Netherlands, Spain, and the United Kingdom.

The heterogeneity of the responses turns out to be quite striking. At one end we have countries like France, Italy, and Spain, where the effects of pandemic are much larger (3–4% for France, Italy and Spain). This is in contrast to the Anglo-Saxon bloc of Germany, the Netherlands and the United Kingdom, with far more modest effects on the natural rate.

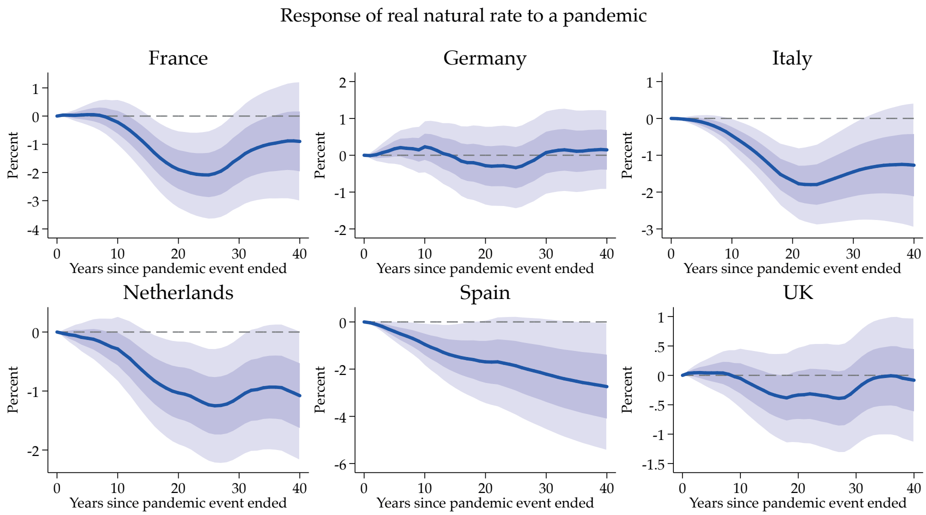

Figure 3 Country-specific response of the real natural rate of interest following pandemics

Notes: Responses calculated using Equation 2. Shaded areas are 1 and 2 s.e. bands around response estimates. See text.

This heterogeneity reflects, among other explanations, the timing of the pandemics across countries, the relative exposure of each country to the pandemic, the relative size of the working population, and how industrialised each economy was relative to one another. By defining pandemics as events with 100,000 deaths or more, we identified episodes with large contractions in the labor force and, hence, the ratio of labour to capital. We see this as one explanation for the response of interest rates. If so, we should see a countervailing response in real wages. To explore whether this is indeed the case, we use a similar local projection estimator in Figure 4 where, instead of the real interest rate, we use real wages in the left-hand side and in the control set.

The response of real wages is almost the mirror image of the response of the natural rate of interest, with its effects being felt over decades. The figure shows that real wages gradually increase until about three decades after the pandemic, where the cumulative deviation in the real wage peaks at about 5%. These results match the predictions of the neoclassical model, and accord with historical narratives: the Black Death induced labour scarcity in the European economy and pushed real wages up. In equilibrium, this went hand-in-hand with lower returns to capital.

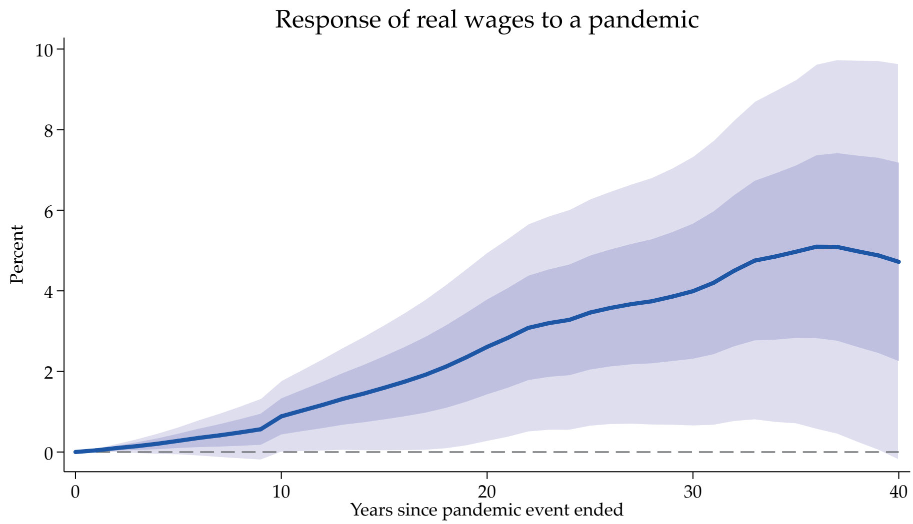

Figure 4 The response of real wages in Europe following pandemics

Notes: Response calculated using Equation 2. Shaded areas are 1 and 2 s.e. bands around response estimates. See text.

5. Pandemics versus wars

A natural concern might be omitted variables, specifically the historical occurrence of other macro-salient events that could persistently disturb real interest rates. One obvious concern is war. A clear confounding potential stems from the privations of wartime conditions which make diseases more likely. For example, a plague, possibly the first recorded influenza outbreak, occurred among the Athenians during the Peloponnesian War (Thucydides, 2.47–54). However, the correlation of war and disease outbreaks is not exactly one.

On the other hand, for the economic indicator of interest in this study, the bias could easily go the other way. Sovereign bond markets were to a large degree an innovation whose mother was military necessity, and the fiscal state had perhaps its most important role as an instrument of war (Brewer, 1990). Yet here the burden of raising large sums via debt finance could just as easily imply higher real interest rates via conventional crowding out arguments, or via risk-premium (e.g., default) channels, or simply due to capital scarcity created by wartime physical capital destruction (a feature absent in pandemics).

To address this concern, here we control for wars by using an indicator variable Wart which is set equal to one in any year in which war-time deaths in Europe exceed 20,000. We obtain the war-time military personnel casualties from Schmelzing (2020) dataset who draws data from Table 4.1 in Levy (1983).[9,10]

We then estimate an augmented local projection, now including the contemporaneous and lagged values of this indicator:

$$r^*_{t+h} - r^*_t = \alpha^h + \beta^h P_t + \gamma^h War_t + \sum_{l=1}^{L} \rho_l^h r^*_{t-l} + \sum_{l=1}^{L} \phi_l^h War_{t-l} + e^h_{t+h}\ ;\ h = 1, \ldots, H, \quad (4)$$

where the lags of the war variable are present as controls, and the coefficients γ^h are the impulse response of the real interest to a war event in year 0.

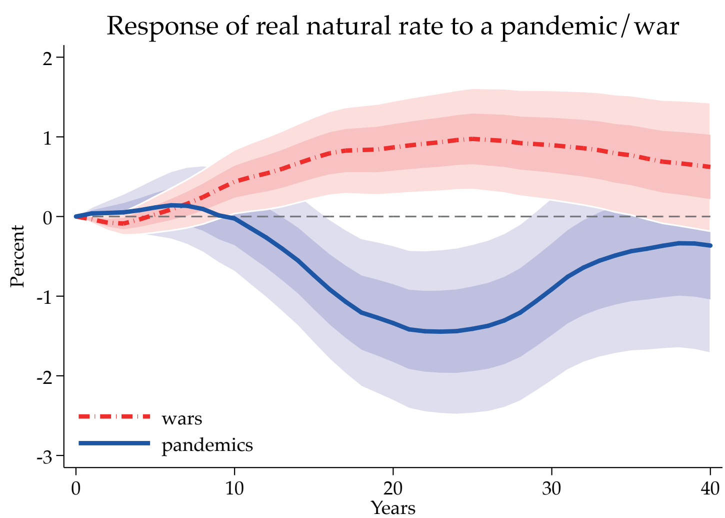

Figure 5 Response of the European real natural rate of interest following pandemics and wars

Notes: Response calculated using Equation 4. Shaded areas are 1 and 2 s.e. bands around response estimates. See text.

9 Total number of battle deaths are divided by duration of the battle (in years) to obtain an annual series of battle deaths. Since battles lasted more than a year, sometimes more than a decade, we think 20,000 deaths per year is comparable to the pandemic death toll threshold of 100,000 we employ.

10 6Readers interested in the debate on severity of pre 19th century epidemics may refer to Alfani and Murphy (2017), Roosen and Curtis (2018) and Biraben (1975) among others.

Figure 5 shows the result of this exercise. Our main finding is robust. The dynamic response of the real natural rates to pandemics is as before, and even slightly amplified: lowered for 30–40 years and in a statistically significant way. As we anticipated, the effect of war activity goes the other way: wars tend to leave real interest rates elevated for 30–40 years and in an economically (and statistically) significantly way.

6. Robustness

6.1 Robustness to possible major trend breaks

Schmelzing (2020) notes three historical dates at which the trend for the real interest rate could have changed. These are associated with 'post-Bullion famine' following the end of the global monetary contraction (1494), the 'North-Weingast' institutional revolution that led to emergence of credible debt mechanisms in Britain (1694), and the 'post-Napoleonic' trend due to the founding of the modern international state system (1820). Although the state-space model from Equation 3 is sufficiently flexible, to confirm that our results are not affected by such shifts, we now add controls for linear time trends starting at these historical dates. Figure 6 plots the new estimated impulse response of the European real natural interest rate following a pandemic event. As the figure shows, our baseline result is largely unchanged. The trough happens at about the same value (almost 2%) and at around the same time.

6.2 Robustness when excluding the Black Death and the Spanish Flu events

Figure 7 contains two additional robustness checks. In the left-hand panel, we verify that our results are not significantly affected by the Black Death by omitting this episode (i.e., setting the indicator to zero). Similarly, since the Great Depression followed the Spanish flu a decade later, one might be concerned that the decline in the natural interest rate was due to the Great Depression and not the Spanish flu. Thus, in the right-hand panel, we omit this pandemic from the sample. The main results are largely unaffected by omitting either of these two events.[11]

11 Furthermore, three historical pandemic events (London, Seville and Marseille) presented in Table 1 are largely localised at city level than the wider European region. One may surmise that local shocks attenuate the effects on the aggregate Europe real natural interest rate. In additional robustness, we corroborate this intuition by omitting London, Seville and Marseille plagues (i.e., setting the indicator to zero). The peak decline in real natural interest rate is about 185 basis points with global events. Results available on request.

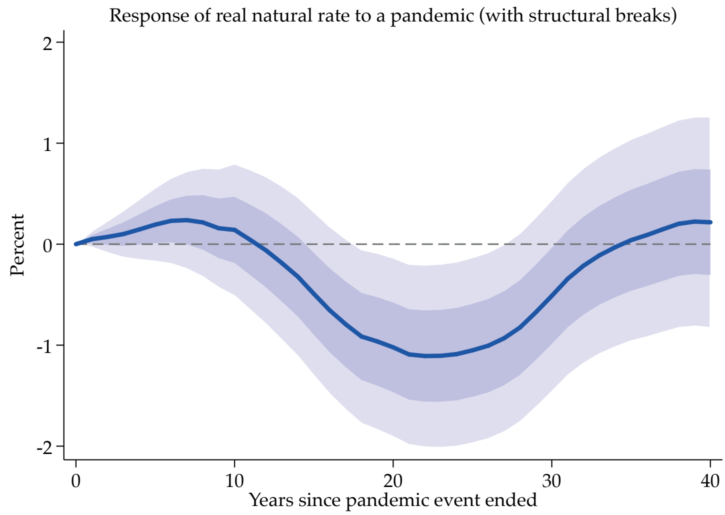

Figure 6 Response of the European real natural rate of interest allowing for trend breaks

Notes: Response calculated using Equation 2. Shaded areas are 1 and 2 s.e. bands around response estimates. See text.

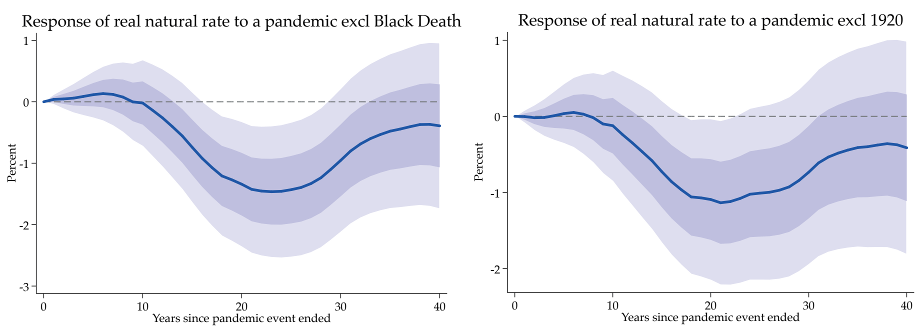

Figure 7 Response of the European real natural rate of interest following pandemics

Notes: Response calculated using Equation 2. Shaded areas are 1 and 2 s.e. bands around response estimates. See text.

7. Conclusions

Summing up our findings, the great historical pandemics of the last millennium have typically been associated with subsequent low returns to assets, as far as the limited data allow us to conclude. These responses are huge. Smaller responses are found in real wages, but still statistically significant, and consistent with the baseline neoclassical model.

Measured by deviations in a benchmark economic statistic, the real natural rate of interest, these responses indicate that pandemics are followed by sustained periods – over multiple decades – with depressed investment opportunities, possibly due to excess capital per unit of surviving labour, and/or heightened desires to save, possibly due to an increase in precautionary saving or a rebuilding of depleted wealth.

Either way, if the trends play out similarly in the wake of Covid-19 – adjusted to the scale of this pandemic – the global economic trajectory will be very different than was expected only a few weeks ago. If low real interest rates are sustained for decades, they will provide welcome fiscal space for governments to mitigate the consequences of the pandemic. The major caveat is that past pandemics occurred at time when virtually no members of society survived to old age. The Black Death and other plagues hit populations with the great mass of the age pyramid below 60, so this time may be different.

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How many jobs can be done at home?

Jonathan Dingel[1] and Brent Neiman[2]

Date submitted: 28 March 2020; **Date accepted:** 30 March 2020

We classify the feasibility of working at home for all occupations. About 34% of US jobs, accounting for 44% of overall wages, can plausibly be performed at home. This share varies considerably across cities and industries. We hope our results are useful for understanding the economic impact of social distancing and formulating policy responses. Our classifications could be easily applied to other countries.

1. Introduction

Evaluating the economic impact of 'social distancing' measures taken to arrest the spread of Covid-19 raises a number of fundamental questions about the modern economy: How many jobs can be performed at home? What share of total wages are paid to such jobs? How does the scope for working from home vary across cities or industries?

To answer these questions, we classify the feasibility of working at home for all occupations and merge this classification with occupational employment counts for the United States. Our feasibility measure is based on responses to two Occupational Information Network (O*NET) surveys[3] covering 'work context' and 'generalised work activities'. For example, if answers to those surveys reveal that an occupation requires daily 'work outdoors' or that 'operating vehicles, mechanised devices, or equipment' is very important to that occupation's performance, we determine that the occupation cannot be performed from

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3 https://www.onetcenter.org/questionnaires.html

home.[4] We merge this classification of O*NET occupations with information from the US Bureau of Labor Statistics (BLS) on the prevalence of each occupation in the aggregate as well as in particular metropolitan statistical areas and 2-digit NAICS industries.

2. Results

Our classification implies that 34% of US jobs can plausibly be performed at home. We obtain our estimate by identifying job characteristics that clearly rule out the possibility of working entirely from home, neglecting many characteristics that would make working from home difficult.[5] Our estimate is therefore an upper bound on what might be feasible and greatly exceeds the share of jobs that in fact have been performed entirely at home in recent years. According to the 2018 American Time Use Survey, fewer than a quarter of all full-time workers work at all from home on an average day, and even those workers typically spend well under half of their working hours at home. Workers in occupations that can be performed at home typically earn more. If we assume all occupations involve the same number of hours of work, the 34% of jobs that can plausibly be performed at home account for 44% of all wages.

There is significant variation in this percentage across cities and industries. Table 1 reports the top five and bottom five metropolitan statistical areas (from among the 100 largest, by employment) in terms of the share of jobs that could be done from home. More than 40% of jobs in San Francisco, San Jose, and Washington, DC could be performed at home, whereas this is the case for fewer than 30% of jobs in Fort Myers, Grand Rapids, or Las Vegas. Figure 1 depicts the geographic distribution of our unweighted measure of the share of jobs that can be done at home across metropolitan areas. As shown in Table 2, whereas most jobs in finance, corporate management, and professional and scientific services could plausibly be performed at home, very few jobs in agriculture, hotels and restaurants, or retail could be. The full results for all metropolitan areas and industries, together with our classifications of occupations, are available at https://github.com/jdingel/DingelNeiman-workathome.

4 See the Appendix for a more detailed description of our classification based on O*NET survey responses. Using our replication package, researchers can modify this classification scheme to produce results based on their own assessment of the plausibility of working at home for each type of job.

5 For example, our classification codes 82% of the 8.8 million teachers as able to work from home, which seems sensible given the large number of schools currently employing remote learning. Re-coding these teaching jobs as unable to be performed from home would, in the aggregate, reduce our estimate of the share of jobs that can be performed at home by about five percentage points.

As an alternative to our baseline classification, we each manually assigned values of 0, 0.5, or 1 to each 5-digit SOC code based on introspection. Averaging our two judgements resulted in values of 0, 0.25, 0.5, 0.75, and 1.[6] Using this alternative measure, we find that approximately 32% of all US jobs, accounting for 42% of overall wages, can be performed almost entirely at home.

The city-level and industry-level results generated by this alternative classification, which are included in our replication package,[7] are very similar to those presented in Table 1, Table 2, and Figure 1. Table 3 reports the share of jobs that can be performed at home by major group of occupation for both measures. The reported shares are generally quite similar across the two methods.

For a small set of occupations, however, the two methodologies do reach opposite conclusions. Appendix Table A.1 reports the 5-digit occupation codes for which the two measures differ by 0.8 or more.[8] Our baseline classification based on O*NET survey responses says that fundraisers, for example, cannot work from home, whereas our manual classification says that they can; our baseline classification codes mail clerks as able to work from home, whereas the manual classification says that they cannot.

	Unweighted	**Weighted by wage**
Top five		
San Jose-Sunnyvale-Santa Clara, CA	0.48	0.63
Washington-Arlington-Alexandria, DC-VA-MD-WV	0.46	0.61
Durham-Chapel Hill, NC	0.43	0.54
Austin-Round Rock, TX	0.43	0.55
San Francisco-Oakland-Hayward, CA	0.42	0.55
Bottom five		
Grand Rapids-Wyoming, MI	0.27	0.35
Bakersfield, CA	0.27	0.33
McAllen-Edinburg-Mission, TX	0.27	0.28
Cape Coral-Fort Myers, FL	0.26	0.33
Stockton-Lodi, CA	0.26	0.30

Table 1 Share of jobs that can be done from home, by metropolitan area

6 Our two assessments about whether an occupation could be done at home or not agreed in about 85% of the cases, and our disagreements were only rarely greater than 0.5.

7 Available at https://github.com/jdingel/DingelNeiman-workathome.

8 Since the O*NET-derived measure is defined for 6-digit occupations, this measure is not necessarily 0 or 1 at the 5-digit level. We aggregate 6-digit occupations weighting by employment counts.

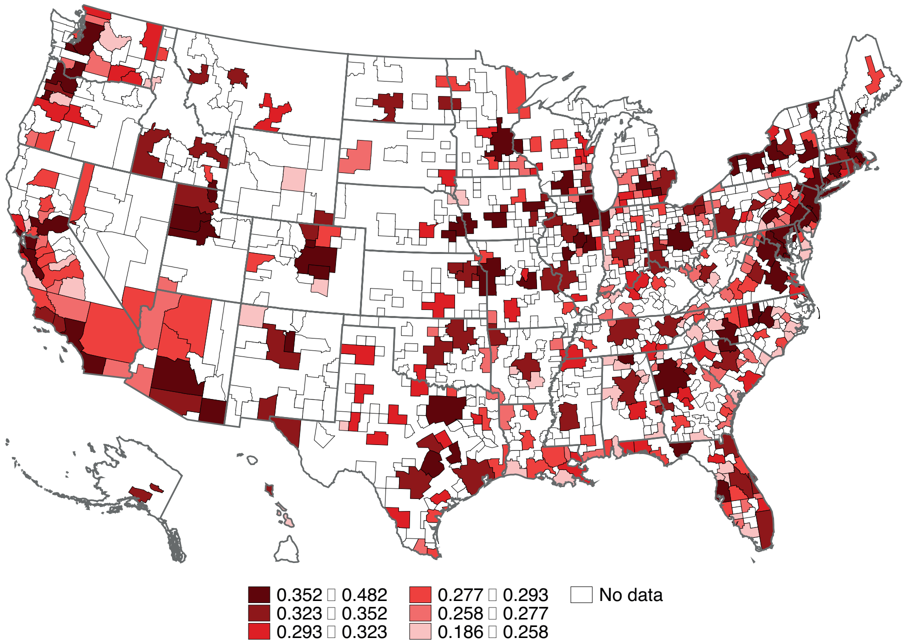

Figure 1 Share of jobs that can be done from home

	Unweighted	Weighted by wage
Top five		
Professional, Scientific, and Technical Services	0.77	0.83
Management of Companies and Enterprises	0.76	0.82
Educational Services	0.74	0.63
Finance and Insurance	0.73	0.82
Information	0.68	0.76
Bottom five		
Transportation and Warehousing	0.18	0.24
Construction	0.16	0.19
Retail Trade	0.14	0.21
Agriculture, Forestry, Fishing and Hunting	0.08	0.13
Accommodation and Food Services	0.03	0.07

Table 2 Share of jobs that can be done from home, by industry

		O*NET-derived baseline	Manual alternative
23	Legal Occupations	0.97	0.84
15	Computer and Mathematical Occupations	0.95	1.00
11	Management Occupations	0.84	0.84
25	Education, Training, and Library Occupations	0.82	0.85
13	Business and Financial Operations Occupations	0.78	0.92
27	Arts, Design, Entertainment, Sports, and Media Occupations	0.73	0.57
43	Office and Administrative Support Occupations	0.65	0.51
19	Life, Physical, and Social Science Occupations	0.51	0.36
17	Architecture and Engineering Occupations	0.50	0.88
21	Community and Social Service Occupations	0.37	0.50
41	Sales and Related Occupations	0.28	0.21
39	Personal Care and Service Occupations	0.18	0.00
33	Protective Service Occupations	0.06	0.00
29	Healthcare Practitioners and Technical Occupations	0.05	0.06
53	Transportation and Material Moving Occupations	0.03	0.00
31	Healthcare Support Occupations	0.02	0.00
45	Farming, Fishing, and Forestry Occupations	0.01	0.00
51	Production Occupations	0.01	0.00
49	Installation, Maintenance, and Repair Occupations	0.01	0.00
47	Construction and Extraction Occupations	0.00	0.00
35	Food Preparation and Serving Related Occupations	0.00	0.00
37	Building and Grounds Cleaning and Maintenance Occupations	0.00	0.00

Table 3 Share of jobs that can be performed at home, by occupation's major group

3. Related literature

Our coding of occupational characteristics to determine how flexibly certain jobs can be re- located has clear roots in the exercise in Blinder (2009) that assessed the 'offshorability' of jobs. While our approach is similar, we cannot simply use Blinder's index because the feasibility of working from home is quite distinct from offshorability. For example, Blinder and Krueger (2013) write, 'we know that all textile manufacturing jobs in the United States are offshorable'. Textile manufacturing jobs, of course, cannot be performed at home using current production technologies.

Our work also relates to Mas and Pallais (2020), who offer a detailed and helpful overview of the prevalence, features, and demand for alternative working arrangements, including the ability to work from home. Citing the Quality of Worklife Survey and the Understanding American Study, they report that fewer than 13% of full-time and part-time jobs have a formal 'work-from- home' arrangement, even though twice that amount work often from home. According to Mas and Pallais, the 'median worker reports that only 6% of their job could be feasibly done from home,' but plenty of jobs, including those in 'computer and mathematical' and 'business and financial operations' can do a majority of their work from home. We note that, in the context of the response to Covid-19, there is an important distinction between being able to do most and all of one's work at home.

Finally, a recently released paper by the UK Office for National Statistics (2020) reports that while 27% of the UK workforce said they've previously worked from home, only about 5% said they mainly work from home. Whether people have actually worked from home differs conceptually from the focal question of this paper, which is whether these people could feasibly work from home.

4. Conclusion

Due to Covid-19, many employees are unable to travel to work. Identifying which jobs cannot be performed from home may be useful as policymakers try to target social insurance payments to those that most need them. Likewise, the share of jobs that could be performed at home is an important input to predicting the economy's performance during this or subsequent periods of social distancing. We note, however, that it is not straightforward to use these values to estimate the share of output that would be produced under stringent stay-at-home policies. An individual worker's productivity may differ considerably when working at home rather than her usual workplace. More importantly, there are likely important complementarities between jobs that can be performed at home and those that cannot. Incorporating our measures together with these richer considerations is a fruitful avenue for future research.

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Appendix

Our baseline results use the responses to two O*NET surveys to designate any given occupation, based on the standard occupational classification (SOC) code, as able or unable to be performed at home. We then merge this information with BLS data on the number and wages of workers in each SOC in the country as a whole as well as in metropolitan areas and industries.

If any of the following conditions in the 'Work Context' survey responses are true, we code the occupation as one that cannot be performed at home:

- Average respondent says they use email less than once per month (Q4)
- Majority of respondents say they work outdoors every day (Q17)
- Average respondent says they deal with violent people at least once a week (Q14)
- Average respondent says they spent majority of time wearing common or specialized protective or safety equipment (Q43)
- Average respondent says they spent majority of time walking or running (Q37)
- Average respondent says they are exposed to minor burns, cuts, bites, or stings at least once a week (Q33)
- Average respondent says they are exposed to diseases or infection at least once a week (Q29)

If any of the following conditions in the 'Generalized Work Activities' survey responses are true, we code the occupation as one that cannot be performed at home:

- Performing General Physical Activities is very important (Q16A)
- Handling and Moving Objects is very important (Q17A)
- Controlling Machines and Processes [not computers nor vehicles] is very important (Q18A)
- Operating Vehicles, Mechanized Devices, or Equipment is very important (Q20A)
- Performing for or Working Directly with the Public is very important (Q32A)
- Repairing and Maintaining Mechanical Equipment is very important (Q22A)
- Repairing and Maintaining Electronic Equipment is very important (Q23A)
- Inspecting Equipment, Structures, or Materials is very important (Q4A)

	Occupation	O*NET-derived baseline	Manual alternative
11-3110	Compensation and Benefits Managers	0.00	1
13-1130	Fundraisers	0.00	1
13-2080	Tax Examiners, Collectors and Preparers, and Revenue Agents	0.00	1
19-3050	Urban and Regional Planners	0.00	1
41-3040	Travel Agents	0.00	1
43-2010	Switchboard Operators, Including Answering Service	0.00	1
43-2020	Telephone Operators	0.00	1
43-4180	Reservation and Transportation Ticket Agents and Travel Clerks	0.00	1
43-9080	Proofreaders and Copy Markers	0.00	1
13-2070	Credit Counselors and Loan Officers	0.07	1
17-3020	Engineering Technicians, Except Drafters	0.17	1
27-3090	Miscellaneous Media and Communication Workers	0.20	1
39-3010	Gaming Services Workers	0.85	0
25-2050	Special Education Teachers	0.92	0
27-2020	Athletes, Coaches, Umpires, and Related Workers	0.93	0
25-4030	Library Technicians	1.00	0
27-4020	Photographers	1.00	0
33-9020	Private Detectives and Investigators	1.00	0
39-3030	Ushers, Lobby Attendants, and Ticket Takers	1.00	0
39-9040	Residential Advisors	1.00	0
43-1010	First-Line Supervisors of Office and Administrative Support Workers	1.00	0
43-5020	Couriers and Messengers	1.00	0
43-9050	Mail Clerks and Mail Machine Operators, Except Postal Service	1.00	0
43-9070	Office Machine Operators, Except Computer	1.00	0

Table A.1 Occupations for which survey-derived and alternative measures differ considerably

Measuring the impact of the German public shutdown on the spread of Covid-19

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Date submitted: 28 March 2020; **Date accepted:** 29 March 2020

We investigate the impact of the German public shutdown from 13 March 2020 on the spread of Covid-19. In a simple model, we search for a trend break in cumulated confirmed Covid-19 cases as reported by the Johns Hopkins University (2020). We identify a trend break on 20 March that is in line with the expected lagged impact of the German policies and which reduces the growth rate by 48.2%. While the growth rate has almost halved, the number of cases is still doubling every 5.35 days.

1. Introduction

There is no need to stress the importance of the coronavirus disease (Covid-19) for public health, economic consequences and the wellbeing of individuals. Yet, there is a need for more careful analysis of what we actually know. Knowledge is probably needed most urgently from an epidemiological perspective, but just as important is the need to know what the effects of public health measures are on the spread of Covid-19.

This paper aims to understand the effects of the decision of German authorities on 13 March 2020 to shut down schools and stop major sports events, which was closely followed by further decisions regarding restaurants, shops and others. Given a median incubation of 5.2 days (Lauer et al., 2020; Linton et al., 2020)

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and a certain delay between feeling symptoms, contacting a doctor, and the case being reported (say, 2-3 days), we would expect the consequences of these decisions and the resulting measures to be visible as of 20 or 21 March 2020. If the policy measures impact the spread of Covid- 19, as we expect, the growth rate of the number of reported sick individuals should display a drop around 20 or 21 March. In fact, this is what we investigate.

We employ data from the Johns Hopkins University (2020). While official data for Germany that evolve similarly can also be obtained from the Robert Koch Institute (2020), we prefer the former source as it links data from the Robert Koch Institute, the World Health Organization, and the European Centre for Disease Prevention and Control. Furthermore, official statistics from the Robert Koch Institute are downward biased on weekends, as some local administrations only report their case numbers on workdays. The data then enter the official statistics on Monday and Tuesday, yielding an upward bias of the statistics on new infections. We find that the data from the Johns Hopkins University (2020) are more robust to these biases.

In a simple model, we search for a trend break in the cumulated confirmed Covid-19 cases by means of maximum likelihood. We find that a trend break around 20 March fits the data best and is highly significant. Our main finding is that confirmed Covid-19 cases in Germany grew at a daily rate of 26.7% until 19 March. From March 20 onwards, the growth rate drops by half to 13.8%, which is in line with the lagged impact of the policies implemented by the German administration on 13 March and implies a doubling of confirmed cases every 5.35 days. Before 20 March, cases doubled every 2.93 days.

The structure of the paper is as follows. In Section 2 we describe the data on confirmed cases of Covid-19 in Germany obtained from the Johns Hopkins University (2020). Next, a model is set up to estimate average growth of log confirmed cases and test for a trend break in Section 3. We present estimation results and show that the implemented polices are likely to have affected the spread of Covid-19. Section 4 concludes.

2. The data

To address these questions, we study the development of the number of confirmed cases of Covid-19 in Germany. Due to the high testing capacities of Germany compared to other industrialised countries – while acknowledging the natural uncertainty regarding unperceived cases – we consider German data on the number of confirmed cases of the novel coronavirus as a more reliable source of the actual number of people infected. For several other industrialised countries – such as Italy, where the measured mortality rate is clearly higher – the number of people who are unaware they are infected can be expected to be substantial, and the reported number of confirmed cases thus a less reliable source for the overall spread of Covid-19 compared to the German data.

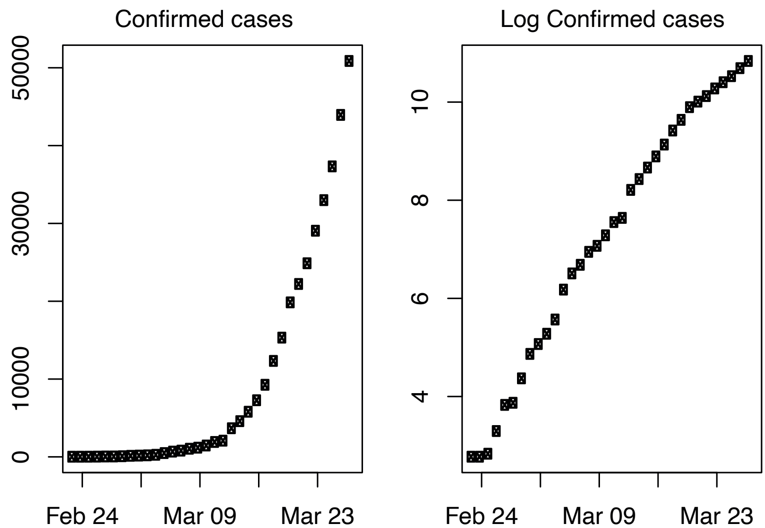

Figure 1 Number of confirmed cases with the new corona virus.

Notes: The left plot shows the data in levels, the right plot takes logs.

Source: Data obtained from the Johns Hopkins Coronavirus Resource Center.

Figure 1 plots the dynamics of the spread of Covid-19 in Germany in levels and logs from 23 February to 27 March. As the figure shows, the number of confirmed cases grew exponentially, such that taking logs yields a time series with a linear trend. The figure suggests that a linear time trend may capture the dynamics of log confirmed cases well, although there are small outliers at the beginning of the sample (where variation was relatively small and case numbers are low) and around 10 March (when an outbreak of Covid-19 among ski tourists from Austria increased the case numbers).

In light of the rapid growth of confirmed cases, the German administration implemented several measures to contain the spread of Covid-19, including closing schools, cancelling mass events, and the shuting down universities from 14 March onwards. Several additional measures have since been implemented to reduce public contact, including the closure of public spaces, churches, mosques and synagogues, restaurants, shops, hairdressers, theatres and libraries. In addition, public awareness of Covid-19 was likely affected by the increased media coverage.

These policies cannot be expected to immediately slow down the spread of Covid-19, since there is a time lag between infection with the virus and the case entering the statistics of approximately seven to eight days. The incubation period of the coronavirus is estimated to be five days (Lauer et al.; 2020; Linton et al.; 2020), and it may take another 1-2 days to get tested. Finally, 1-2 days are required until the case is reported. Thus, we can expect to see any impact of the implemented policies and of changed individual behaviour in the case numbers from 20 March onwards.

In fact, visual inspection of log confirmed cases in Figure 1 shows a slowdown of the spread of Covid-19 from 20 March onwards. However, distinguishing between unsystematic random impacts and a systematic reduction of the growth rate requires a proper statistical analysis of the Covid-19 data.

3. Testing for a trend break

In order to investigate the impact of the aforementioned policies, we search for a trend break in the spread of Covid-19. For this purpose, we specify a simple linear trend model for log confirmed cases that is given by

$$y_t = \mu_0 + \mu_1 \mathbb{1}(t \geq t^*) + \gamma_0 t + \gamma_1 \mathbb{1}(t \geq t^{**})(t - t^{**} + 1) + u_t, \qquad t = 1, \dots, n, \tag{1}$$

where μ_0 is a constant, μ_1 allows for a level shift, γ_0 measures the linear growth rate, γ_1 allows for a trend break and $\mathbb{1}(t \geq s)$ is an indicator function that becomes one for $t \geq s$, else zero. The residuals u_t are assumed to be normally distributed white noise $u_t \sim \text{NID}(0,\sigma_u^2)$. Since log confirmed cases increase quite linearly in t, as Figure 1 shows, we expect specification (1) to capture the dynamics well. More sophisticated models may be required for a proper understanding of the drivers of log confirmed cases, such as weather and seasonal effects. But since such effects are currently unlikely to correlate with a linear trend, we expect the estimates of (1) to hardly be affected. Furthermore, the time series on confirmed cases is relatively short, hindering a more sophisticated modelling of the data. Lags of the endogenous variable turned out to be irrelevant.

As a first approach to measuring the growth of log confirmed cases, we fit a linear trend to the data via ordinary least squares, thereby setting $\gamma_1 = 0$. Since visual inspection of Figure 1 shows a level shift on 29 February, we include a shift dummy by allowing for $\mu_1 \neq 0$ from that date onwards. For the simple model without trend break, we estimate the intercepts $\hat{\mu}_0 = 2.387$ (0.100), $\hat{\mu}_1 = 0.761$ (0.143), together with a trend parameter $\hat{\gamma}_0 = 0.240$ (0.006), where standard errors are denoted in parentheses and all parameters are significant at a 1%

level. The residual standard error is estimated to be $\hat{\sigma}_u = 0.239$. Our results show a mean growth rate of 24.0%, implying a doubling of confirmed cases every 3.22 days on average.

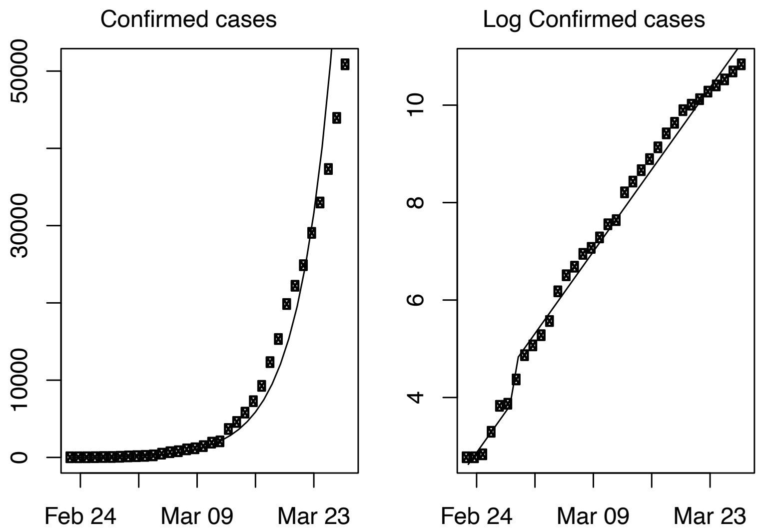

Figure 2 Fitted values for model (1) without trend break

Notes: The dots show the number of (log) confirmed cases; the solid line shows estimated confirmed cases. The data was obtained from the Johns Hopkins Coronavirus Resource Center.

Figure 2 plots the fitted values from (1) with $\mu_1 = 0$. As the figure shows, a specification without trend break catches the dynamics of confirmed cases well at the beginning and the middle of the sample. On the right of the time series, the linear trend overestimates the spread of Covid-19, which may indicate a trend break.

Hence, our estimation results together with the Covid-19 data suggest that growth has slowed down at the end of March. To take this into account, we include a trend break – i.e., we set $\gamma_1 \neq 0$. Since the date of the trend break is unknown, we search for a t^{**} thatmaximises the likelihood of (1), which is identical to a minimisation of the residual sum of squares (Bai, 1997; Bai and Perron, 1998). Hence, we estimate (1) for $t^{**} = 2, 3, ..., n$ sequentially and choose the specification t^{**} that maximises the likelihood.

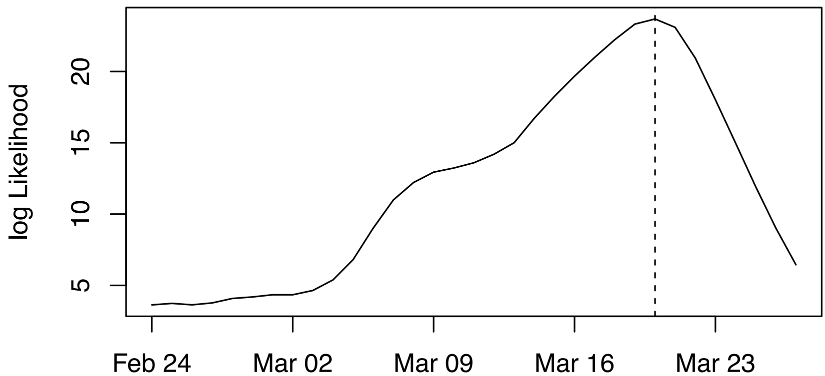

Figure 3 Sequential trend break search

Note: The figure plots the likelihood values corresponding to a trend break at t^{**}.

Figure 3 plots the estimated likelihood against t^{**}. As the figure shows, a trend break on 20 March yields the highest likelihood and therefore minimises the residual sum of squares. The likelihood is steep around 19–21 March, suggesting only a little uncertainty about the actual period where the trend break occurred. While breaks on 19–21 March yield a similar fit, all other possible trend break points perform substantially worse. Uncertainty regarding the exact break point within the small window between 19 March and 21 March remains, which is likely to reflect the gradually increasing impact of the different policy measures that start to kick in at this period of time. We add a trend break on 20 March to our model, but choosing 19 or 21 March would not lead to any relevant differences.

Estimation results with $\gamma_1 \neq 0$ and a trend break on 20 March 20 as follows. For the intercepts, we estimate $\hat{\mu}_0 = 2.325$ (0.052) and $\hat{\mu}_1 = 0.460$ (0.086). The slope estimates are $\hat{\gamma}_0 = 0.267$ (0.005) and $\hat{\gamma}_1 = -0.128$ (0.016). All parameters are significant at a 1% level,[4] and $\hat{\sigma} = 0.128$. We do not find evidence for a violation of the normality assumption of the residuals from the Jarque-Bera test, which yields a p-value of 0.994. The slope estimates can be interpreted as follows. From 23 February to 19 March we estimate a daily growth of 26.7%, indicating a doubling of confirmed cases every 2.93 days. From 20 March onwards, the daily growth reduces to 13.8%, which implies a doubling of confirmed cases each 5.35 days. Hence, we find that the growth of confirmed cases slowed considerably (by 48.2%) from 20 March onwards.

4 Note that the trend break search induces additional uncertainty to our model, since test statistics are calculated under the hypothesis that the model is correctly specified, while in reality the true date of the trend break is uncertain. But since the t-statistic for $\hat{\gamma}_1$ is 8.219, simulation-based critical values that account for the model selection uncertainty would not change our test results.

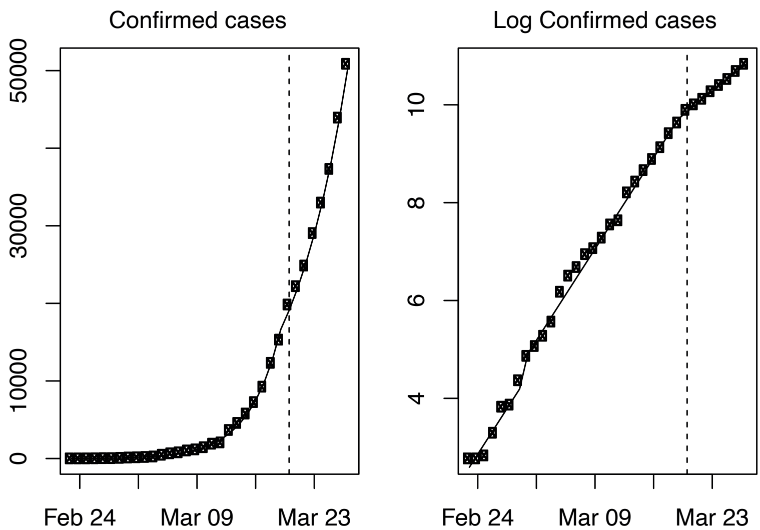

Figure 4 Fitted values for model (1) with trend break on 20 March

Notes: The dots show the number of (log) confirmed cases, while the solid line sketches estimated confirmed cases. The dashed line indicates the trend break.

Source: Data obtained from the Johns Hopkins Coronavirus Resource Center.

Figure 4 plots the fitted values of (1) with $\mu_1 /= 0$ allowed and a trend break on 20 March. It shows that a specification with trend break captures the development of confirmed cases well, in particular at the end of the time series. A trend break on 20 March is clearly visible and captures the slowdown in the growth of confirmed cases.

4. Conclusion

Our analysis confirms a pronounced slowdown in the growth of confirmed Covid-19 infections in Germany around 20 March. While the growth rate has almost halved, the number of cases is still doubling every 5.35 days. Due to substantial delays between new infections and their measurement in statistics, we could see further effects from the German lockdown measures in the next few days. We will follow the development of growth rates closely, as they are central to both public health and to the economy. Our findings will also be employed by Donsimoni et al. (2020) for future projections of the Covid-19 epidemic in Germany.

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The unprecedented stock market reaction to Covid-19

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No previous infectious disease outbreak, including the Spanish flu, has impacted the stock market as powerfully as the Covid-19 pandemic. We use text-based methods to develop this point with respect to large daily stock market moves back to 1900 and with respect to overall stock market volatility back to 1985. We also argue that policy responses to the Covid-19 pandemic provide the most compelling explanation for its unprecedented stock market impact.

As the novel coronavirus (Covid-19) spread from a regional crisis in China's Hubei Province to a global pandemic, equities plummeted and market volatility rocketed upwards around the world. In the United States, recent volatility levels rival or surpass those last seen in October 1987 and December 2008 and, before that, in late 1929 and the early 1930s (Figure 1). Motivated by these observations, we consider the role of Covid-19 developments in recent stock market behaviour and draw comparisons to previous infectious disease outbreaks.

To quantify the role of news about infectious disease outbreaks, we use automated and human readings of newspaper articles. Looking back to 1985, we find no other infectious disease outbreak that had more than a tiny effect on US stock market volatility. Looking back to 1900, we find not a single instance in which contemporary newspaper accounts attributed a large daily market move

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to pandemic-related developments. That includes the Spanish Flu of 1918-20, which killed an estimated 2.0% of the world's population (Barro et al. 2020). In striking contrast, news related to Covid-19 developments is overwhelmingly the dominant driver of large daily US stock market moves since 24 February 2020.

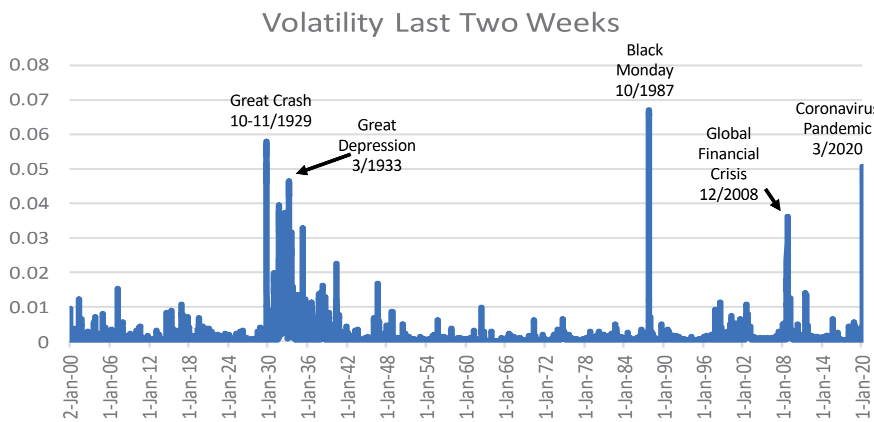

Figure 1 Realised US stock market volatility, January 1900 to March 2020

Notes: Sample period, 1/1/1900-3/23/2020. From 12/1925-Present, returns are computed using Yahoo Finance's 'adjusted close' series for the S&P 500 (^GSPC). Before that, returns are from the Global Financial Data extension of the Dow Jones Index. Volatility last two weeks is the sum of squared returns over the past 10 trading days.

1. Characterising daily stock market jumps

In Baker et al. (2019a), we examine next-day newspaper explanations for each daily move in the US stock market greater than 2.5%, up or down. By this criterion, there were 1,129 stock market jumps from 2 January 1900 to 24 March 2020. Jump days account for 3.5% of all trading days and 47% of total squared daily return variation.

To characterise these jumps, we read the lead article about each jump in next-day (or same-evening) newspapers to classify the journalist's explanation into one of 16 categories, which include 'Macroeconomic News and Outlook', 'Government Spending', 'Monetary Policy', 'Unknown or No Explanation Offered', and 'Other – Specify'. Our coding guide in Baker et al. (2018) describes the methodology in detail.

Table 1 draws on our classification effort to underscore the unprecedented impact of the Covid-19 pandemic on the US stock market. In the period before 24 February 2020 – spanning 120 years and more than 1,100 jumps – contemporary journalistic accounts attributed not a single daily stock market jump to infectious disease outbreaks or policy responses to such outbreaks.[7] Perhaps surprisingly, even the Spanish Flu fails to register in next-day journalistic explanations for large daily stock market moves.

	Number of daily US stock market jumps greater than |2.5%|	**Number attributed to economic fallout of pandemics**	**Number attributed to policy responses to pandemics**
2 January 1900 to 21 February 2020	1,116	0	0
24 February 2020 to 24 March 2020	18	7.4	8

Table 1 The unprecedented stock market impact of the coronavirus

Note: Tabulated from results in Baker, Bloom, Davis and Sammon (2020), who consider all daily jumps in the U.S. stock market greater than 2.5%, up or down, since 1900. They classify the reason for each jump into 16 categories based on human readings of nextday (or same-evening) accounts in the *Wall Street Journal* (and *New York Times* in 2020). Fractional counts arise when newspapers differ in their jump attribution or human readers differ in their classification of the attribution. Number Attributed to Economic Fallout of Pandemics includes jumps on 3/12 and 3/16 that a subset of coders classified as Macroeconomic Outlook. It's clear from reading these articles that the journalist regarded the deterioration in the Macroeconomic Outlook as due to the spread of the coronavirus.

Data for the past month tell a dramatically different story. From 24 February to 24 March 2020, there were 22 trading days and 18 market jumps – more than any other period in history with the same number of trading days. Jump frequency during this period is 23 times the average pace since 1900. Moreover, next-day newspaper accounts attribute 15 or 16 of the 18 jumps to news about Covid-19 developments and policy responses to the pandemic.[8] In short, no previous infectious disease episode led to daily stock market swings that even remotely resemble the response in the past month to Covid-19 developments.

7 Originally, we did not record whether journalistic accounts attributed specific jumps to policy responses to infectious disease outbreaks. After the Covid-19 pandemic, we reread lead newspaper articles about stock market jumps from January 1918 to December 1920. There were 32 jumps during these years, 23 from March 1918 to June 1920. None attributed a jump to policy responses to the Spanish flu pandemic.

8 The *New York Times* offered no clear explanation for the downward jump on 20 March, while the *Wall Street Journal* attributed it to pandemic-related policy responses. Both papers attributed the upward jump on 4 March to Elections and Political Transitions (i.e., Biden's strong showing in primary elections) and the downward jump on 9 March 2020 to Commodity Markets. Both papers attributed all other jumps since 24 February to Covid-19 developments or policy responses thereto.

2. Quantifying the contribution of Covid-19 to US stock market volatility

As in Baker et al. (2019b) (henceforth, 'BBDK'), we use a mechanised approach to quantify the role of Covid-19 and other infectious diseases in US stock market volatility. In a first step, BBDK calculate the monthly fraction of articles in 11 major US newspapers that contain (a) terms related to the economy, (b) terms related to equity markets, and (c) terms related to market volatility. We multiplicatively rescale this monthly series to match the mean value of the VIX since 1985. Figure 2 plots our resulting newspaper-based Equity Market Volatility (EMV) tracker alongside the VIX itself. As the figure shows, our EMV tracker performs well in the sense of mirroring the time-series behaviour of implied stock market volatility. The same is true with respect to realized stock market volatility.

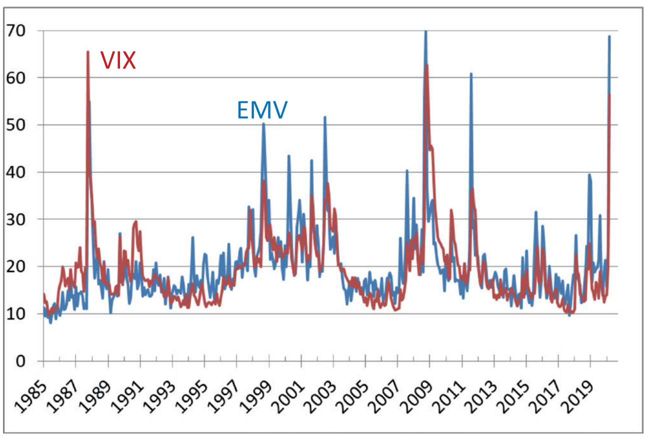

Figure 2 Newspaper-based equity market volatility tracker and the 30-day VIX, January 1985 to March 2020

Notes: The Equity Market Volatility Tracker reflects the frequency of articles about stock market volatility in leading U.S. newspapers, as quantified by Baker, Bloom, Davis and Kost (2019). The 30-Day VIX is constructed as the monthly average of daily closing VIX values collected from Yahoo Finance. March 2020 reflects data through March 20th.

In a second step, we identify the subset of EMV articles that contain one or more terms related to Covid-19 or other infectious diseases. Specifically, we flag EMV articles that mention one of the following terms: 'epidemic', 'pandemic', 'virus', 'flu', 'disease', 'coronavirus', 'MERS', 'SARS', 'Ebola', 'H5N1', or 'H1N1'. Multiplying the fraction of EMV articles that contain one of these terms by our

EMV tracker yields our infectious disease EMV tracker displayed in Figure 3. The inset portion of Figure 3 displays the results of the same quantification exercise at a weekly frequency.

Figure 3 establishes three points. First, before the Covid-19 pandemic, no infectious disease outbreak made a sizable contribution to US stock market volatility. The 2003 SARS epidemic and the 2015 Ebola epidemic led to modest, short-lived spikes in volatility, and the bird flu and swine flu epidemics barely registered. Second, the Covid-19 pandemic drove the tremendous surge in stock market volatility since late February. Recall from Figure 1 that this surge led to the third highest realised volatility peak since 1900. So, the volatility peak is extraordinarily high by historical standards (Figure 1), and it is almost entirely triggered by Covid-19 developments, including policy responses to the pandemic. Third, the Covid-19 volatility surge took off in the fourth week of February 2020.

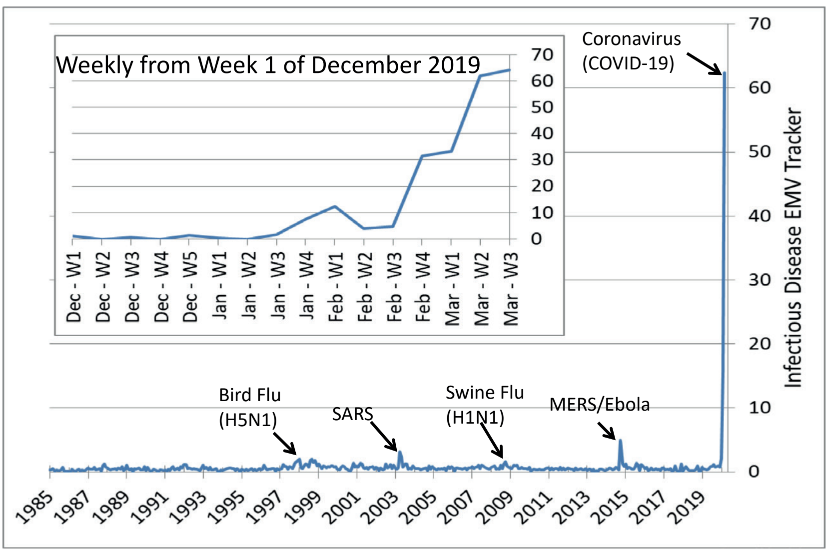

Figure 3 Infectious disease EMV index, weekly and monthly data from 1985 to March 2020

Notes: The Infectious Disease EMV Tracker is computed as the overall EMV tracker value multiplied by the share of EMV Articles that contain one or more of the following terms: epidemic, pandemic, virus, flu, disease, coronavirus, mers, sars, ebola., H5N1, H1N1. March 2020 data includes through March 20th.

		Average values for the indicated time period		
	Time period	**(1) Infectious disease EMV tracker level**	**(2) % of EMV articles with infectious disease terms**	**(3) % of EPU articles with infectious disease terms**
Bird Flu (H5N1)	Nov-1997 to Nov-1998	1.36	4.52	8.00
SARS	April-August 2003	1.75	8.10	9.79
Swine Flu (H1N1)	March-May 2009	0.99	3.60	4.58
Ebola & MERS	Oct-2014 to Jan-2015	2.06	10.62	12.80
Coronavirus (Covid-19)	December 2019	0.79	3.68	6.42
	January 2020	2.11	13.45	7.43
	February 2020	15.54	65.73	32.62
	March 2020	60.46	90.81	92.41
Full Period	Jan 1985-Mar 2020	0.76	3.37	5.67

Table 2 Stock market volatility in selected infectious disease episodes

Notes: The Infectious Disease term set is {epidemic, pandemic, virus, flu, disease, coronavirus, mers, sars, ebola, H5N1, H1N1}. We use the following newspapers in the analysis: Wall Street Journal, NY Times, Chicago Tribune, Washington Post, LA Times, Boston Globe, Miami Herald, USA Today, SF Chronicle, Dallas Morning News, and Houston Chronicle. We selected periods with relatively high levels of our Infectious Disease EMV tracker and labelled the time periods based on the prevalence of specific terms (e.g., SARS) in the EMV articles. Both "Ebola" and "MERS" appear in EMV articles from October 2014 to January 2015, but references to "Ebola" are much more frequent. March 2020 data includes through March 20th.

Table 2 provides more information about newspaper coverage of various infectious disease outbreaks since 1985. For each episode, we report the mean value of our infectious disease EMV tracker, the fraction of EMV articles that contains one of our infectious disease terms (as listed above), and the fraction of articles about Economic Policy Uncertainty (EPU) that contains one of those terms. Here, we use the EPU index developed by Baker et al. (2016). The bottom row shows averages for the full period from January 1985 to March 2020.

By these metrics, the early-phase impact of Covid-19 looks similar to the impact of other infectious disease outbreaks in the past 35 years. In January 2020, for example, the infectious disease EMV tracker is only modestly elevated, and the percentage of EMV and EPU articles that discuss Covid-19 developments is roughly in line with previous experiences during the SARS and Ebola epidemics. By February, however, Covid-19 developments began to dominate newspaper coverage of stock market volatility and figure prominently in newspaper discussions of economic policy uncertainty. By March, Covid-19 developments receive attention in more than 90% of all newspaper discussions of market volatility and policy uncertainty. These data confirm the unprecedented impact of the Covid-19 pandemic.

3. Why such a powerful stock market impact?

Why have Covid-19 developments exerted such powerful effects on the stock market since late February? Clearly, the current pandemic has grave implications for public health and for the economy. So, part of the answer surely lies in the severity of the pandemic, the apparent ease with which Covid-19 spreads, and the non-negligible mortality rate among those who contract the virus. Still, we think this answer is highly incomplete. Like Barro et al. (2020), we regard the mortality rates experienced during the Spanish flu as a worst-case upper bound on the potential mortality induced by Covid-19. Yet, as Table 1 shows, the Spanish flu did not trigger even a small number of daily stock market jumps.

A second potential answer, particularly in comparison to the Spanish flu, is that information about pandemics is richer and diffuses much more rapidly now than a century earlier.[9] According to this explanation, the stock market impact of the Covid-19 pandemic is more temporally concentrated and more likely to trigger daily stock market jumps and high stock market volatility than Spanish flu developments a century earlier. Here as well, there may be something to this explanation, but it is also highly incomplete. As Velde (2020) discusses, the

9 As a related point, the first wave of the Spanish flu occurred during World War I when news about the true extent of the outbreak was censored (Honigsbaum, 2013).

negative stock market impact of the Spanish flu was fairly modest even over time spans of several months. Hence, explanations that stress greater information availability and its more rapid diffusion do not take us very far in rationalising the huge stock market drop since 24 February.

A third explanation stresses the interconnectedness of the modern economy: the commonplace nature of long-distance travel and, in Europe, cross-border commuting; decades of falling communication costs, falling transport costs and, until recently, falling tariffs; dense, geographically expansive supply chains; and the ubiquity of just-in-time inventory systems, which are highly vulnerable to supply disruptions.[10] In addition, the structure of the economy has shifted over time to services, many of which involve face-to-face interactions. An abrupt uptake of voluntary and compulsory social distancing practices brings a sharp drop in demand for such services. Again, there is merit in this explanation, but it also strikes us as insufficient on its own to explain the stock market reaction.

That brings us to behavioural and policy reactions to the Covid-19 pandemic. As Baldwin (2020) puts it, "Covid-19 and the containment policies have directly and massively reduced the flow of labour to businesses. The result has been a sudden and massive reduction in the output of goods and services." Voluntary adoption of social distancing practices has also played a significant role. Current containment efforts are much more extensive and widespread than similar efforts in the past, including during the Spanish flu. They also have more potent effects in the modern economy for reasons sketched above. In our view, the policy response to the Covid-19 pandemic provides the most compelling explanation for its unprecedented impact on the stock market. Oddly enough, this somewhat mirrors the impact of Covid-19 in more severe cases, where an autoimmune response generates a cytokine storm, damaging lung tissue (Shi et al., 2020)

The healthcare rationale for travel restrictions, social distancing mandates, and other containment policies is clear. These policies also bring great economic damage. Recent stock market behaviour is an early and visible reflection of the (expected) damage. There is an urgent need to address the health crisis created by Covid-19 while shifting to less sweeping containment policies that do not strangle the economy, as argued by Cochrane (2020), Dewatripont et al. (2020), Ichino et al. (2020) and Monras (2020), among others.

10 On supply chains, see Baldwin and Tomiura (2020); on cross-border commuting, see Meninno and Wolf (2020), on falling trade costs, see Jacks, Meissner and Novy (2011).

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Susceptible-infected-recovered (SIR) dynamics of Covid-19 and economic impact[1]

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I estimate the susceptible-infected-recovered (SIR) epidemic model for the novel coronavirus disease (Covid-19). The transmission rate is heterogeneous across countries and far exceeds the recovery rate, which enables a fast spread. In the benchmark model, 24.4% of the population may be simultaneously infected at the peak, potentially overwhelming the healthcare system. The peak reduces to 5.6% under the optimal mitigation policy that controls the timing and intensity of social distancing. A stylised asset pricing model suggests that the stock price temporarily decreases by 50% in the benchmark case but shows a W-shaped, moderate but longer bear market under the optimal policy.

1. Introduction

The novel coronavirus disease (COVID-19) that was first reported in Wuhan, China in December 2019 is quickly spreading around the world. As of 27 March, 2020, the total number of cases exceeds 590,000 and the disease has claimed more than 27,000 lives globally. Since March 2020, while new cases in China appear to have settled down, the number of cases is exponentially growing in the rest of the world. To prevent the spread of the new virus, many governments have introduced draconian measures such as restricting travel, ordering social distancing, and closing schools, bars, restaurants, and other businesses.

1 Some of the figures and the analysis in this paper are updated daily at the author's website (https://sites.google.com/site/aatoda111/misc/covid19).

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In a time of such extreme uncertainty, making economic decisions becomes challenging, especially because pandemics are such rare events. The most recent comparable episode is the Spanish flu of 1918 (Trilla et al. 2008). Nevertheless, individuals need to make everyday decisions such as how to manage inventories of staples, how much to consume and save, when to buy or sell stocks, and these decisions depend on the expectations of how long and severe the epidemic will be. Governments must also make decisions, such as to what extent and for how long to impose travel restrictions, social distancing, and closures of schools and businesses (Anderson et al. 2020).

While past experiences and data are particularly relevant for new situations such as the COVID-19 pandemic, simple mathematical models are useful for analysing the current situation and predicting the near future. This paper aims to help decision-making by building a mathematical epidemic model, estimating it using the up-to-date data of COVID-19 cases around the world, making out-of-sample predictions, and discussing optimal policy and economic impact. I use the Kermack and McKendrick (1927) Susceptible-Infected-Recovered (SIR) model, which is relatively simple. An infected individual interacts with other agents and transmits the disease at a certain rate to susceptible agents. An infected individual also recovers (or dies) at a certain rate. The model can be described as a system of ordinary differential equations, which is nonlinear due to the interaction between the infected and susceptible. The behaviour of the model is completely determined by the transmission rate (β), the recovery rate (γ), and the initial condition. Despite the nonlinearity, the model admits an exact analytical solution in parametric form (Harko et al. 2014), which is convenient for estimation and prediction. Using this model, I theoretically derive the condition under which an epidemic occurs and characterise the peak of the epidemic.

I next take this model to the data. Because the situation and policies surrounding COVID-19 are rapidly evolving, I use the most recent two weeks (14 days) of cases and estimate the model parameters by nonlinear least squares. Except for China, Japan, and Korea, which are early epicentres of the outbreak, the transmission rate β is around 0.2–0.4, and is heterogeneous across countries. The estimated transmission rates far exceed the recovery rate, γ, which is about 0.1 based on the clinical course of COVID-19. Due to the high transmission rate and lack of herd immunity, in the absence of mitigation measures such as social distancing, the virus spreads quickly and may infect around 24.4% of the population at the peak of the epidemic. Using the model, I conduct an experiment where the government introduces temporary mitigation measures and succeeds in reducing the transmission rate. If the mitigation measures are taken too early, the peak is delayed but the epidemic restarts with no effect on the peak because the population does not acquire herd immunity. Assuming the government can take drastic measures for up to 12 weeks, the optimal policy is start mitigation measures once the number of cases reaches 6.3% of the population. Under the optimal policy, the peak infection rate reduces to 5.6%. Therefore, unless vaccines are expected to be developed in the near future, the draconian measures currently taken in many countries may be suboptimal, and it may be desirable to postpone them.

To evaluate the potential economic impact of COVID-19, I build a stylised production-based asset pricing model. Capitalists hire labour in competitive markets and infected workers are unable to work. Because the epidemic (temporarily) drastically reduces the labour supply, output goes down and the model calibration suggests that the stock market crashes by 50% during the epidemic, though the crash is short-lived. Under the optimal policy, the stock price exhibits a W-shaped pattern and remains about 10% undervalued relative to the steady state for about half a year.

2. SIR epidemic model

I first present the Kermack and McKendrick (1927) susceptible-infected-recovered (SIR) model, which is the most basic epidemic model. The model has various extensions such as (i) adding an 'exposed' state[3] (i.e. individuals that are already infected but have not yet developed the disease to infect others) or (ii) considering inflow and outflow of individuals between multiple regions. The basic SIR model has two advantages over other more sophisticated models. First, it admits an exact analytic solution in parametric form, which is useful for studying theoretical properties and estimating the model as discussed below. Second, it has only a few parameters, which is convenient for estimation when data are limited.

2.1 Model

The society consists of N individuals, among which S are susceptible to an infectious disease (i.e. they are neither infected nor have immunity) and I are infected.[4] Let $R = N - S - I$ be the number of individuals who are immune (possibly because they are vaccinated, infected and recovered, or dead). Suppose that individuals meet each other randomly, and let $\beta > 0$ be the rate at which

3 Atkeson (2020) considers this SEIR model
4 We ignore population growth because an epidemic occurs in a relatively short interval.

an infected individual meets a person and transmits the disease if the latter is susceptible. Let $\gamma > 0$ be the rate at which an infected individual recovers or dies. Then the following differential equations hold:

$$\mathrm{d}S/\mathrm{d}t = -\beta SI/N, \tag{2.1a}$$
$$\mathrm{d}I/\mathrm{d}t = -\beta SI/N - \gamma I, \tag{2.1b}$$
$$\mathrm{d}R/\mathrm{d}t = \gamma I. \tag{2.1c}$$

To see why (2.1a) holds, note that an infected individual can transmit to β people per unit of time if all of them are susceptible, but the probability of meeting a susceptible individual is only S/N. Thus, I infected individuals can transmit to $I \times \beta \times (S/N) = \beta SI/N$ individuals per unit of time. (2.1b) holds because the change in the number of infected individuals equals the newly infected minus closed cases (either due to recovery or death).

Letting $x = S/N$, $y = I/N$, and $z = R/N$ be the fraction of susceptible, infected, and recovered individuals in the society, respectively. Dividing all equations in (2.1) by N, we obtain:

$$\dot{x} = -\beta xy, \tag{2.2a}$$
$$\dot{y} = \beta xy - \gamma y, \tag{2.2b}$$
$$\dot{z} = \gamma y. \tag{2.2c}$$

where $\dot{x} = \mathrm{d}x/\mathrm{d}t$. Although the system of differential equations (2.2) is non-linear, Harko et al. (2014) obtain an exact analytical solution in parametric form.

Proposition 2.1. *Let $x(0) = x_0 > 0$, $y(0) = y_0 > 0$, $z(0) = z_0 \geq 0$ be given, where $x_0 + y_0 + z_0 = 1$. Then the solution to (2.2) is parametrised as*

$$x(t) = x_0 v, \tag{2.3a}$$
$$y(t) = \frac{\gamma}{\beta}\log v - x_0 v + x_0 + y_0, \tag{2.3b}$$
$$z(t) = -\frac{\gamma}{\beta}\log v + z_0, \tag{2.3c}$$

where

$$t = \int_v^1 \frac{\mathrm{d}\xi}{\xi(\beta x_0(1-\xi) + \beta y_0 + \gamma \log \xi)}. \tag{2.4}$$

Proof. See Equations (26)-(29) in Harko et al. (2014). The parametrisation has been changed slightly for convenience.

2.2 Theoretical properties

Using Proposition 2.1, we can study the qualitative properties of the epidemic.

Proposition 2.2. *Let everything be as in Proposition 2.1. Then the following is true*:

1. *In the long run, the fraction* $v^* \in (0,1)$ *of susceptible individuals will not be infected (fraction* $1 - v^*$ *infected), where* v^* *is the unique solution to*

$$x_0(1-v) + y_0 + \frac{\gamma}{\beta}\log v = 0. \tag{2.5}$$

2. *If* $\beta x_0 \leq \gamma$, *then* $\mathrm{d}y/\mathrm{d}t \leq 0$: *there is no epidemic. Furthermore,* $v^* \to 1$ *as* $y_0 \to 0$.
3. *If* $\beta x_0 > \gamma$, *then there is an epidemic. The number of infected individuals reaches the maximum when* $\beta x(t_{max}) = \gamma$, *at which point the fraction*

$$y_{\max} = y(t_{\max}) = \frac{\gamma}{\beta}\log\frac{\gamma}{\beta x_0} - \frac{\gamma}{\beta} + x_0 + y_0 \tag{2.6}$$

of the population is infected. The maximum infection rate, y_{max}, *is increasing in* x_0, y_0 *and decreasing in* γ/β.

Proof: Let $f(v) = x_0(1 - v) + y_0 + \frac{\gamma}{\beta}\log v$ for $v \in (0,1]$. Then (2.4) implies

$$t = \int_{v(t)}^{1} \frac{\mathrm{d}\xi}{\beta\xi f(\xi)}. \tag{2.7}$$

Since $f(1) = y_0 > 0$, it must be $v(0) = 1$. The definite integral (2.7) is well-defined in the range $f(v) > 0$. Since

$$f'(v) = -x_0 + \frac{\gamma}{\beta v},$$
$$f''(v) = -\frac{\gamma}{\beta v^2} < 0,$$

f is concave so the set $V = \{v \in (0,1] | f(v) > 0\}$ is an interval. Since $f(v) \to -\infty$ as $v \downarrow 0$, we have $V = (v^*,1]$ for $v^* \in (0,1)$, where v^* solves (2.5). Because can be approximated by a linear function around v^*, we get

$$\infty = \int_{v^*}^{1} \frac{\mathrm{d}\xi}{\beta\xi f(\xi)},$$

So $v(\infty) = v^*$. Using (2.3a), in the long run, the fraction $x(\infty)/x_0 = v^*$ of susceptible individuals is not infected.

Since $f(v) > 0$ on $V = (v^*,1]$, we have $v(t) \in (v^*,1]$ for all $t \geq 0$. By (2.7), $v(t)$ is clearly decreasing in t. If $\beta x_0 \leq \gamma$, it follows from (2.3b) that

$$\dot{y} = \left(\frac{\gamma}{\beta v} - x_0\right)\dot{v} = \frac{\gamma - \beta x_0 v}{\beta v}\dot{v} \leq 0$$

because $\dot{v} \leq 0$ and $v \leq 1$ implies $\gamma - \beta x_0 v \geq \gamma - \beta x_0 \geq 0$. Since $f(1) = 0$ when $y_0 = 0$, $f'(1) = -x_0 + \gamma/\beta \geq 0$ if $\beta x_0 \leq \gamma$, and $f''(v) < 0$, it must be $v^* \to 1$ as $y_0 \to 0$.

Finally, assume $\beta x_0 > \gamma$. Then $\dot{y}(0) = (\beta x_0 - \gamma)y_0 > 0$, so $y(t)$ initially increases. By (2.2b), $y(t)$ reaches the maximum when $0 = \dot{y} = \beta xy - \gamma y \Leftrightarrow x = \gamma/\beta$. Using (2.3a), this is achieved when $\gamma/\beta = x_0 v \Leftrightarrow v = \frac{\gamma}{\beta x_0}$. Substituting into (2.3b), we obtain (2.6). Letting

$$y(\theta, x_0, y_0) = \theta \log \frac{\theta}{x_0} - \theta + x_0 + y_0$$

for $\theta = \gamma/\beta$, it follows from simple algebra that

$$\begin{aligned}
\partial y/\partial y_0 &= 1, \\
\partial y/\partial x_0 &= -\frac{\theta}{x_0} + 1 = \frac{\beta x_0 - \gamma}{\beta x_0} > 0, \\
\partial y/\partial \theta &= \log \frac{\gamma}{\beta x_0} < 0,
\end{aligned}$$

so $y_{\max}$ is increasing in x_0, y_0 and decreasing in $\theta = \gamma/\beta$.

Proposition 2.2 has several policy implications for dealing with epidemics. First, the policymaker may want to prevent an epidemic. This is achieved when the condition $\beta x_0 \leq \gamma$ holds. Since before the epidemic the fraction of infected individuals y_0 is negligible, we can rewrite the no-epidemic condition as $\beta(1 - z_0) \leq \gamma$. Unlike bacterial infections, for which a large variety of antibiotics are available, there is generally no curative care for viral infections.[5] Therefore the recovery/death rate γ is generally out of control. Hence, the only way to satisfy the no-epidemic condition $\beta(1 - z_0) \leq \gamma$ is either (i) control transmission (reduce β), for example by washing hands, wearing protective gear, restricting travel, or social distancing; or (ii) immunisation (increase z_0). The required minimum immunisation rate to prevent an epidemic is $z_0 = 1 - \gamma/\beta$.

5 Currently, the only viruses against which antiviral drugs are available are the human immunodeficiency virus (HIV), herpes, hepatitis, and influenza viruses. See Razonable (2011) for a review of treatments of the latter three viruses.

Second, the policymaker may want to limit the economic impact once an epidemic occurs. Because the supply of healthcare services is inelastic in the short run, it is important to keep the maximum infection rate $y_{\max}$ in (2.6) within the capacity of the existing healthcare system. This is achieved by lowering the transmission rate β.

3. Estimation and prediction

In this section I estimate the SIR model in Section 2 and use it to predict the evolution of the COVID-19 pandemic.

3.1 Data

The number of cases of COVID-19 is provided by Center for Systems Science and Engineering at Johns Hopkins University (henceforth CSSE). The cumulative number of confirmed cases and deaths can be downloaded from the GitHub repository.[6] The time series starts on 22 January, 2020 and is updated daily. Because countries are added as new cases are reported, the cross-sectional size increases every day. The CSSE data are primarily at the country level. However, for some countries such as Australia, Canada, and China, regional data at the level of province or state are available. For such countries, I aggregate across regions and use the country level data. Figure 1 shows the number of COVID-19 cases in early epicentres, namely China, Iran, Italy, Japan, and Korea.

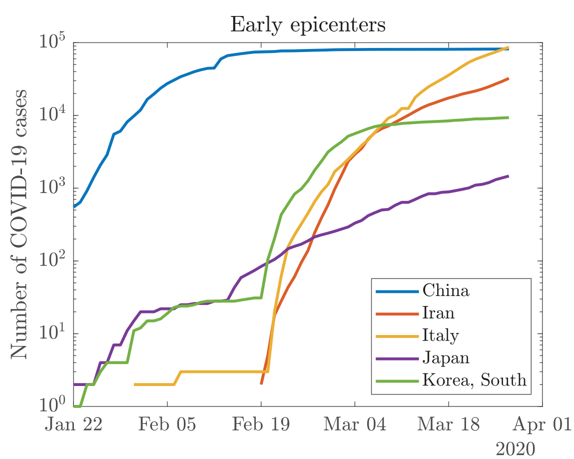

Figure 1 Number of COVID-19 cases in early epicenters

6 The data are available at https://github.com/CSSEGISandData/COVID-19/tree/master/csse_covid_19_data/csse_covid_19_time_series.

3.2 Estimation

Estimation of the model poses significant challenges because the situation of COVID-19 is rapidly evolving. The model parameters are likely time-varying because new policies are introduced on a day-to-day basis, temperature and weather may affect the virus activity, and the virus itself my genetically mutate. For these reasons, I only use the data from the two most recent weeks (14 days).

I estimate the model parameters by nonlinear least squares, minimising the distance between model outputs (x, y, z) and data. Because the CSSE data only contains confirmed cases and deaths, but the SIR model abstracts from deaths, I define $c = y + z = 1 - x$ to be the fraction of infected or recovered cases in the model. The counterpart in the data is $\hat{c} = C/N$, where C is the number of confirmed cases and N is population.[7] Because the number of cases grows by many orders of magnitude within a short period of time, I define the loss function using log cases:

$$L(\beta, \gamma, y_0, z_0) = \sum_t \left(\log \widehat{c}(t) - \log c(t)\right)^2 . \tag{3.1}$$

Since I only include c in the loss function (3.1), the parameters γ and z_0, which govern the dynamics of fraction of recovered z, are not identified. Therefore I exogenously fix these two parameters. For the recovery rate γ, because the majority of patients with COVID-19 experience mild symptoms that resemble a common cold or influenza (Zhou et al. 2020), which takes about 10 days to recover from, I set $\gamma = 1/10 = 0.1$. For z_0, I set it to one divided by population8. Although the fraction of cases $c(t)$ is likely significantly underestimated because infected individuals do not appear in the data unless they are tested, it does not cause problems for estimating the parameter of interest (the transmission rate β) because under-reporting is absorbed by the constant y_0 in (2.3b), which only affects the onset of the epidemic by a few weeks without changing the overall dynamics (see Figure 5). To sum up, I estimate the remaining parameters β and y_0 by numerically minimising the loss function (3.1). Standard errors are calculated using the asymptotic theory of M-estimators. See Appendix A for the solution algorithm of the SIR model.

7 I use the 2015 population data from World Bank available here.
8 This number is likely a significant underestimate, but the results are not sensitive to z_0 as long as it is small

3.3 Results

I estimate the SIR model for all countries that meet the following inclusion criteria: (i) the number of confirmed cases as of 27 March, 2020 exceeds 1,000, and (ii) the number of confirmed cases at the beginning of the estimation sample exceeds 10. These countries are mostly early epicentres (China, Japan, Korea), European countries, and North America. Table 1 shows the estimated transmission rate (β), its standard error, the fraction of infected individuals at the peak ($y_{\max}$), number of days to reach the peak ($t_{\max}$), and the fraction of the population that is eventually infected. Figure 2 shows the time evolution of COVID-19 cases in Italy, which is the earliest epicentre outside East Asia.

We can make a few observations from Table 1. First, the estimated transmission rates are heterogeneous across countries. While β is low in China, the origin of COVID-19, and the neighbouring countries (Japan and Korea), where the virus spread first, β is very high at around 0.2–0.4 in other countries and the no-epidemic condition $\beta x_0 \leq \gamma$ fails. Despite the short time series (14 days), the transmission rate is precisely estimated in most countries.

Although current data are insufficient to draw any conclusion, there are a few possible explanations for the heterogeneity of β. First, the transmission rate β may artificially appear high in later epicentres such as Europe and North America just because these countries were slow in adopting tests of COVID-19 and the testing (hence reporting) rate is increasing. Second, the heterogeneity in β may be due to the fact that early epicentres have already taken mitigation measures against COVID-19. For example, while Japan closed all schools starting on 2 March, many states in the US only started implementing similar measures around 16 March. So, we may not have yet seen the effect of such policies. Finally, it is possible that there are cultural differences. For example, school children in Japan are taught to wash their hands before eating and to gargle after returning home, which they practise, and (from personal experience) Japanese cities tend to be much cleaner than most cities in the world.

Country	β	s.e.	$y_{\max}$ (%)	$t_{\max}$ (days)	Total (%)
Australia	0.28	0.007	27	69	92
Austria	0.26	0.002	25	62	90
Belgium	0.25	0.041	23	69	89
Brazil	0.34	0.013	35	63	96
Canada	0.32	0.026	32	59	95
Chile	0.32	0.004	33	60	95
China	0.0015	0	0.0059	0	0.006
Czechia	0.26	0.002	24	72	90
Denmark	0.12	0	1	356	26
Ecuador	0.44	0.002	44	43	99
Finland	0.18	0	12	120	74
France	0.22	0.015	19	81	84
Germany	0.25	0	23	67	89
Indonesia	0.26	0.001	24	97	90
Iran	0.11	0.008	0.15	636	10
Ireland	0.31	0.017	31	55	95
Israel	0.31	0.066	32	56	95
Italy	0.16	0.001	8.6	114	65
Japan	0.077	0	0.00057	0	0.0024
Korea, South	0.02	0	0.016	0	0.02
Luxembourg	0.37	3.163	37	39	97
Malaysia	0.21	0.027	17	104	82
Netherlands	0.24	0	21	74	87
Norway	0.14	0.001	5.1	165	53
Pakistan	0.34	0.037	35	66	96
Poland	0.27	0.002	27	77	92
Portugal	0.32	0.005	33	53	95
Romania	0.26	0.004	24	81	90
Russia	0.3	0.001	30	79	94
Saudi Arabia	0.28	0.002	27	77	92
South Africa	0.35	0.001	35	62	96
Spain	0.25	0	23	63	89
Sweden	0.14	0.03	4.3	201	50
Switzerland	0.24	0.005	22	64	88
Thailand	0.28	0.188	28	79	92
US	0.37	0.001	38	47	97
United Kingdom	0.27	0.005	27	67	92

Table 1 Estimation of SIR model

Note: The table presents the estimation results of the SIR model in Section 2. β (s.e.): the transmission rate and standard error; $y_{\max}$: the fraction of infected individuals at the peak in (2.6); $t_{\max}$: the number of days to reach the peak; “Total”: the fraction of the population that is eventually infected.

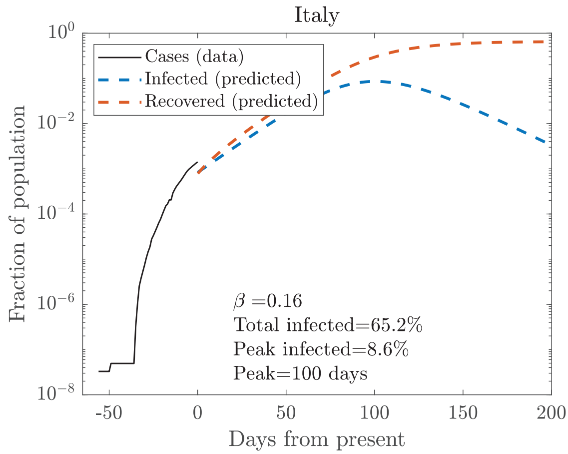

Figure 2 Time evolution of COVID-19 cases in Italy

Second, according to the model, countries other than China, Japan, and Korea are significantly affected by the epidemic. If the current trend in the transmission rate β continues, the epidemic will peak in May 2020, at which point around 30% of the population will be infected by the virus simultaneously. By the time the epidemic ends, more than 90% of the population would eventually be infected. These numbers can be used to do a back-of-the-envelope calculation of health outcomes. In February 2020, the cruise ship Diamond Princess was put under quarantine for two weeks after COVID-19 was detected on board. All passengers were tested and tracked, among whom 712 tested positive and eight died. Although this is not a representative sample because the cruise ship passengers tend to be older and wealthier, the mortality of COVID-19 should be around 1% for this group and possibly lower for the general population. Zhou et al. (2020) document that 54 patients died among 191 that required hospitalisation in two hospitals in Wuhan. Therefore, the ratio of patients requiring hospitalisation to death is 191/54 = 3.56. Thus, based on the model, the fraction of people requiring hospitalisation at the peak is $y_{\max} \times 0.01 \times 3.56 = 1.0\%$, assuming $y_{\max} = 24.4\%$, the median value in Table 1.

3.4 Optimal mitigation policy

Using the estimated model parameters, we can predict the course of the epidemic. For this exercise, I consider the following scenario. The epidemic starts with the initial condition $(y_0, z_0) = (10^{-8}, 0)$ The benchmark transmission rate is set to the median value in Table 1, which is $\beta = 0.26$. When the number of total cases $c = y + z$ exceeds 10^{-5}, the government introduces mitigation measures such as social distancing, and the transmission rate changes to either $\beta = 0.2$ or $\beta = 0.1$.[9] Mitigation measures are lifted after 12 weeks and the transmission rate returns to the benchmark value. I also consider the optimal mitigation policy, where the government chooses the threshold of cases $\bar{c}$ to introduce mitigation measures as well as the transmission rate β to minimise the maximum infection rate ymax.

Figure 3 shows the fraction of infected and recovered over time. When the government introduces early but temporary mitigation measures (top panel), the epidemic is delayed but the peak is unaffected. This is because the maximum infection rate $y_{\max}$ in (2.6) is mostly determined by β and γ since $(x_0, y_0) \approx (1, 0)$, and the epidemic persists until the population acquires herd immunity so that the no-epidemic condition $\beta x \leq \gamma$ holds. While early drastic mitigation measures might be useful to buy time to develop a vaccine, they may not be effective in mitigating the peak unless they are permanent.

The bottom panel in Figure 3 shows the course of the epidemic under the optimal policy, which is to introduce mitigation measures such that $\beta = 0.13$ when the number of cases reaches $\bar{c} = 6.3\%$ cof the population. Under this scenario, only $y_{\max} = 5.6\%$ of the population is simultaneously infected at the peak, as opposed to 28% under the benchmark scenario. The intuition is that by waiting to introduce mitigation measures, a sufficient fraction of the population is infected (and acquires herd immunity) and thus reduces the peak.

Finally, I discuss the assumptions and how they affect the policy conclusions. First, in the above numerical exercise, I assumed the government commits to a mitigation policy for 12 weeks. In reality, the duration of the mitigation is also a policy parameter. If the policy goal is to reduce the peak infection rate $y_{\max}$ below the capacity of the healthcare system, then the duration needs to be chosen to meet this constraint. However, the qualitative implications that early mitigation is suboptimal does not change. Second, the above analysis assumes that the number of cases is observable. In reality, there is significant underreporting, so the number of true cases is much larger. This implies that the threshold to start mitigation policies $\bar{c}$ needs to be adjusted for underreporting. To estimate the number of true cases, it is important to conduct random testing as suggested by Stock (2020). Finally, the above optimal mitigation policy assumes that the policy goal is to minimise the peak infection rate. Other welfare measures are possible, some of which are discussed in calibrated models in Alvarez et al. (2020) and Eichenbaum et al. (2020).

9 Using high-frequency data on influenza prevalence and quasi-experimental variation in mitigation measures, Adda (2016) documents that school closures and travel restrictions are generally not cost-effective.

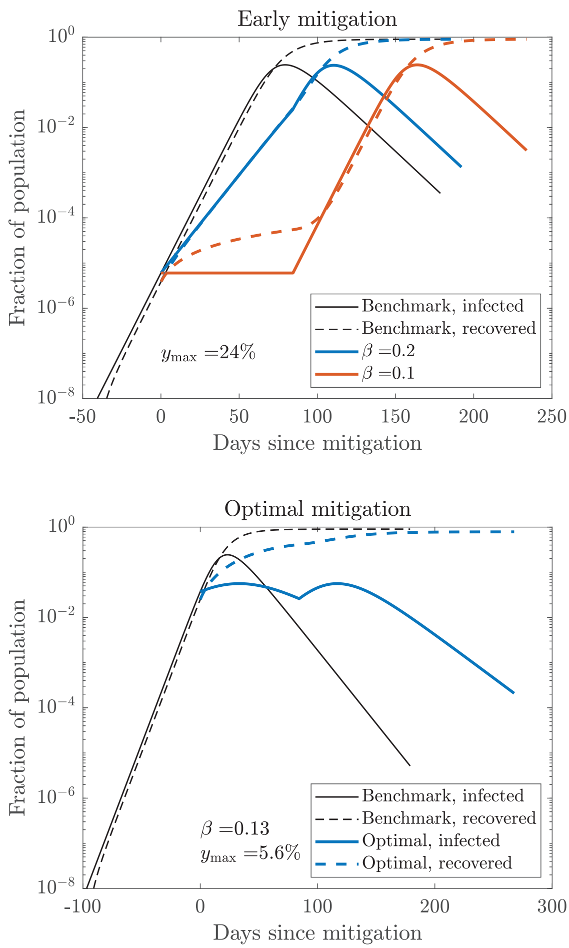

Figure 3 Dynamics of epidemic with mitigation measures

4. Asset pricing with epidemic

How does the epidemic and mitigation policy affect economic outcomes? Using data on the 1918 Spanish flu, Karlsson et al. (2014) find that the epidemic had negative effects on poverty and capital income but no effect on earnings. To evaluate the potential economic impact of the COVID-19 epidemic, in this section I solve a stylised production-based asset pricing model.

4.1 Model

The economy consists of two agent types, capitalists and workers, who respectively own the capital stock and labour. The capital stock at time t is denoted by K_t. The capital growth rate is exogenous, lognormal, and i.i.d. over time:

$$log(K_{t+1} = K_t) \sim N(\mu, \sigma^2).$$

Capitalists hire labour in competitive markets and produce a perishable good using a Cobb-Douglas production technology $Y = K^\alpha L^{1-\alpha}$, where $\alpha \in (0, 1)$ is the capital share. The labour supply is exogenous, deterministic, and normalised to 1 during normal times. During an epidemic, workers are either susceptible, infected, or recovered, and only non-infected agents can supply labour. For simplicity, I assume that workers are hand-to-mouth and consume their entire wage. The financial market is complete, and capitalists maximise the constant relative risk aversion (CRRA) utility

$$\mathrm{E}_t \sum_{s=0}^{\infty} \beta^s \frac{C_{t+s}^{1-\gamma}}{1-\gamma},$$

where $\beta > 0$ is the discount factor and $\gamma > 0$ is the relative risk aversion coefficient. A stock is a claim to the representative firm's profit $K^\alpha L^{1-\alpha} - wL$, where w is the wage.

Given the sequence of labour supply $\{L_t\}_{t=0}^{\infty}$ we can solve for the equilibrium stock price semi-analytically as follows. The first-order condition for profit-maximisation implies $w = (1 - \alpha)(K/L)^\alpha$. Hence the firm's profit, which by market clearing must equal consumption of capitalists, is

$$C = K^\alpha L^{1-\alpha} - wL = \alpha K^\alpha L^{1-\alpha}. \tag{4.1}$$

Because the marginal buyer of the stock is a capitalist, the stochastic discount factor of the economy is given by $M_{t+1} = \beta(C_{t+1}/C_t)^{-\gamma}$. Letting P_t be the stock price, the no-arbitrage condition implies

$$P_t = \mathrm{E}_t\left[\beta\left(\frac{C_{t+1}}{C_t}\right)^{-\gamma}(P_{t+1}+C_{t+1})\right]. \tag{4.2}$$

Dividing both sides of (4.2) by C_t, letting $V_t = P_t/C_t$ be the price-dividend ratio, and using (4.1), we obtain

$$\begin{aligned} V_t &= \mathrm{E}_t\left[\beta\left(\frac{C_{t+1}}{C_t}\right)^{1-\gamma}(V_{t+1}+1)\right] \\ &= \mathrm{E}_t\left[\beta\left((K_{t+1}/K_t)^{\alpha}(L_{t+1}/L_t)^{1-\alpha}\right)^{1-\gamma}(V_{t+1}+1)\right]. \end{aligned}$$

Because capital growth is i.i.d. normal and labour supply is deterministic, we can rewrite the price-dividend ratio as

$$V_t = \kappa(L_{t+1}/L_t)^{(1-\alpha)(1-\gamma)}(V_{t+1}+1), \tag{4.3}$$

Where $\kappa = \beta e^{\alpha(1-\gamma)\mu+[\alpha(1-\gamma)]^2\sigma^2/2}$. In normal times, we have $L_t \equiv 1$ and $V_t \equiv \frac{K}{1-K}$, where we need $\kappa < 1$ for convergence. During an epidemic, it is straightforward to compute the price-dividend ration by iterating (4.3) using the boundary condition $V_\infty \equiv \frac{K}{1-K}$.

4.2 Calibration

I calibrate the model at daily frequency. I set the capital share to $\alpha = 0.38$ and the relative risk aversion to $\gamma = 3$, which are standard values. I assume a 4% annual discount rate, so $\beta = \exp(-0.04/N_d)$, where $N_d = 365.25$ is the number of days in a year. To calibrate capital growth and volatility, note that in normal times we have L = 1 and hence $Y = K^\alpha$. Taking the log difference, we obtain $\log(Y_{t+1})/Y_t) = \alpha\log(K_{t+1}/K_t)$.Therefore according to the model, capital growth rate and volatility are $1/\alpha$ times those of output. I calibrate these parameters from US quarterly real GDP per capita between 1947Q1 and 2019Q4 and obtain $\mu = 0.0511$ and $\sigma = 0.0487$ at the annual frequency.[10] For the transmission rate, using the point estimates in Section 3, I consider $\beta_0 = 0.26$. The recovery rate is $\gamma_0 = 0.1$. The initial condition is $(y_0, z_0) = (10^{-8}, 0)$.

Figure 4 shows the stock price relative to potential output P_t/Y_t^*, where $Y_t^* = K_t^\alpha$ is the full employment output. The top and bottom panels are under the benchmark case and optimal policy, respectively. In the benchmark model, the stock price decreases sharply during the epidemic by about 50%. However, the

10 At daily frequency, we need to divide these numbers by N_d and $\sqrt{N_d}$, respectively.

stock market crash is short-lived, and prices recover quickly after the epidemic. This observation is in sharp contrast to the prediction from rare disasters models (Rietz 1988 and Barro 2006), where shocks are permanent. Under the optimal policy, because the infection rate y has two peaks, the stock price shows a W-shaped pattern. However, the decline is much more moderate at around 10%.

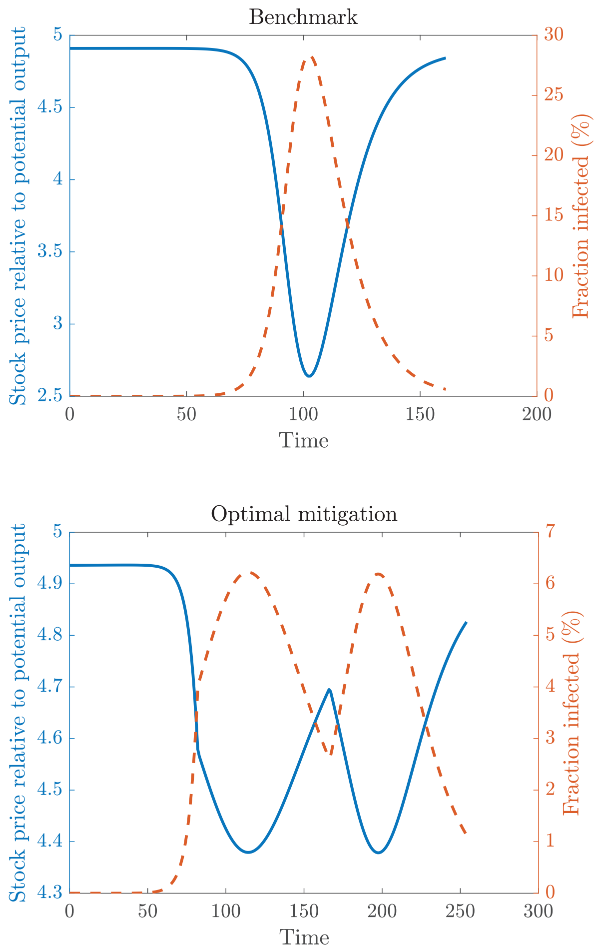

Figure 4 Asset prices during epidemic

5. Conclusion

Because the situation with COVID-19 is rapidly evolving, any analysis based on current data will quickly become out of date. However, any analysis based on available data is better than no analysis. With these caveats in mind, I draw the following conclusions from the present analysis.

The COVID-19 epidemic is spreading except in China, Japan, and Korea. In many countries, the transmission rate at present (27 March, 2020) is very high at around $\beta = 0.3$. This number implies that it takes only $1/\beta \approx 3$ days for a patient to infect another individual. Since it takes around 10 days to recover from the illness, the number of patients will grow exponentially and may overwhelm the healthcare system if no actions are taken. If the current trend continues, the epidemic will peak in early May 2020 in Europe and North America, at which point around 30% of the population will be infected. Because the recovery rate γ is an uncontrollable biological parameter, the only way to control the epidemic is to reduce the transmission rate β, perhaps by restricting travel or social distancing. However, temporary measures only slow the onset of the epidemic but have no effect on the peak because the epidemic persists until the population acquires herd immunity. The optimal policy that minimises the peak is to wait to introduce mitigation measures until a sufficient fraction of the population is infected, which can reduce the peak to 6.2%. Policymakers in affected countries may also want to look at measures taken in China, Japan, and Korea, which have so far been relatively successful in controlling the spread.

Using the estimated transmission rates, I have solved a stylised production-based asset pricing model. The model predicts that the stock price decreases by 50% during the epidemic but recovers quickly afterwards because the epidemic is a short-lived labour supply shock. Under the optimal policy, the stock price exhibits a W-shaped pattern and remains about 10% undervalued relative to the steady state level for half a year.

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Appendix: Solving the SIR model numerically

In principle, solving the SIR model numerically is straightforward using the following algorithm.

1. Given the parameters (β, γ) and initial condition (x_0, y_0), solve for v^* as the unique solution to (2.5).
2. Take a grid $1 = v_0 > v_1 > v_2 > \dots > v_N > v^*$. For each $n = 1, \dots, N$, compute the integral

$$I_n = \int_{v_n}^{v_{n-1}} \frac{\mathrm{d}\xi}{\xi(\beta x_0(1-\xi) + \beta y_0 + \gamma \log \xi)} \tag{A.1}$$

numerically.

3. Define $t_0 = 0$ and $t_0 = \sum_{k=1}^{n} I_n$ for $n \geq 1$. Compute (x_n, y_n, z_n) using (2.3) evaluated at $v = v_n$. Then $\{t_n\ (x_n, y_n, z_n)\}_{n=0}^{N}$ gives the numerical solution to the SIR model.

Although the above algorithm is conceptually straightforward, there are two potential numerical issues. First, the integrand

$$g(\xi) := \frac{1}{\xi(\beta x_0(1-\xi) + \beta y_0 + \gamma \log \xi)} \tag{A.2}$$

in (2.4) is not well-behaved near $\xi = 1$. In fact, setting $\xi = 1$ we obtain $g(1) = 1/\beta y_0$, which is typically a very large number since y_0 (the fraction of infected at $t = 0$) is typically small, say of the order 10^{-6}. This makes the numerical integral I_n in (A.1) inaccurate for small n. Second, for applications we would like the dates $\{t_n\}_{n=0}^{N}$ to be well-behaved (say approximately evenly spaced), which requires the appropriate choice of the grid $\{v_n\}_{n=0}^{N}$.

To deal with the first issue, let us express g as $g = h_1 + h_2$, where h_1 has a closed-form primitive function and h_2 is well-behaved near $\xi = 1$. Since $\log \xi \approx \xi - 1$ near $\xi = 1$, a natural candidate is

$$\begin{aligned} h_1(\xi) &:= \frac{1}{\xi(\beta x_0(1-\xi) + \beta y_0 + \gamma(\xi - 1))} \\ &= \begin{cases} \frac{1}{\beta(x_0+y_0)-\gamma}\left(\frac{1}{\xi} + \frac{\beta x_0 - \gamma}{(\beta x_0-\gamma)(1-\xi)+\beta y_0}\right), & (\beta(x_0+y_0) \neq \gamma) \\ \frac{1}{\beta y_0 \xi^2}. & (\beta(x_0+y_0) = \gamma) \end{cases} \end{aligned}$$

Then by simple algebra, (2.4) becomes

$$t = \int_v^1 h_2(\xi)\,\mathrm{d}\xi + \begin{cases} \frac{1}{\beta(x_0+y_0)-\gamma} \log \frac{(\beta x_0-\gamma)(1-v)+\beta y_0}{\beta y_0 v}, & (\beta(x_0+y_0) \neq \gamma) \\ \frac{1}{\beta y_0}\left(\frac{1}{v}-1\right), & (\beta(x_0+y_0) = \gamma) \end{cases} \tag{A.3}$$

where

$$h_2(\xi) := \frac{1}{\xi(\beta x_0(1-\xi)+\beta y_0+\gamma\log\xi)} - \frac{1}{\xi((\beta x_0-\gamma)(1-\xi)+\beta y_0)}. \tag{A.4}$$

Because $h_2(\xi)$ is approximately 0 to the first order around $\xi = 1$, we can calculate the numerical integrals in (A.1) accurately.

To deal with the second issue, consider the SIR model in (2.2) with $\gamma = 0$. Then (2.2a) becomes $\dot{x} = -\beta x(1 - x)$, and by separation of variables we obtain the analytical solution

$$x(t) = \frac{x_0}{x_0 + (1-x_0)\mathrm{e}^{\beta t}}.$$

Using (2.3a), for the case $\gamma = 0$, time t and parameter v are related as

$$v = \frac{1}{x_0 + (1-x_0)\mathrm{e}^{\beta t}}.$$

Define t^* by

$$v^* = \frac{1}{x_0 + (1-x_0)\mathrm{e}^{\beta t^*}} \iff t^* = \frac{1}{\beta}\log\frac{1/v^* - x_0}{1-x_0}.$$

Finally, define

$$v_n = \frac{1}{x_0 + (1-x_0)\mathrm{e}^{\beta t^* n/N}}.$$

Then t_n implied by (2.4) is evenly spaced when $\gamma = 0$, and we can expect that the grid $\{v_n\}_{n=0}^N$ gives reasonable values of $\{t_n\}_{n=0}^N$ even when $\gamma > 0$.

For numerical implementation, I set $N = 1000$ and use the 11-point Gauss-Legendre quadrature and (A.3) to numerically compute the integral in (A.1). Figure 5 shows the dynamics of the SIR model when $(\beta, \gamma) = (0.2, 0.1)$, $y_0 = 10^{-6}, 10^{-5}, 10^{-4}$ and $z_0 = 0$. For this example, $1 - v^* = 80.0\%$ of the population is eventually infected, and $y_{\max} = 15.4\%$ of the population is infected at the peak of the epidemic. The initial condition (y_0) affects the timing of the epidemic but not its dynamics.

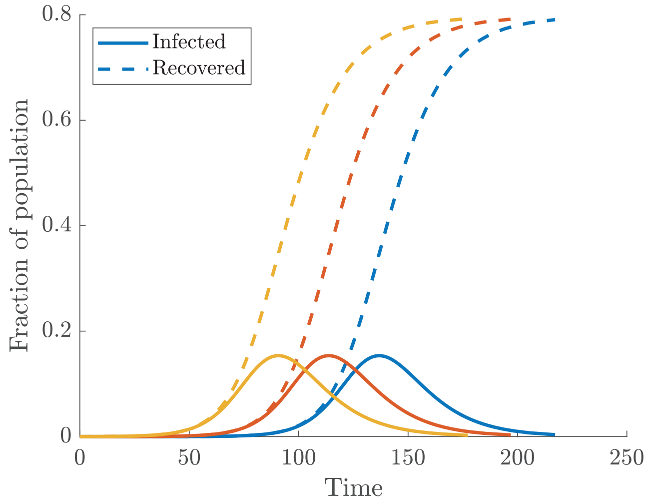

Figure 5 Dynamics of SIR model when $(\beta, \gamma) = (0.2, 0.1)$, $y_0 = 10^{-6}, 10^{-5}, 10^{-4}$, and $z_0 = 0$. Smaller y_0 corresponds to later onset of epidemic.

Economic resilience, globalisation and market governance: Facing the Covid-19 test

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The lack of anticipation of a worldwide disruptive event such as the spread of Covid-19, combined with the breakdown of market mechanisms for the most essential products needed to fight the disease, has left the governments of many countries unsure of how to react and has often constrained their ability to make strategic choices. The humanitarian goal of saving as many lives as possible has come, in some countries, at the cost of confining the entire population, considered the only option available given the circumstances. The economic cost of such a solution, which brings the economies of these countries to a standstill and disrupts global value chains, is likely to be followed by several years of economic depression that will dwarf the cost of the 2008 financial and economic crisis. In the light of this experience, this paper revisits some of the implicit assumptions underlying the design of our economic systems and discusses some of the dilemmas and trade-offs faced during this stressful period. The lessons learned could help us better anticipate or deal with future black swan events.

The Covid-19 epidemic struck the world with exceptional speed, severity and breadth. Globalisation contributed to the rapid spread of this modern-day plague to all corners of the world, and the international market mechanisms on which we have relied over the past three decades to promote economic growth and welfare and on the flexibility of which we counted to weather exceptional and unexpected events failed to deliver the hoped-for relief in a timely fashion,

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thereby slowing down many governments in their desperate attempt to fight the spread of the virus. The lack of anticipation of the possible occurrence of such an event combined with the breakdown of market mechanisms for the most essential products needed to fight the disease left the governments of many countries unsure of how to react and often constrained their ability to make strategic choices. The humanitarian goal of saving as many lives as possible came, in some countries, at the cost of confining the entire population, considered the only option available given the circumstances. The economic cost of such a solution, which has brought the economies of these countries to a standstill and disrupted global value chains, is likely to be followed by several years of economic depression that will dwarf the cost of the 2008 financial and economic crisis.

The dramatic events of the first quarter of 2020 lead us to reconsider some of the implicit assumptions underlying the design of our economic systems and to think about some of the dilemmas and trade- offs that we have faced during this stressful period. The lessons learned could help us better anticipate or deal with future 'black swans'.

1. Science and politics

The 24th of March 2020 was a day of panic in the US because, for the second time, Anthony Fauci, Director of the US National Institute of Allergy and Infectious Diseases, was not alongside President Trump during the president's daily press conference. In France, we are told that all decisions of the president or the prime minister are taken after consulting a scientific council in charge of advising the government on the Covid-19 epidemic or are justified by the positions taken by this scientific council. Democratically elected politicians are considered to have a mandate from the people; scientists are considered legitimate authorities because they know more than the average citizen. Yet, it is clear that in a period of crisis, the public puts more trust in scientists than in politicians to advise on the appropriate course of action to fight an epidemic. However, this raises many questions about the respective roles of scientists and politicians in public policy decision making in times of crisis. Can scientists raise issues on their own initiative to influence political decisions? Or should their role be limited to answering questions raised by political leaders? Do we expect that political leaders will always follow the advice of scientists, and if not, how will we be made aware of differences in their views? This issue has been raised in France by the government's decision to allow the administration of hydroxychloroquine (not yet scientifically tested for use against Covid-19) for patients in very grave states. The decision was taken by the government after seeking the advice of scientists. We know that the scientific community has been very critical of the professor in Marseilles who first suggested that hydroxychloroquine could be a useful medicine for Covid-19 patients. Apparently, the preliminary research did not meet the scientific criteria for a complete clinical test. The question then is how did the scientific council come to suggest or support the political decision? Did the council act in support of the government or did it fulfil its scientific role?

There are related questions about the responsibility of doctors in the development and containment of the epidemic. Their work and their devotion to helping the population overcome this disease are admirable and doctors are paying a heavy tribute. They are our heroes, and they have our respect and our admiration. But one thing that is very unsettling is the fact that specialists in virology are divided on the correct way to proceed. There are clearly very different views on the best strategy to fight a pandemic of this nature (Confine the whole population? Test everyone to try to identify all the individuals at risk?); different ideas about the usefulness of masks; different ideas about what how medicines untested for Covid-19 should be used; different ideas about whether China did the right thing or not; and so on. So the disagreements among doctors are not limited to secondary issues. Even if it comes as no surprise that doctors can disagree, the question then is what is the legitimacy of an advisory body made up of doctors who disagree? (The doctor who has been advocating the use of hydroxychloroquine and was a member of the scientific council to the government has just announced that he will no longer participate in the scientific council's work.)

2. Human rights and the response to the health crisis

Less-democratic countries such as China and Vietnam, where individual freedom is limited, seem better able to take adequate measures (confinement in China or targeted action in Vietnam, for example) to limit the spread of the virus than elsewhere. In some western countries (the United States, the United Kingdom, France, etc.) there seems to have been, at the very beginning at least, more hesitation about confinement measures (or less drastic confinement measures) and therefore a greater tendency for the virus to spread.

Another aspect of this interface is the reticence expressed in a number of countries (based on an attachment to individual freedom and the respect of privacy) regarding the use of modern invasive technologies such as facial recognition or geolocation, which could help public authorities to monitor the strict enforcement of a confinement order when a government has acknowledged that the order is not being well followed by the public. The degree of resistance to the use of such technologies to track potential victims of Covid-19 varies from one country to another. For example, Slovakia – following in the footsteps of countries such as Singapore, South Korea and Taiwan, where aggressive contact tracing has crucially contributed to limiting the spread of the virus – passed a law on 25 March 2020 which allows the government to use data from telecom companies to track the movements of people infected by Covid-19 to ensure that they are abiding by the quarantine rules. The adoption of this law was not easy, but the Slovak justice minister insisted that in the face of this epidemic, the right to privacy could not be absolute.[2] In Germany, the government was less successful and was forced to abandon its proposal to use "technical means" to identify who had been in contact with persons infected by Covid-19. In France, the government decided to use police patrols to monitor whether confinement measures were being followed by people found outside their homes. However, it seems obvious that the use of more advanced technology might have allowed us to save scarce human resources, which could then have been allocated to important alternative tasks such as the logistics of supplying hospitals and their security. This raises the question of how we should deal with the trade-off between public health and the protection of human rights.

3. Scientific methodology and the precautionary principle

Third, there is a question about the respective merits of a scientific methodology and the precautionary principle to inform public policymaking. This question is not new in Europe, but the current crisis offers a new illustration of the dilemma to be faced. When it comes to hydroxychloroquine, the scientific community insists that the correct clinical methodology has not been followed and that more testing is necessary. However, the question that can be asked is whether, in a crisis, we have the time to follow the correct methodology. What took place in Marseilles shows that the response of many citizens is, "*I do not care if the correct scientific methodology has been followed, I want to be tested and to have this drug prescribed if I have the virus because there is no alternative medicine and I risk dying*". To a certain extent, governments – including the French government and President Trump – have felt an irrepressible urge to side with their citizens against scientists (hence the position of the French government that this drug can be given to dying patients under some circumstances). The implicit questions this rasies are: Is the scientific (rational) approach a luxury that we

2 See "Slovakia to track victims through telecoms data", *Financial Times*, 26 March (https://www.ft.com/content/64539a44-6e87-11ea-89df-41bea055720b).

cannot always afford? Is the precautionary principle, at least in some cases, a better alternative? Do we have a systematic method to propose for dealing with the dilemma?

Another aspect of this debate is the discussion about whether the French government should have kept larger stocks of masks, respirators, medicines, and so on. In 2009, the government, worried about the development of the H1N1 virus, bought massive quantities of the vaccine to treat this disease and massive quantities of masks. H1N1 never became an epidemic in France and the government was accused of having wasted public money. After that, the government let France's stock of protective medical equipment diminish to such an extent that the country is now unable to react when there is an epidemic. From a public policy standpoint, the questions are: How should we deal with the risk of rare, but exceptionally destructive events (such as epidemics, major earthquakes, extreme weather events or nuclear accidents)? To what extent should we provide for these risks, which have a small probability of occurring, when doing so will be costly but could save many lives? Or should we admit that we do not want to prepare for such events, both because of the cost involved and because of their unpredictability? In which case, what should we do to ensure that our economic systems remain flexible enough that they can react in a timely manner when such catastrophes do occur?

4. The economic costs of public health strategies

Fourth, there is a question as to whether there can be a trade-off between the public health strategy and the economic strategy used to overcome the crisis and, if there is such a trade-off, what policy prescription should be followed. The idea that there may be a trade-off comes from the fact that the confinement policies adopted in an number of countries, which are designed to minimise the number of deaths from the Covid-19 and lessen the impact of the epidemic in terms of the number of people infected, decrease economic output and therefore increase the severity of the economic crisis because citizens are prevented from to working if they are not able to work from home. The sector most affected by the current confinement measures is the services sector (air transport, hotels, restaurants, retail distribution, cinemas etc.) because in these industries, working from home is for the most part impossible. The more extensive and the longer the confinement, the more severe the adverse effects on this sector and the larger the decrease in GDP. There are two alternative health strategies. One is to let the epidemic run its course, which would imply many more deaths but a much lower decrease in GDP, as people not infected and those who suffer only light symptoms (which represents the large majority of people infected with

Covid-19) would continue to work. The other strategy is to test the population widely and confine only people infected by the virus. In this second case, which is reminiscent of the strategy adopted in countries Korea,[3] there would both be fewer deaths than if nothing were done and more people working than if a strategy of general confinement of the population were followed. The strategy chosen in European countries may well worsen the economic crisis compared to alternative strategies. We can thus expect that the economic cost of the pandemic will be much worse than the cost of the 2008 financial crisis for the simple reason that people, for the most part, kept working during the financial crisis. It is said by some that this strategy could impose a loss on Western economies of up to 15% of GDP in the short run and may require many years of effort to try to get back to where these economies were before the epidemic. What the trade-off between health strategy and economic strategy actually is, and how we should consider it when determining public policy, raises both empirical questions (requiring assumptions about the severity of the economic crisis in different policy configurations, the speed of recovery, and so on) and ethical questions (such as whether, when it comes to health policy, one can or should put an economic value on lives). President Trump's call to reopen the US for business by Easter Sunday and his argument that you cannot run a country by listening to doctors because the solution they would favour (i.e., confinement) could be worse than the disease was a particularly brutal way of raising the issue.

5. Globalisation, global supply chains and national sovereignty

The benefits of globalisation have been much discussed over the past 20 years. One view is that the decline in obstacles to trade and foreign investment and the development of new communication technologies have allowed the international reallocation of resources through a restructuring of production processes, and that this has benefited developed countries by allowing them to secure their consumption needs at a lower cost and allowed developing countries to benefit from economic opportunities thanks to the development of export-oriented activities. It is often pointed out that globalisation has lifted hundreds of millions of people in developing countries out of poverty.

3 Between the beginning of February 2020 and 10 March 2020, more than 200.000 people were tested in Korea in 600 testing centres, and confinement was limited to infected people. As a comparison, during the same period only 15,000 tests were carried out in France but starting on 16 March 2020, a general confinement of the population was implemented. During the month of February 2020, US authorities tested 472 people.

However, the Covid-19 crisis could strengthen the hand of those who, in developed countries, see economic globalisation and trade and investment liberalisation as unacceptable threats to the sovereignty of their nation state. In the eyes of those sceptical of the benefits of globalisation, there are several ways in which trade and investment liberalisation limits the ability of nation states to pursue independent domestic policies.

First, the granting of trade concessions necessary to guarantee effective access to the domestic market of goods or services by foreign trading partners usually implies giving up trade protection tools which could have been used to alleviate a domestic crisis.

Second, liberal trade policies allow firms operating in very different domestic regulatory environments to compete on world markets. Firms from countries with the highest domestic standards in terms of human and social rights, property rights, environmental protection food security, and so on may be at a competitive disadvantage to firms from countries with less exacting standards. Thus, to a certain extent, opening up to international trade constrains the ability of countries to freely make the domestic societal choices that they may wish to make.

Third, the development of international trade, together with a number of recent technological developments in the communication and transportation sectors, has led to an internationalisation of supply chains whereby domestic firms externalise a number of functions in countries where these functions can be fulfilled at a lower cost (such as accounting and finance in India and production in China, or more recently in Vietnam). But this internationalisation of the value chain, often combined with just-in-time policies of keeping stocks at the lowest possible level in order to reduce costs, make firms very much dependent on the smooth functioning of the international value chain. This smooth functioning can break down when an external shock affects the economy of any of the countries in which firms contributing to the value chain are located. In a world characterised by economic globalisation, disruptions due either to a natural catastrophe affecting another country or to political decisions by a foreign government can hinder the ability of firms to serve their domestic markets.

Thus, whether through trade concessions or the risk of seeing their domestic firms displaced through international competition or the unavoidable consequences of foreign disruptions, trading nations may seem to have given up the ability to protect their firms or their citizens.

It is this latter mechanism which has, so far, been a source of concern in Western countries during the Covid-19 epidemic.

European and North American countries now depend to a large extent on foreign countries, such as China, for their supply of a number of essential medical products of which they did not have enough stocks to face the Covid-19 health crisis. This dependency became a major source of concern when countries, including China, where the sourcing firms are located were hit by the epidemic and decided to follow a strict confinement policy which halted their production. European and North American countries were then unable to restock masks, respirators or active ingredients used for testing, and this limited their options for fighting the virus.

In France, for example, since the beginning of the Covid-19 epidemic there has been an acute shortage of FFP2 masks, which are supposed to protect the wearer both against the aerial transmission of the virus and against the possibility of inhaling the virus. It has been even difficult to provide enough surgical masks (which offer a lesser level of protection) for the health professionals dealing with patients infected by the virus.

The reasons for this shortage of masks are twofold. First, in 2011 and 2012 the French authorities reversed a decision to maintain an important stock of masks on the basis that China, which produces about 70% of the world's supply of masks, would be able to provide France with the necessary masks in case of an emergency. Second, in late February – by the time it had become clear that the epidemic was going to hit France severely and that the country needed masks – the epidemic had already hit China with full force and a large portion of the Chinese population had been confined. As a result, although the Chinese production capacity was estimated to be about 20 million masks per day, it was only producing 15 million masks due to confinement measures and at the same time, the Chinese domestic demand for masks had shot to between 50 and 60 million masks per day. Not only was China not in a position to export its masks to France, but it had become a large importer of masks from Indonesia and Vietnam. When the French firms whose employees need to use protective masks (such as construction companies and other industrial firms whose workers are exposed to dust and small particles) became aware of the impending difficulty in obtaining these masks, they reacted by attempting to increase their own reserves of the most protective masks (FFP2). The lack of availability of masks in pharmacies created a panic which led the French president, on 3 March 2020, to requisition all available FFP2 masks.

With slight variations, the same story occurred in other European countries such as Italy and Germany.

On the day that the French president requisitioned all available FFP2 masks, Germany banned the export of masks. Taiwan and India also took steps to stop exports of medical equipment.

The situation in the United States seems to have followed a similar path. In the early 2005 and 2006, the US government advocated the stockpiling of protective gear in preparation for pandemic influenza and a strategic stockpile of 52 million surgical masks and 104 million N95 respirator masks was amassed. About 100 million of these masks were used in 2009 in the H1N1 pandemic and were never replaced in the stockpile. As the Covid-19 outbreak worsened in the US in the early days of March 2020 and as the demand for masks grew rapidly, the shortage of masks – particularly N95 masks – became a topic of controversy. The shortage was attributed to a combination of low strategic stocks, widespread buying of masks by anxious citizens and dwindling supply (either due to hoarding or to reduced production) from China.[4] Interestingly, on 17 March 2020, when the Center for Disease Control published an updated set of recommendations for optimising the use of protective gear by medical professionals and suggested that surgical masks were acceptable when examining or treating a Covid-19 patient (a suggestion that aligned with advice from the World Health Organization), the suggestion was considered with great suspicion by some medical professionals and in particular by the American Nurses Association, which argued that the CDC's new recommendations were based "solely on supply chain and manufacturing challenges", thus suggesting that national sovereignty in the health sector was compromised by the economic forces of the global market.[5]

Besides the fact that the spread of the Covid-19 epidemic may have further eroded the faith of some in the benefits of economic globalisation (possibly unfairly because in most countries a better appraisal by national governments of the possible catastrophic risks which could disrupt the welfare of their citizens and the adoption of public precautionary measures against those risks could have significantly decreased the impact of the disruptions in markets for essential goods), it should be noted that the adoption of necessarily far-reaching measures to alleviate the economic crisis which will follow the pandemic is also likely to lead to a retreat from the logic of globalisation. Indeed, as seen previously, it is clear that national governments will need to inject massive amounts of money

4 See, in particular, "The US runs out of face masks", *New York Times*, 26 March.
5 See "Where Are All the Masks?", *New York Times*, 22 March.

into their economies in the hope that firms will, with this financial help, survive long enough to weather the disruption caused by the epidemic, the confinement measures and the subsequent economic depression.

For the reasons I have analysed earlier, the bailout of our economies will require financial measures many more times more significant than those taken in the aftermath of the 2008 financial crisis. But one of the lessons we learned from that financial crisis is that when national governments use economic stimulus to shore up their economies following an exogeneous shock, they should make sure that their stimulus does not end up shoring up other economies through a surge in imports. To ensure that there is no leakage they tend to resort to protectionist tools. As Simon Evenett and the Global Trade Alert team have documented, a massive increase in protectionist measures followed the 2008 crisis. It is hard to believe that the same cause is not going to lead to the same effects, particularly in view of the importance of the financial commitments which have already been announced.

6. The need for industrial policy

Sixth, a concern related to the previously discussed question is the apparent inability of market-oriented countries to pursue an effective industrial policy which is both pro-competitive and also allows them to maintain fundamental strength in strategic industries and resources which can be called upon (or quickly activated) in a time of crisis. The issue is not new and has been actively discussed in France and Germany over the past few years. But whereas this discussion was limited to economists and bureaucrats, the difficulties experienced by a number of countries (including France) in having an adequate supply of simple things such as masks or active ingredients for tests are seen by the general public as resulting from a failure to follow an effective industrial policy. Furthermore, at a time when we would very much want to see domestic firms which still have production facilities in our countries switch their production to products or services that are urgently needed to face the crisis (say, for example, the production of respirators for emergency rooms in hospitals), in France there is no one in charge of planning, organising, enforcing and supervising this move because the country no longer has a ministry of industry. So, what has been gained in efficiency by relying on markets to direct the economy has created a loss of ability to mount a coordinated response to an unanticipated economic disaster.

7. Privacy, digital technologies and public health

Seventh, there are interesting questions about data and digital policy. As the *Financial Times* reported on 42 March 2020, "*[t]he coronavirus crisis is forcing the EU to redraw its digital strategy*". The previous calls for EU data sovereignty shows its limitation at a time when, in order to anticipate the expected path of the epidemic and to find a vaccine, we need the largest possible pooling of data and to get this pooling of data, we need the cooperation of non-EU countries such as China.

It was only a month ago that EU Internal Market Commissioner Thierry Breton was reported to be flirting with the idea of forcing European companies to store and retain at least some of their data in Europe and told lawmakers that data produced in Europe "should be processed in Europe". We are clearly caught in a dilemma between, on the one hand, the desire to protect our privacy and to prevent the GAFAM6 from becoming ever more dominant by feeding their artificial intelligence algorithms with our data, and on the other hand, the fact that in the health sector (as in other sectors) the performance artificial intelligence algorithms that we count on to produce scientific advances depends on the quantity of data which can be gathered to train them.

8. What future for competition law and policy?

Eighth, there are a number of questions concerning if and how the role of competition law and competition policy should be redefined in a time of deep economic crisis. A discussion of the goals, achievements and failures of competition law enforcement and competition policy was begun a few years ago. But in Europe this discussion was largely focused, first, on questions related to government intervention in countries such as China which allowed subsidised, state-owned enterprises to gain a substantial advantage over their Western competitors by means considered to be both unfair and anticompetitive; and second, on the question of whether the focus on the protection against competition within Europe (for example, through merger control) had impaired the development of national or European champions and accelerated the de-industrialisation of the continent. In the US, there was also a concern over the unfairness of international competition among countries which had vastly different economic systems and a suspicion that the narrow focus of US antitrust authorities on the protection of consumer surplus in the short run, coupled with a permissive attitude toward economic concentration and an excessive fear of

6 Google, Amazon, Facebook, Apple, and Microsoft.

type I errors (i.e., the risk of misguided intervention by competition authorities leading to a restriction in competition), had led to under-enforcement of antitrust laws, increased macroeconomic concentration and profit margins and the domination of the digital economy by the GAFAM.

The brutal economic crisis we are now experiencing requires different types of adjustments, depending on the time perspective we consider.

In the very short term, the main issue to be confronted is the brutal disruption to the value chains of a number of products, leading to shortages either because of insufficient level of production or because of difficulties in product distribution due to confinement measures. The issue for consumers is not, as it is in a normally functioning economy, being able to choose the best price/quality ratio among products offered by competing suppliers, but simply being able find the product (even if in smaller quantity than what would be desirable).

In such circumstances, cooperation between suppliers (and/or government intervention) to identify both the needs and the existing stocks may be necessary to permit an adequate supply of essential goods and services. For example, as the US Federal Trade Commission and the US Department of Justice have suggested, health care facilities may need to coordinate on the provision resources and services, and other businesses may temporarily need to combine production, distribution, or service networks to facilitate production and distribution of Covid-related supplies.

In addition, consumers need to be protected against abuses resulting in price gouging of products in short supply. This requires two adjustments for competition authorities: the first is to take a more nuanced approach with respect to cooperation among competitors than the approach they have taken in the past; the second is to focus on exploitative abuses of market power rather than on exclusionary practices (the creation of barriers to entry) on which they have focused in the past.

Competition authorities both in the context of the European Competition Network and outside the EU (for example, in the United Kingdom and in the United States) have already signalled their willingness to allow, at least temporarily, cooperation or coordination between competitors whenever such cooperation or coordination is necessary to avoid a shortage of supply due to the Covid-19 crisis or to ensure security of supply.[7] They have also signalled their intention to fight price gouging.

In the medium run – say, over next two to three years – our economies will be depressed, with the risk of a large number of bankruptcies of firms either directly hit hard by the Covid-19 epidemic (in the services sector, for example) or affected by the disruption of their supply chain, rising unemployment and dwindling demand.

As is widely known, competition is a virtuous economic mechanism when economies are at full employment of their resources because it allows them, in a static perspective, to grow through a more efficient use of scarce resources. But with the aftermath of the Covid-19 pandemic, in the medium run we face the risk of an economic depression and a high level of bankruptcies and unemployment for a number of years. In such an environment, the important goals are to quickly stimulate economic growth, to engage in the kind of redistribution mechanisms which will alleviate the economic suffering of the poor, and to ensure that the economic framework that we create will be more resilient in the future. It will thus be necessary to stimulate employment and to prevent firms in the sectors affected by the crisis – particularly SMEs but also a number of larger firms – from going bankrupt.

Massive amounts of state aid, tax deductions or deferments and subsidies of various kinds, or perhaps even the nationalisation of entire sectors, will be necessary and the initial financial packages have already been put together by the governments of many countries in Europe and in the US.

In this context, it is clear that there is a possibility for conflict between (i) the need to artificially keep a large number of firms going in the short run in order to kick start the economy in the medium run and allow it to retain its footing in the long run, and (ii) a policy of competition law enforcement which assumes explicitly or implicitly that the economy is already in a stable equilibrium with full or near full employment of the factors of production and that the most important problem is to ensure that the competitive process in the short run guides the allocation of resources to maximise consumer welfare.

7 See, for example, the CMA approach to business cooperation in response to Covid-19 published on 25 March 2020 or the "Joint statement" issued by the European Competition Network on the "application of competition law during the Corona crisis", on 23 March 2020 which states that "necessary and temporary measures put in place in order to avoid a shortage of supply… are unlikely to be problematic, since they would either not amount to a restriction of competition under Article 101 TFEU… or generate efficiencies that would most likely outweigh any such restriction".

The promotion of competition may not be as central an economic preoccupation in the near future as it was during the first two decades of the 21st century (although it would be useful to review the lessons of the period which followed the Great Depression), and to the extent that it is still useful we will have to think again about the trade-offs between static efficiency, reallocation of resources through industrial policies, dynamic efficiencies and economic resilience.

At the very least, competition authorities will have to take a longer and more dynamic view of the process of competition than they have had until now, and adapt their reasoning with respect to state aid, cartels and mergers to circumstances of disequilibrium caused by an exogenous shock to the economic system.

Finally, in a longer-term perspective, the challenges raised by the Covid-19 crisis and the need to be better prepared to face future epidemics require a massive reallocation of resources towards the health sector. This is not the only notable reallocation of resources that must be implemented; we also must deal head on with climate change and redirect our resources toward clean energies. The development of the digital economy also requires a reallocation of resources to allow firms in traditional sectors to fully benefit from the new technologies at their disposal.

A number of economists have convincingly argued that market forces are by themselves insufficient to reallocate resources at the level and the speed required to face those challenges. This means that even though competition is necessary, it is not be sufficient to meet the challenges we face in the 21st century. Competition policy must be better integrated in a wider context of complementary economic policies.

9. Conclusion

Black swan events and major humanitarian crises do occur, and they can have long-lasting effects on developed countries as well as developing countries. One of the policy questions we have to think about is what amount of our resources we want to devote to achieving more resilient and agile economic systems that are better able to withstand rare but potentially catastrophic events. There is no easy answer to this question because neither the probability of such events nor, in some cases, their nature or their potential for destruction are known. Yet, as Jean Tirole recently argued in Le Monde (on 25 March 2020), and as the experience of the Covid-19 crisis has shown, the choice is between making reasoned choices for the future which may allow us to maintain some degree of control even in dire situations or letting future events run their course, decide for us and possibly destroy us all. It is time to move to a longer-term perspective and to better integrate risk factors in our economic analysis and policy decisions.