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THE ECONOMIC IMPACT OF COVID-19[‡]

Adapting to the COVID-19 Pandemic[†]

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From early in the COVID-19 pandemic, economists have stressed the importance of individuals endogenously changing their behavior, both economic and noneconomic, to reduce their risk of infection. Starting with Eichenbaum, Rebelo, and Trabandt (2020), a literature studying the pandemic through the lens of calibrated structural models has found that this endogenous response is an important channel mediating the spread of the pandemic: fear of infection reduces both labor supply and demand for high-contact services, which in turn reduces contacts and transmission and dampens spread of the virus.

As of this session, ten months into the pandemic, there is reason to suspect that the strength of this behavioral response has changed. The initial spring wave of the pandemic saw a plunge in economic activity, which a large body of research convincingly shows to be largely a consequence of individuals' endogenous responses (see the survey in Gupta, Simon and Wing 2020). As the pandemic progressed, additional waves of deaths—a small, regional wave in the summer and a much larger late-fall wave—were not, however, associated with comparable declines in economic activity. For example, the US daily death rate (seven-day moving average) hit 2,714 on December 22, 2020, 20 percent above the spring peak. At the same time, high-frequency measures of economic activity (e.g., the New York Fed/Dallas Fed Weekly Economic Index) remained roughly constant over November and December. A change in the endogenous behavioral response, if it occurred, has important implications going forward both for the potential economic impact on future waves of deaths and for the effectiveness of future economic lock-downs to control transmission.

This paper quantifies the time-variation in the endogenous behavioral response of economic activity to the prevalence of the virus. Because current infections are unobserved, we examine the response of activity to the observed daily death rate. We do so using a behavioral SIR model with four time-varying parameters. The time-varying parameters allow us to distinguish between four sources of time variation: the endogenous self-protective response, the effect of economic activity on transmission (such as masking while shopping), nondeath shocks to economic activity (such as fiscal shocks), and nonactivity shocks to transmission (such as churchgoing and social gatherings).

We fit the model to daily data on deaths and labor hours for the United States using a rolling eight-week estimation window. Figure 1 displays our rolling estimates of the self-protective response—specifically, the semi-elasticity of daily labor hours with respect to an additional 1,000 deaths on the previous day. The early months of the pandemic saw a strong self-protective response: 1,000 additional daily deaths led to a 6–7 percent reduction in hours. This semi-elasticity diminished to nearly zero over the summer, before returning to its initial value by August. In late fall, this self-protective response again abated and remained close to zero throughout the late-fall wave.

In a closely related paper also in this session, Atkeson, Kopecky, and Zha (2021) use regional and international evidence to show that

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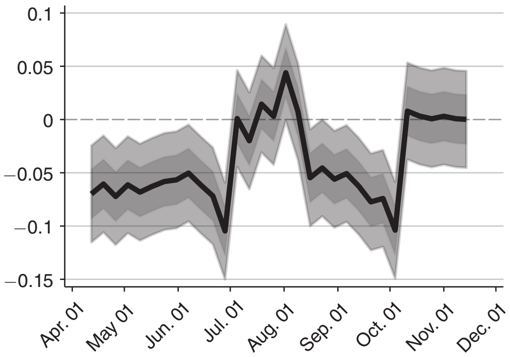

Figure 1. Estimated Semi-elasticity of Economy-Wide Hours with Respect to the Prior Day's Death Rate, Estimated by Rolling System Estimation of a Behavioral SEIRD Model

Note: Rolling estimates based on an eight-week window, with 67 percent and 95 percent heteroskedasticity- and autocorrelation-robust pointwise confidence bands.

Source: Authors' calculations

behavioral SIR models without time variation cannot fit the path of the pandemic. Here, we quantify this time variation for the United States in terms of interpretable parameters that reflect technical and psychological adaptations to the pandemic.

I. Model and Estimation

We use a susceptible-infected-recovered (SIR) epidemiological model, augmented with an exposed (E) state in which individuals are not yet infectious and a deceased state (D). We incorporate a seasonal factor of transmission, calibrated from Tzampoglou and Loukidis (2020). In addition, we allow for time variation in the population infection-fatality rate resulting from improvements in medical treatment, calibrated from Ledford (2020). For details, see the online Appendix.

Our SEIRD model has seven equations. The first five are transition equations for the S, E, I, R, and D compartments. For example, the transition equation for the S state describes the rate at which susceptible individuals become exposed to the SARS-CoV-2 virus:

$$dS/dt = -\beta_t \varphi_t (I_t/N_t) S_t, \tag{1}$$

where φ_t is the seasonal factor in contagion; S_t and I_t are the numbers of susceptible and infected individuals, respectively; and N_t is the total population.

The remaining two equations characterize the relationship between the economic activity and virus prevalence. In principle, self-protection should depend on the current risk of infection. However, the true number of infections is unobserved, and time variation in confirmed infection is difficult to interpret due to time-varying testing rates and selection into testing. In contrast, deaths are highly salient and reported promptly. We therefore model economic activity as a function of deaths:

$$s_t = \kappa_{0t} + \kappa_{1t} DR_{t-1}, \tag{2}$$

where s_t is an index of daily labor hours, relative to hours in February 2020, and DR_{t-1} is the average daily death rate on the previous two days. The time-varying coefficient κ_{1t} is the semi-elasticity of economic activity with respect to daily deaths and is the object of primary interest in this paper. The parameter κ_{0t} collects all shocks to hours other than deaths and infections, such as fiscal shocks and general adaptation to the pandemic in ways that are not linked to current deaths.

The final equation describes the effect of economic activity on viral transmission:

$$\beta_t = \exp(\beta_{0t} + \beta_{1t} s_t), \tag{3}$$

where β_t is the coefficient of transmission in equation (2) and β_{0t} and β_{1t} are time-varying parameters. In the SIR model, the time-varying current reproduction number, R_t, is proportional to β_t, so β_{1t} is the elasticity of R_t with respect to a change in labor hours. This elasticity captures multiple channels, such as reduced contacts from reduced economic activity and reduced probability of transmission for a given level of economic transmission, such as by wearing masks while shopping. The coefficient β_{0t} represents time-varying factors affecting transmission unrelated to economic activity.

The full system of nonlinear equations has seven equations, two observable variables (daily deaths and s_t), four latent state variables, and six parameters: E_0, I_0, κ_{0t}, κ_{1t}, β_{0t}, and β_{1t}, where

E_0 and I_0 are initial conditions for the number of exposed and infected.[1]

In this model, death and economic activity are simultaneously determined. We rely on a combination of timing restrictions, cross-equation restrictions, and functional form restrictions to identify the parameters in equations (2) and (3). The timing restrictions arise from the disease progression: economic activity contemporaneously determines exposure, but becoming infectious and dying occur with a lag. Also, deaths are only known with a one-day lag. The SIR model provides cross-equation restrictions. We view the functional form restrictions in equations (2) and (3) as technical; we adopt those functional forms for ease of interpretation.

We estimate our model with nonlinear least squares, fit to daily data on deaths (seven-day moving average) and labor hours, using rolling eight-week estimation windows. Daily labor hours are total labor hours for production and nonsupervisory workers, fixed to the twelfth of each month (the establishment survey reference date) and interpolated to daily frequency using the daily employment data provided by Chetty et al. (2020) and, when those data are unavailable, a mobility index using Google cell phone data. Standard errors are heteroskedasticity- and autocorrelation-robust. The full estimation sample is March 15 to December 17, 2020. For additional detail on the model, refer to the online Appendix.

II. Time-Varying Estimates

Figure 1 plots our baseline estimates of κ_{1t}, the time-varying semi-elasticity of labor hours with respect to 1,000 additional daily deaths. These estimates are obtained with rolling eight-week estimation samples.[2] In the spring, the semi-elasticity is large. For example, on April 18, when a seven-day moving average of deaths reached a peak of 2,241 deaths/day, our estimate of κ_{1t} is -0.062. This implies that the endogenous response to deaths was responsible for a 13.3 percent decline in labor hours relative to February 2020. The actual shortfall in labor hours was 18.2 percent, leaving 5 percentage points of the decline due to other factors. In contrast, in the last two weeks of October and the first two weeks of November, the semi-elasticity was close to, and statistically indistinguishable from, zero, leaving factors other than the death rate to explain the 4.4 percent decline in labor hours.

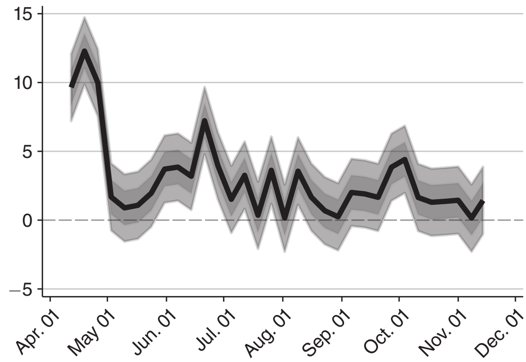

Figure 2. Estimated Elasticity of the Reproduction Number R_t with Respect to Economy-Wide Labor Hours, Estimated by Rolling System Estimation of a Behavioral SEIRD Model

Note: Rolling estimates of β_{1t} based on an eight-week window, with 67 percent and 95 percent heteroskedasticity- and autocorrelation-robust pointwise confidence bands.

Source: Authors' calculations

Figure 2 documents our estimates of the elasticity of the basic reproduction number, R_t, with respect to economic activity; that is, β_{1t} in equation (3). This elasticity is initially large, averaging 10.1 through April, then falls sharply and fluctuates more or less randomly around its mean of 2.3 from June through November.

III. Counterfactuals

We conduct two counterfactual exercises to assess the significance of our estimates.

In the first, we suppose that all the parameters in (2) and (3) remained constant from June 6 through the end of our sample. Figure 3 documents the resulting predicted and actual values for weekly deaths. Had those spring values held through the summer and fall, deaths would have

[1] The initial number of susceptibles S_0 is also an unknown free parameter. Because this evolves slowly as a fraction of N, we avoid estimating another parameter by absorbing S_0 into β_{0t}. See the online Appendix for additional discussion.

[2] As shown in the online Appendix, using a six-week window yields similar results, with larger standard errors. The local fit deteriorates substantially using a 12-week window, indicating that the time variation in the parameters is too rapid to be picked up by the longer window.

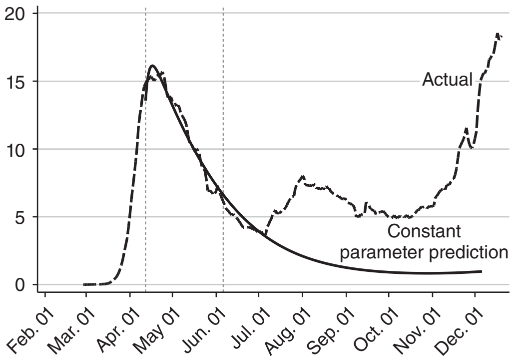

Figure 3. Weekly COVID-19 Deaths: Actual and Counterfactual Prediction without Time-Varying Parameters

Note: Vertical lines denote parameter estimation window; subsequent predicted values are model simulation using those parameters.

Source: Authors' calculations

Table 1— Decomposition of Contributions of Parameter Changes in the Early Weeks of the Summer Wave

Parameters held at spring values:	Total deaths (thousands)	Mean hours (index)
κ_{1t}	−3.4	−0.065
κ_{0t}	3.8	0.055
κ_{0t} and κ_{1t}	−0.2	−0.015
β_{0t} and β_{1t}	−30.7	−0.008
All	−30.0	0.023

Notes: The entries are the deviation of the counterfactual prediction specified in the row from the baseline prediction using the estimated time-varying parameters. The hours index is normalized to equal 1 on February 12, 2020. Each counterfactual is specified in terms of the row parameter being held constant at its April 12–June 6 ("spring") value, with the others taking on their time-varying values. Total deaths over this summer period are 46,700, and the mean value of the hours index is 0.909. Values do not add due to nonlinearity of the model.

continued their late-spring decline, with only a small seasonal uptick as winter approached. The summer and late fall waves of deaths therefore are both associated with time variation in the parameters in the behavioral SIR, consistent with the findings of Atkeson, Kopecky, and Zha (2021). In addition, under this counterfactual, economic activity would have been higher than it was in July and August because of the lower level of deaths (see the online Appendix).

Our second counterfactual decomposes deaths and economic activity during the onset of the summer wave (June 21–August 15) into contributions by the time-varying parameters. Specifically, we evaluate the effect of holding constant one or more parameters at their spring (April 12–June 6) values, allowing the remaining parameters to take on their June 21–August 15 values.

The results of this exercise are summarized in Table 1. Notably, the attenuation of the behavioral response (κ_{1t}) from the spring to the summer increased deaths very modestly, and that contribution was offset by the other shocks to hours (κ_{0t}). In contrast, the model associates 30,700 deaths with the change in the transmission parameters β_{0t} and β_{1t}. These findings are reversed for economic activity, where the diminution of κ_{1t} contributed significantly to the increase in hours over the summer, although that effect was partially offset by other shocks (κ_{0t}). Collectively, the changes to β_{0t} and β_{1t} had little effect on hours. Overall, had the spring values of all the parameters persisted, deaths would have been lower by 30,000 and hours would have been higher by 2.3 percentage points.

IV. Discussion

To be sure, this highly aggregated model misses many important features of the pandemic, such as its regional variation and its differential threat to the elderly. Moreover, this model focuses on dynamics during the pandemic, and assessing the postpandemic recovery would require incorporating more normal business cycle dynamics. Even with these caveats, the four time-varying parameters provide a coherent interpretation of the evolution of the pandemic and economic crisis.

Taken together, the time-variation in the parameters shows an initially strong reaction of economic activity to deaths and of transmission to economic activity. With the advent of protective measures—for instance, shopping using masks, working from home, and goods delivery replacing in-person purchases—the effect of economic activity on transmission fell by a factor of five and remained low through the end of our sample. The summer's diminution of the strongly protective economic response to deaths has some responsibility for the summer wave, although that surge is mainly associated with other activity that permitted the virus to spread. The near-zero value of the behavioral elasticity κ_{1t} at the end of the sample is consistent with psychological adaptation to the high level of deaths and pandemic fatigue.

Our results suggest two observations that are relevant for the next stage of the pandemic. First, given the low value of β_{1t}, exogenous actions to reduce activity (such as lock-downs) are likely to have only a limited effect on reducing contagion and spread, although they could reduce activity as a negative shock to κ_{0t}. This is consistent with a large body of evidence in favor of low-cost mechanisms for controlling the virus that simultaneously support public health and economic activity, for instance, universal mask mandates and low-cost screening test programs (see Chernozhukov, Kasahara, Schrimpf 2020 and Atkeson et al. 2020 for a discussions of mask mandates and screening tests, respectively). The US failure to control the virus has largely been a failure to embrace known, feasible technologies to mitigate the spread of the virus.

Second, the near-zero economic response (κ_{1t}) at the end of the sample suggests that even if the more contagious UK variant leads to a midwinter surge of deaths, that surge would be associated with an extended plateau in the economic recovery, not a second contraction. The end-of-sample estimate of κ_{0t}, however, is only 0.938, indicating that a large amount of slack remains regardless of the insensitivity of hours to deaths. This slack reflects adaptations to the pandemic, such as reluctance to fly and purchase high-contact in-person services, that seem likely to persist at least until the pandemic itself is defeated.

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