Forecasting the Economy During COVID-19

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The COVID-19 crisis has left economists scrambling to rejigger their forecasts. In this note, we briefly describe how forecasters have updated their outlook for the US economy, what sort of data they use in their projections, and how economists link the public health outlook to the economic outlook.

Even in normal times, forecasters have a tough job but do it well on average. For example, analysis of a large data set on forecasts—the Survey of Professional Forecasters—shows that forecasters are most accurate looking one quarter ahead, and beat simple model forecasts like no-change forecasts or autoregressive models. Over a longer time horizon, the accuracy of projections declines.

At the beginning of 2020, the Bloomberg consensus saw Q2 real GDP growing at 1.7%, and the unemployment rate at 3.6% (following convention, the quarterly growth numbers we reference are the annualized quarter-over-quarter growth rate). Before the crisis hit, the economy was cooling slowly: growth in 2018, 2019, and 2020 (expected) was 2.9%, 2.3%, and 1.7%, respectively. In a typical recession, the economy gradually adjusts to lower output and higher unemployment via financial channels. But the virus, and especially the government response to the virus, have accelerated the normal process as workers are laid off because they physically cannot work safely.

Accordingly, consensus growth estimates quickly fell, as shown in Figure 1. From March 12 to April 12, consensus Q2 growth fell 24 percentage points (PP) from 1.8% to -22%. The consensus unemployment forecast in Q2 grew from 3.6% to 12% over the same period. As forecasters downgraded Q2, they upgraded Q3—implying a "V" shaped recovery. From March 12 to April 12, Q3 estimated GDP growth grew roughly 8pp to 9.8%. News over the following month revised Q2 forecasts even lower to -33.5% and an unemployment rate exceeding 16.5%. Expected growth for the full year fell from 1.7% to -5.8%.

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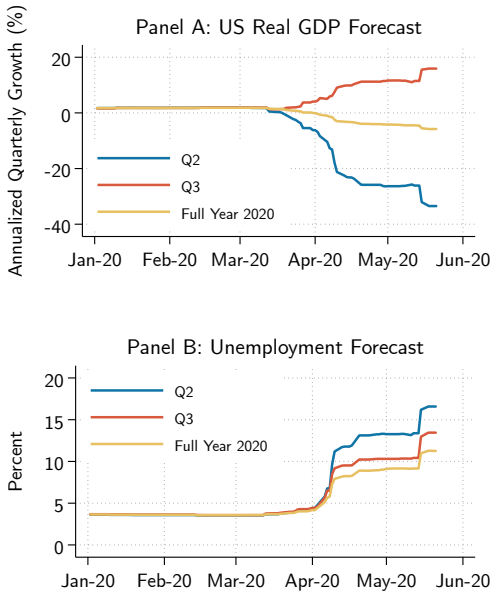
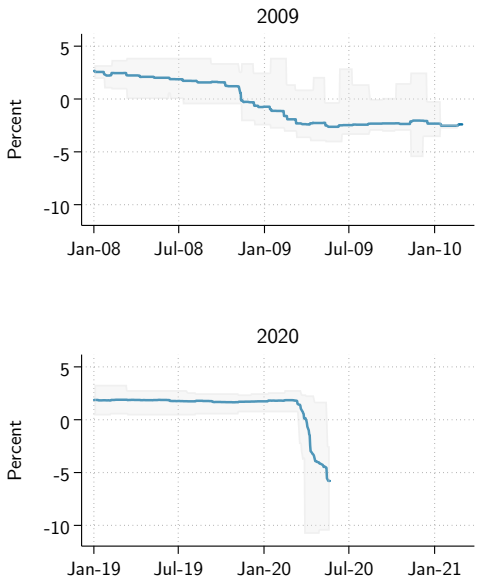
Figure 1: Consensus Forecasts



Source: Bloomberg

Figure 2: Dispersion in Forecasts



Note: Grey shading reflects range from the lowest to highest forecast.
Source: Bloomberg

Hidden in these point estimates is a tremendous amount of uncertainty, as shown in Figure 2. The spread between the low and high forecast for 2020 full year growth was 2.9pp on January 1 and rose to 13pp by May. This level of dispersion in forecasts is unprecedented. Even in the worst year (in terms of growth) of the global financial crisis, 2009, the maximum dispersion in forecasts was 7pp.

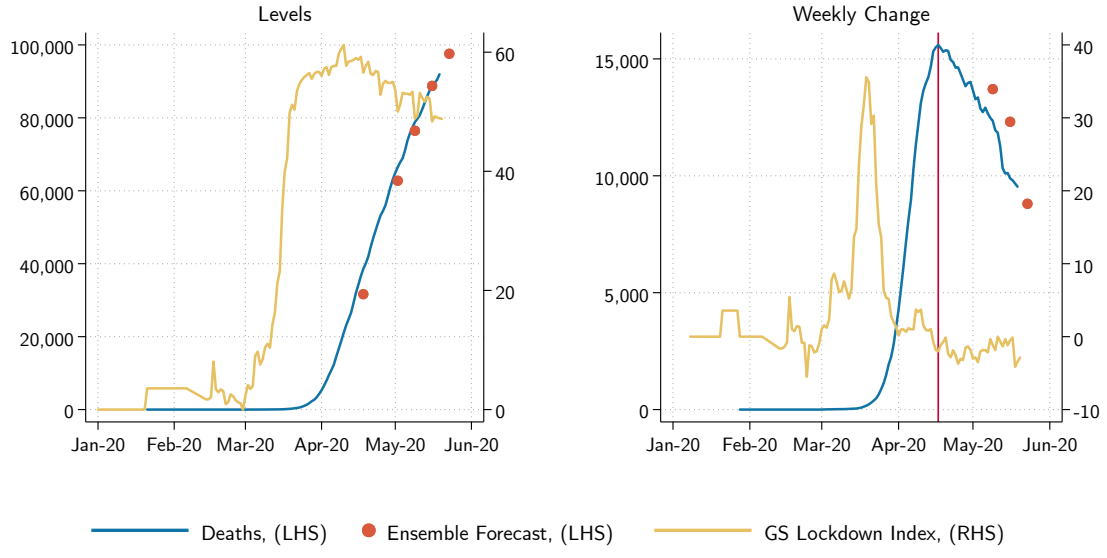
Several high-frequency data points have become particularly important in recent weeks. A non-exhaustive list of commonly used high-frequency indicators includes: Google Mobility Reports, movie attendance, electricity utility generation, Redbook same-store retail sales, initial unemployment insurance claims, fuel sales to end-users, the Rasmussen Consumer Index, American Staffing Index, raw steel production, TSA traveler numbers, bankruptcy statistics, San Francisco Fed's news sentiment, and the list goes on. Google Mobility data is particularly novel, as it provides granular location data, giving some sense of how strict lockdowns are and what share of the labor force is staying at home. The Federal Reserve Bank of New York now releases a Weekly Economic Index, which aggregates several high-frequency indicators to GDP units.

While each forecaster's process varies, many use models like the IHS Markit's Macroeconomics Advisors' MA/US model, or the Federal Reserve FRB/US model. Both models are large-scale structural econometric models and produce estimates for all major categories in the US national accounts. Reasonably, the models do not explicitly account for pandemics, nor do they expressly embed epidemiological assumptions into their forecasts in normal times.

A common approach to producing forecasts during the COVID-19 crisis involves three steps. First, the forecasters use high-frequency data to forecast granular industry-level effects—e.g., hospitals, outpatient care, hotels, food services, and car rentals. The step also involves overlaying the government's classification of "essential critical infrastructure workforce," the ability for an industry to work from home, and state-by-state lockdowns. Google Mobility data is especially useful in capacity utilization estimates.

Second, the forecaster aggregates these granular location-industry specific forecasts to produce shocks to aggregate demand components, which themselves can be fed into a model like MA/US. The forecasters also need to make assumptions about fiscal stimulus, global growth (excluding the US), and financial conditions. Often, the latter category includes assumptions about short- and long-term Treasury yields. At banks and broker/dealers—where many private-sector forecasters work—economists often take interest rate forecasts from their "interest rate strategy" team, and so there is a nontrivial effort to make

Figure 3: US Lockdown Index and COVID-19 Deaths



Source: Goldman Sachs, Oxford University's Blavatnik School of Government, Google, New York Times, COVID-19 Forecast Hub

sure the different teams' estimates are internally consistent.

Third, the forecasters plug their aggregated shocks into the model. Armed with the resultantGDP forecasts, many forecasters will use rules of thumb like Okun's Law to produce unemployment forecasts. For example, if the GDP projection implies a 10pp output gap, then unemployment would increase 5PP—but the forecaster has to make a subjective judgment about how quickly job losses will occur.

Complicating the forecasting process, official data is subject to more uncertainty now. For example, the net jobs created by births and deaths are roughly stable, and the BLS models account for this typically-flat relationship. The COVID-19 crisis breaks the validity of that assumption, and so the BLS updated its model specifically in response to the challenges of the crisis. Moreover, whether or not the BLS would impute zero employment for non-responding companies was a first-order question for forecasters. Forecasting with considerable uncertainty about the official data estimates' methodology is not new, as experienced in the aftermath of Hurricane Katrina and the October 2013 government shutdown. During the 2013 shutdown, the BLS did not release payroll employment (ultimately releasing the report two weeks later), and the Commerce Department suspended publishing construction spending and factory orders.

As the public health crisis continues and states contemplate relieving lockdown restrictions, we look into what matters for macro forecasts—is it realized deaths, lockdown, or both?

The Goldman Sachs Effective Lockdown Index measures the intensity of virus control measures. The daily lockdown index equal-weights two measures: a government policy measure and a policy effect measure which are constructed using data from Oxford University's Blavatnik School of Government dataset on government virus policy measures and data from Google on personal smartphone behavior, respectively.

In Figure 3, we plot the time series and weekly change in the lockdown index and actual deaths in the United States, which is compiled by The New York Times and begins on January 21.

The lockdown index increased rapidly in early March as markets teetered, liquidity became constrained, and the Federal Reserve announced rate cuts and other interventions. The increase in the lockdown index occurred ahead of actual deaths, but since the peak weekly increase in deaths, the weekly differences have been positively correlated: as new deaths decrease, the lockdown index has declined.

Many epidemiology models forecast COVID-19 deaths. As economists, we are not experts in assessing the best model, so we look to the COVID-19 Forecast Hub's en-

Figure 4: Forecasting Forecast Changes

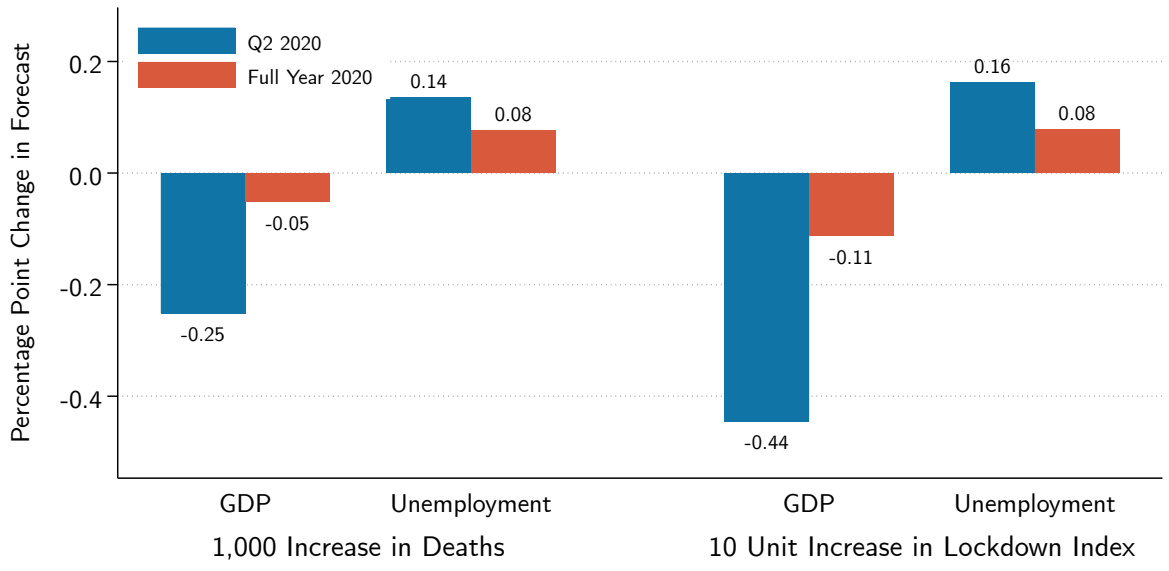
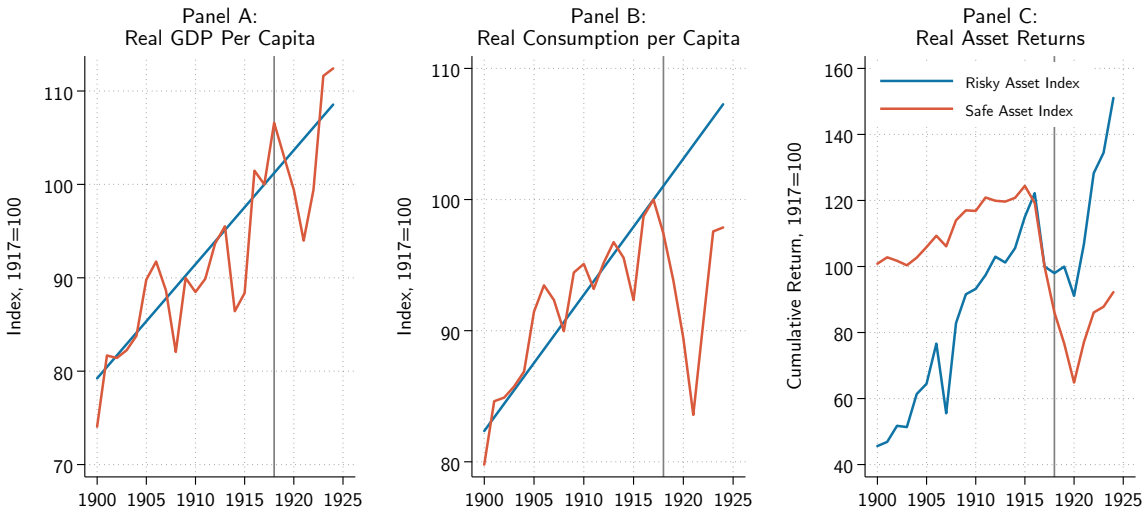


Figure 5: 1918 Spanish Flu



Note: Vertical line denotes year of Spanish Flu
Source: Jordà-Schularick-Taylor Macrohistory Database

semble forecast, which takes the average estimate across many models. This data includes forecasts for deaths 1- to 4-weeks ahead: Figure 3 shows the ensemble 1-week forecasted deaths. The forecasts are plotted by the target date, meaning that the forecast was made one week prior. The ensemble forecast appears to move closely with actual deaths both in level terms and one-week changes. If the ensemble forecast were 100% correct, the red dots would line up on the blue line exactly. Importantly, the ensemble forecast is weekly and only begins in April, but as more data comes out, market participants may look toward how forecasted deaths fluctuate with the Lockdown Index and macro forecasts.

Empirically, both deaths and the degree of lockdown are correlated with macro forecasts. We regress daily changes in consensus GDP and unemployment forecasts on daily changes in deaths, lagged by one day, and we regress daily changes in the macro forecasts on daily changes in the Lockdown Index, lagged by one day. We plot the regression coefficients in Figure 4. Broadly the results highlight that as deaths and the lockdown increased, the consensus GDP forecasts declined, and the unemployment forecasts notched higher.

The regression results coefficient says that for an increase of 1,000 new deaths is correlated with a decline in Q2 GDP consensus forecast of 0.25PP, and a 10 unit increase in the lockdown index is associated with a 0.44PP drop in the Q2 GDP forecast. Meanwhile, the Q2 unemployment forecast increases by 0.14PP when deaths increase by 1,000 and by 0.16PP for a 10 unit increase in the lockdown index.

Over a longer horizon, an increase of 1,000 new deaths is associated with a 0.05PP decline in the 2020 GDP forecast and a 0.08PP increase in 2020 unemployment rate. Unsurprisingly, the coefficients show that lockdown and deaths hurt Q2 macro variables more than growth and employment for the full year.

Of course, this back of the envelope analysis does not suggest that the key to boosting growth and lowering unemployment is simply relaxing lockdowns. Economic outcomes follow the public health crisis; lockdowns may have curbed deaths from ramping even higher. The virus will continue to hamper growth and employment until the general public has confidence in the ability to resume normal life. Thoughtful policy remains critical for both health and growth outcomes.

Pandemics are thankfully rare enough that we have limited data to study the effects of a virus on the economy. Data available from the Jordà-Schularick-Taylor Macrohistory Database give a sense of the impact of the most notorious pandemic, the 1918 Spanish Flu, on the US economy. It's not possible, of course, to isolate the effect of the pandemic on the economy as many other important

events were simultaneously occurring: namely, the end of the Great War and considerable inflation in the late 1910s.

We plot real GDP per capita and real consumption per capita relative to their pre-1918 trends in Figure 5, panels A and B. Real GDP fell to a low of 11PP below trend. Consumption dropped considerably from 1917 to 1921, amounting to a fall of about 20PP below trend. We also show the real cumulative return for safe assets, including bonds and bills, and risky assets, including housing and equities. In real terms, safe assets lost 35PP and risky assets 9PP, owing in part to high levels of inflation. It's not possible to ascribe these fluctuations to the 1918 Spanish flu alone, but the exercise provides a useful historical benchmark.

The past 60 days of economic data have been historic in the worst way. An annual growth rate of -6% means there has been, and will continue to be, tremendous human misery at levels unseen in our lifetimes. Last week, Chair Powell noted:

> John Kenneth Galbraith famously said that economic forecasting exists to make astrology look respectable. We are now experiencing a whole new level of uncertainty, as questions only the virus can answer complicate the outlook.

Consensus, however, is optimistic and forecasts a rebound in Q3 growth. Let's hope.