

Economic Uncertainty Before and During the COVID-19 Pandemic

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Abstract: We consider several economic uncertainty indicators for the US and UK before and during the COVID-19 pandemic: implied stock market volatility, newspaper-based policy uncertainty, twitter chatter about economic uncertainty, subjective uncertainty about business growth, forecaster disagreement about future GDP growth, and a model-based measure of macro uncertainty. Four results emerge. First, all indicators show huge uncertainty jumps in reaction to the pandemic and its economic fallout. Indeed, most indicators reach their highest values on record. Second, peak amplitudes differ greatly – from a 35% rise for the model-based measure of US economic uncertainty (relative to January 2020) to a 20-fold rise in forecaster disagreement about UK growth. Third, time paths also differ: Implied volatility rose rapidly from late February, peaked in mid-March, and fell back by late March as stock prices began to recover. In contrast, broader measures of uncertainty peaked later and then plateaued, as job losses mounted, highlighting differences between Wall Street and Main Street uncertainty measures. Fourth, in Cholesky-identified VAR models fit to monthly U.S. data, a COVID-size uncertainty shock foreshadows peak drops in industrial production of 12-19%.

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1. Introduction

Fed Chairman Jerome Powell aptly summarized the level of uncertainty in his May 21st speech, noting “*We are now experiencing a whole new level of uncertainty, as questions only the virus can answer complicate the outlook.*” Indeed, there is massive uncertainty about almost every aspect of the COVID-19 crisis, including the infectiousness and lethality of the virus; the time needed to develop and deploy vaccines; whether a second wave of the pandemic will emerge; the duration and effectiveness of social distancing; the near-term economic impact of the pandemic and policy responses; the speed of economic recovery as the pandemic recedes; whether “temporary” government interventions will become permanent; the extent to which pandemic-induced shifts in consumer spending patterns, business travel, and working from home will persist; and the impact on business formation and research and development.¹

In this light, we examine several measures of economic uncertainty before and during the COVID-19 pandemic. Our focus is on uncertainty measures available in near real-time or with modest delays. We adopt this focus for three reasons. First, many macro indicators become available with lags of months or quarters, which limits their usefulness in producing real-time uncertainty measures. Second, uncertainty measures have different strengths and weaknesses. For example, measures derived from models fit to standard macro data have the upside of being linked to a well-defined concept of uncertainty, but the downside of being based on the premise that past statistical relationships and their interpretation continue to hold in the wake of sudden, novel developments. In reverse, newspaper measures of uncertainty do not correspond to a precise model, but are forward looking and available on a real-time basis. Third, when a large, novel shock hits with great suddenness, it is especially vital for real-time forecasting purposes and for policy formulation to work with measures that capture the uncertainties that economic

¹ On uncertainty about key parameters in epidemiological models of Covid-19 transmission and mortality, see Atkeson (2020a), Bendavid and Bhattacharya (2020), Dewatripont et al. (2020), Fauci et al. (2020), Li et al. (2020), Linton et al. (2020), and Vogel (2020). On what key parameter values imply in standard epidemiological models and extensions that incorporate behavioral responses to the disease and various testing, social distancing, and quarantine regimes, see Anderson et al. (2020), Atkeson (2020b), Berger, Herkenhoff and Mongey (2020), Eichenbaum, Rebello and Trabant (2020), Neil Ferguson et al. (2020), and Stock (2020a). On the potential for vigorous antigen and antibody testing to shift the course of the pandemic, see Romer and Shah (2020) and Stock (2020b). On stock market effects, see Alfaro et al. (2020), Baker et al. (2020) and Toda (2020). On complexities arising from highly uneven supply-side disruptions caused by a major pandemic, see Guerrieri et al. (2020). On the post-pandemic shift to working from home, see Altig et al. (2020a). On potential medium- and long-term macroeconomic consequences, see Barrero, Bloom and Davis (2020), Barro, Ursua and Weng (2020) and Jorda, Singh and Taylor (2020).

agents actually perceive. Many of the forward-looking uncertainty measures we consider can potentially meet that test in a way that other measures cannot.

2. The Extraordinary Economic Fallout of the COVID-19 Pandemic

To appreciate the tremendous speed with which the COVID-19 economic crisis unfolded and the magnitude of the shock, consider some observations for the United States. New claims for unemployment benefits in the early part of 2020 ranged from 200,000-280,000 per week. Relative to covered employment, these figures correspond to the slowest pace of new claims in the history of the series back to 1971. Over the ensuing twelve weeks 40 million Americans filed new claims, an astonishing surge without precedent in US history.² As measured in the Current Population Survey, unemployment rose from 3.5 percent in February 2020 – its lowest rate in over 60 years – to 14.7 percent in April, the highest rate in 80 years.³ US GDP fell 12% from 2019Q4 to 2020Q2, the largest drop since the Great Depression. A similar story of sharply contracting output emerged in the UK, with GDP falling a record 20.4% in April-June after a fall of 2.2% in January-March. In sum, the speed and scale of the COVID-19 contraction dwarfs that of any previous US or UK episode in the modern era.

Another set of observations further underscores the lack of close historic parallels to the economic impact of COVID-19. Barro et al. (2020) estimate that the Spanish Flu pandemic a century ago killed about 40 million people worldwide, or about 2.1 percent of the world’s population. Worldwide deaths attributed to COVID-19 as of 18 August 2020 are about 766,000 on a global population base of 7.7 billion, yielding a global mortality rate of about 0.01 percent.⁴ Although the ultimate death toll will surely be substantially higher, the size of the COVID-19 mortality shock is likely to remain at least an order of magnitude smaller than the one associated with the Spanish Flu. Seen in this light, the economic toll of COVID-19 is anomalous.

² The unemployment claims data are available at https://oui.doleta.gov/unemploy/claims_arch.asp. The figures cited in the text are seasonally adjusted.

³ As noted in the April 2020 BLS Employment Situation Report, an unusually large number of persons classified as “employed but absent from work” during the reference week (April 12-18) for the household survey. As discussed in the FAQs at <https://www.bls.gov/cps/employment-situation-covid19-faq-april-2020.pdf>, it appears that many of the “employed but absent from work” were, in fact, on temporary layoff. Adding these to the 14.7% official unemployment rate for April 2020 yields an unemployment rate of 19.5 percent according to the BLS.

⁴ The global COVID-19 mortality figure is from www.ft.com/content/a2901ce8-5eb7-4633-b89c-cbdf5b386938, accessed 18 August 2020. Epidemiologists typically prefer excess mortality data, because they are more encompassing and less susceptible to underreporting. However, they are available for fewer countries. We use excess mortality data when discussing outcomes in the United Kingdom and the United States.

In terms of mortality, the COVID-19 pandemic is much closer to more recent influenza pandemics. The US Center for Disease Control estimates that the 1957-58 and 1968 influenza pandemics caused 116,000 and 100,000 excess deaths in the United States.⁵ Scaling by population yields excess mortality rates of 0.067 percent in 1957-58 and 0.050 percent in 1968. As of 10 July 2020, US excess mortality during the COVID-19 pandemic is $(175,700/326.69 \text{ million}) = 0.054$ percent.⁶ It was an estimated 0.52 percent during the Spanish Flu (Barro et al., 2020, Table 1). Thus, the COVID-19 impact on excess mortality in the US is similar to that of influenza pandemics in 1957-58 and 1968 and an order of magnitude smaller than that of the Spanish Flu. Yet, as Niall Ferguson (2020) underscores, the 1957-58 pandemic imparted a mild impact on aggregate economic activity. Similarly, US employment and output grew at a healthy pace in 1968, showing no visible effect of the influenza pandemic. These influenza pandemics offer a startling contrast to the enormous economic contraction triggered by COVID-19.⁷

To summarize, the economic response to the COVID-19 pandemic is unprecedented in at least two respects: First, the suddenness and enormity of the economic shock, most visibly in massive job losses and, second, the severity of the economic contraction relative to the size of the mortality shock. There is no close historic parallel to the COVID-19 contraction, which underscores the need for forward-looking measures of uncertainty. The unprecedented nature of the COVID-19 economic crisis also provides some insight into why uncertainty has skyrocketed in its wake.

3. Uncertainty Measures

We now consider several uncertainty measures, with a focus on forward-looking measures.

Stock Market Volatility: Examples include the 1-month and 24-month VIX, which quantify the option-implied volatility of returns on the S&P 500 index over their respective horizons. The 1-month VIX rose from about 15 in January 2020 to a peak daily value of 82.7 on 16 March

⁵ See www.cdc.gov/flu/pandemic-resources/1957-1958-pandemic.html and www.cdc.gov/flu/pandemic-resources/1968-pandemic.html. Glezen (1996) reports similar estimates for excess mortality in the 1957-58 and 1968 pandemics and discusses the concept of excess mortality.

⁶ Based on World Bank population data and excess mortality data at www.economist.com/graphic-detail/2020/07/15/tracking-covid-19-excess-deaths-across-countries, accessed 18 August 2020.

⁷ The main text focuses on the US experience, but COVID-19 mortality rates differ greatly among advanced countries. In the United Kingdom, one of the worst-hit countries, excess mortality during the COVID-18 pandemic (as of 23 July 2020) is 0.096 percent of the population, about ten times greater than in Germany.

before falling below 30 by early May. The second-highest daily value in the history of the 1-month VIX, which dates back to 1990, was 80.9 on 27 October 2008.

Figure 1 plots the evolution of weekly-average values for the 1-month and 24-month VIX. The two series behave similarly in 2020, although the amplitude of the peak upward fluctuation is considerably smaller for the 24-month VIX. To push further back in time, one can calculate the realized volatility of daily market returns using short look-back windows that quickly capture abrupt changes in economic circumstances. Baker, Bloom, Davis, Kost, Sammon and Viratyosin (2020) take this approach. They find five great realized return volatility episodes. Ordered by peak volatility, they are October 1987, the stock market crash of 1929, the coronavirus pandemic in March 2020, March 1933 near the trough of the Great Depression, and December 2008 during the Global Financial Crisis.

Newspaper-Based Uncertainty Measures: Examples include the Economic Policy Uncertainty Indices of Baker, Bloom and Davis (2016).⁸ The daily version of this index reflects the frequency of newspaper articles with one or more terms about “economics,” “policy” and “uncertainty” in roughly 2,000 US newspapers. It is normalized to 100 from 1985 to 2010, so values above 100 reflect higher-than-average uncertainty. Figure 2 plots weekly averages of the daily EPU, which surges from around 100 in January 2020 to over 500 in March and April 2020, reaching its the highest values on record. The monthly US EPU index based on a balanced panel of major US newspapers displays a similar pattern and also reaches its highest values on record in March, April and May 2020.⁹

Newspaper-based measures of uncertainty are forward looking in that they reflect the real-time uncertainty perceived and expressed by journalists. They stretch back to 1900 for the United States and are now available for dozens of countries at www.policyuncertainty.com. They also offer a ready ability to drill down into the sources of economic uncertainty and its movements over time, as contemporaneously perceived. For example, over 90% of newspaper articles about economic policy uncertainty in March 2020 mention “COVID,” “Coronavirus,” “pandemic” or other term related to infectious diseases.

⁸ Available at www.policyuncertainty.com. See, also, the World Uncertainty Index of Ahir, Bloom and Furceri (2019) at www.worlduncertaintyindex.com, which uses Economist Intelligence Unit reports instead of newspapers.

⁹ The monthly EPU index is available at http://www.policyuncertainty.com/us_monthly.html.

Baker, Bloom, Davis and Kost (2019) develop a newspaper-based Equity Market Volatility (EMV) tracker that closely mirrors movements in the VIX. Their index lends itself to a quantitative exploration of news developments that drive stock market volatility, again as contemporaneously perceived by journalists. Applying their approach to infectious diseases, they find that COVID-19 is the dominant topic in newspaper articles about stock market volatility since the last week in February. In comparison, Ebola, SARS, H1N1 and other infectious disease outbreaks since 1985 made only minor contributions to stock market volatility.

Twitter-Based Economic Uncertainty: To construct a twitter-based economic uncertainty index (TEU), we scrape all tweets worldwide that contain both “economic” and “uncertainty” (including variants of each) from January 2010.¹⁰ We then compute weekly EU tweet frequency, which we plot in Figure 2 alongside the weekly newspaper-based EPU index. The two series behave similarly around the COVID-19 crisis.

Subjective Uncertainty Measures Computed from Business Expectation Surveys: Examples include the US monthly panel Survey of Business Uncertainty (SBU) and the UK monthly Decision Maker Panel (DMP).¹¹ These panel surveys recruit participants by phone from databases that cover nearly all public and private companies with employees (about 7 million in the US and about 1 million in the UK, although we only recruit firms with a minimum size of 10 employees, which vastly reduces the number of firms available to survey). The SBU has around 400 respondents per month, and the DMP has around 3,000. Core survey questions elicit five-point probability distributions (mass points and associated probabilities) over each firm’s own future sales growth rates at a one-year look-ahead horizon. By calculating each firm’s subjective standard deviation about its own future growth rate forecast in a given month, and aggregating over firms in that month, we obtain an aggregate measure of subjective uncertainty about future sales growth rates.

Figure 3 plots these survey-based time-series measures of sales growth rate uncertainty for the United States and the United Kingdom. These measures show pronounced increases in uncertainty in March and April 2020, before falling back slightly in May. But all three months are well above any previous peaks in their (short) histories. See Altig et al (2020b) for evidence

¹⁰ See Baker, Bloom, Davis and Renault (2020) for details.

¹¹ At www.frbatlanta.org/research/surveys/business-uncertainty and <http://decisionmakerpanel.com/>

that firm-level growth expectations in the SBU are highly predictive of realized growth rates, and that firm-level subjective uncertainty predicts the magnitudes of future forecast errors and future forecast revisions.

Figure 4 draws on data from the UK Decision Maker Panel to depict how COVID-induced uncertainty rose rapidly in March 2020. Specifically, we exploit the large DMP sample to split the survey response periods and subdivide the monthly data. The percentage of firms reporting that COVID is “their single largest source of uncertainty” rose from about 25% at the beginning of March to almost 90% by early April, and then slowly fell back to about 50% by late July. So, COVID became the overwhelmingly dominant source of uncertainty for UK firms within a period of less than four weeks. This is particularly striking given the ongoing Brexit process in the UK, which is itself a major source of uncertainty for firms. This pattern of a rapid spike in pandemic uncertainty in March in the UK aligns well with the US-oriented evidence in Section 2 that the COVID-19 crisis unfolded with extraordinary speed.

These business expectation surveys are valuable for measuring what firms actually perceive in real time. They yield actionable data within 5 to 20 days of when the survey first goes to field. Their main downside is the substantial cost of building the sample and fielding the survey each month, and the need to accumulate data for comparisons over time. Once in place, however, these surveys are highly flexible and allow for rapid deployment of special questions that target current developments and policy issues. They also allow analysis of uncertainty by region, industry, firm size and age, and growth rates. As an illustration, appendix figures A1 and A2 report UK and US subjective uncertainty data broken down by firm size and broad sector.

Forecaster Disagreement: Figure 5 compares US and UK disagreement among professional forecasters about one-year-ahead GDP growth rate forecasts. The US data are from the Survey of Professional Forecasters (SPF),¹² while the UK data are from the Survey of External Forecasters (SEF). There is a long history of using such disagreement measures to proxy for uncertainty, and also a long history of disagreement about their suitability for that purpose. Our view is that at least for real variables like GDP growth, high levels of disagreement are reasonable proxies for high levels of economic uncertainty. To quantify disagreement, we calculate the standard-

¹² See <https://www.philadelphiafed.org/research-and-data/real-time-center/survey-of-professional-forecasters>.

deviation of GDP growth rate forecasts across forecasters. There are, on average, 41 forecasters per survey response period in the US and 23 in the UK.

As seen in Figure 5, the COVID-19 pandemic triggered historically high levels of disagreement in the growth rate forecasts. US disagreement rose from a standard deviation 0.32 percentage points in 2020Q1 to 2.74 in 2020Q2, a rise of nearly 8-fold. UK forecast disagreement rose from 0.49 percentage points to 10.1, an astounding 20-fold increase.

Model-Based Macro Uncertainty: Figure 6 plots the macro uncertainty measure of Jurado, Ludvigson and Ng (2015). They estimate their measure using a time-series statistical model that incorporates more than a hundred macroeconomic, sectoral and financial indicators.¹³ They adopt an iterative process to estimate innovations in these indicators and use them to construct an overall, or macro, indicator of the future variance (uncertainty) of these innovations. The JLN Macro Uncertainty measure reaches an all-time high in March 2020, rising by 35% over its pre-pandemic January 2020 value. This pandemic peak slightly eclipses its previous peak in 2008.

4. Comparing the Uncertainty Measures

Armed with these uncertainty measures, we turn now to three questions: How much did uncertainty rise in the wake of the COVID pandemic? When did it peak? How much, if it all, has it fallen since the peak?

Table 1 summarizes our answers: First, every uncertainty measure we consider rose sharply in the wake of the COVID-19 pandemic. Most measures reached all-time peaks. The exceptions are the 24-month VIX, which peaked during the Global Financial Crisis, and the US GDP forecast disagreement measure, which peaked in the 1970s.

Second, there is huge variation in the magnitude of the increase. Subjective uncertainty over sales growth rates at a one-year forecast horizon roughly doubles, as does the 24-month VIX. In contrast, disagreement among professional forecasters about real GDP growth over the next year rises roughly 8-fold for the United States and 20-fold for the United Kingdom. The much greater rise in forecaster-based measures of macro uncertainty, as compared to the rise in average firm-level uncertainty, reflects the nature of the COVID-19 shock. It is a huge common shock that hit

¹³ These include real output and income, employment and hours, real retail, manufacturing and trade sales, consumer spending, housing starts, inventories and inventory sales ratios, orders and unfilled orders, compensation and labor costs, capacity utilization measures, price indexes, bond and stock market indexes, and foreign exchange measures.

all firms. Normally, even in recessions, common shocks are modest in size, and firm-level uncertainty is mainly driven by idiosyncratic shocks that are largely diversified away at the aggregate level. Thus, the pre-pandemic level of background risk is much greater at the firm level than at the aggregate level.¹⁴ Against this backdrop, a big jump in a common source of uncertainty triggers a larger percentage increase in macro uncertainty.

The 1-month VIX, the newspaper-based EPU index, and the Twitter EU index also show large upward spikes (in percentage terms) in the wake of the COVID-19 shock. The 1-month VIX focuses on the near term by construction, and the text-based measures are also likely to give more attention to near-term sources of uncertainty rather than distant-future uncertainty. In addition, the text-based measures reflect a mix of macro and micro uncertainty, probably with a larger weight on the former.

Third, the time profiles of uncertainty responses to the COVID-19 shock differ across the various measures. Figure 7 offers a close-up look at the recent behavior of several uncertainty measures that we can track at sub-monthly intervals. It includes a Likert-based measure for the UK derived from responses to the following DMP question: “How would you rate the overall level of uncertainty facing your business at the moment?” Response options are “Very high – very hard to forecast future sales,” “High – hard to forecast future sales,” “Medium – future sales can be approximately forecasted,” “Low – future sales can be accurately forecasted,” and “Very low – future sales can be very accurately forecasted.” For this measure, we display the percentage of firms that report high or very high uncertainty.

Figure 7 shows that the stock market volatility measures peak in mid-March and then fall back to close to their pre-COVID levels by August. In contrast, the real-side uncertainty measures peak later – or continue to remain extremely high through late June in the case of subjective uncertainty and through late July for economic policy uncertainty¹⁵. This contrast highlights the Wall Street/Main Street distinction that is also apparent in first-moment outcomes. The S&P 500 index bottomed out on 23 March 2020, having dropped 34 percent from its level

¹⁴ The smaller percentage rise in subjective uncertainty about firm-level growth rates in the United Kingdom, as compared to the United States, also makes sense. U.K. firms were already contending with Brexit-related uncertainty before the pandemic struck.

¹⁵ This pattern is broadly consistent with the Covid-related risk measure extracted from quarterly earnings conference calls in Hassan et al. (2020)

on 19 February. Since then, the market has risen sharply, recovering three-quarters of its losses by the end of May and all of its losses and reaching new all-time highs by mid-August.

5. Vector Autoregressive Models of the Impact of Uncertainty

We now fit vector autoregressive models (VARs) to estimate the relationship of output and employment to uncertainty in US data. Drawing causal inferences from VARs is challenging – in part because policy, and policy uncertainty, can respond to current and anticipated future economic conditions. Despite the challenges, VARs are useful for characterizing dynamic relationships. At a minimum, they let us gauge whether uncertainty innovations foreshadow weaker macroeconomic performance conditional on standard macro and policy variables.

Given the rapid shifts in economic activity as the COVID-19 pandemic unfolded, we estimate our VAR systems on monthly data and use industrial production as our output measure (since GDP data are quarterly). We consider, in turn, four alternative uncertainty measures for which long time series are available. We adopt a Cholesky decomposition with the following ordering: an uncertainty measure, the log of the S&P 500 index, the federal funds rate, log manufacturing employment, and log industrial production. This specification follows Baker, Bloom, and Davis (2016). Our baseline VAR specification includes three lags of all variables. See the appendix for additional details about the VAR specification and our sources of data.

Figure 8 displays (in red) the model-implied responses of industrial production to a COVID-size uncertainty innovation, which we equate to the uncertainty rise from January 2020 to its COVID-19 peak. For comparison we include (in blue) the model-implied responses to a 2008/09-size increase in uncertainty, which we equate to the difference between the January 2020 value and the peak uncertainty value in 2008/09. As seen in the upper right panel, a COVID-size innovation in the model-based uncertainty measure of JLN foreshadows an estimated 12% fall in industrial production. This response magnitude is very similar to the drop implied by a 2008/09-size uncertainty shock, because the two episodes involve very similar increases in this uncertainty measure. In the lower left panel, a COVID-size innovation in the forecaster disagreement measure of uncertainty foreshadows an estimated 19% fall in industrial production. This response magnitude is about four times as large as the drop implied by a 2008/09-size uncertainty shock based on forecaster disagreement. Using the VIX as the uncertainty measure yields results similar to those of the JLN measure. Using economic policy

uncertainty yields results more similar to the disagreement measure, but with an earlier peak response and a faster bounce back.

All of these VAR specifications predict a very sharp, but rather short-lived reduction in industrial production in reaction to the COVID uncertainty shock. The speed, size and rapid bounce back of industrial production predicted by the VARs is broadly in line with actual experience. US industrial production fell 17% between February and April 2020 and then recovered half its losses by July. This dynamic response path is most similar to the one shown for economic policy uncertainty in the lower right panel of Figure 8.

The appendix contains three additional sets of VAR results. First, employment responses to uncertainty shocks are similar to those for industrial production, but somewhat smaller. Second, when we fit the VAR models to a sample that ends in December 2019, we obtain smaller peak response magnitudes for industrial production, except for the VIX measure. Ending the sample in 2019 has little impact on the shape of the impulse response functions. Third, when we reverse the ordering in the VAR systems, placing the uncertainty measure last in the Cholesky ordering, we find very similar results to the ones displayed in Figure 8.

6. Concluding Remarks

We have examined a variety of economic uncertainty measures. Four results emerge. First, all measures show huge uncertainty jumps in reaction to the pandemic and its economic fallout. Indeed, most indicators reach their highest values on record. Second, peak amplitudes differ greatly. For example, two-year implied volatility on the S&P 500 stock market index and subjective uncertainty about UK sales growth rates rose by around 100% (relative to January 2020), while forecaster disagreement about UK GDP growth rates rose 20-fold. Third, time paths also differ: Implied stock market volatility rose rapidly from late February, peaked in mid-March, and fell back by late March as stock prices partly recovered. In contrast, broader measures peaked later, as job losses continued to mount. Broader measures plateaued or continued rising after March. Fourth, in Cholesky-identified VAR models fit to monthly U.S. data, we find that a COVID-size uncertainty shock foreshadows peak drops in US industrial production of 12-19%, depending on the uncertainty measures used. All VAR specifications we consider imply abrupt, short-lived contractions in industrial production and a rapid bounce back, in line with US experience through July 2020.

We also marshalled evidence that the COVID-19 pandemic and its economic fallout lack close historic parallels in at least two respects: First, the suddenness and enormity of the massive job losses and, second, the severity of the economic contraction relative to the size of the mortality shock. The unprecedented scale and nature of the COVID-19 crisis helps explain why it has generated such an extraordinary surge in economic uncertainty.

It remains to be seen which uncertainty measures will prove most useful in explaining economic developments during and after the COVID-19 pandemic. Our prior is that several, and perhaps all, of these measures will prove useful, because they capture different aspects of economic uncertainty. For example, the subjective uncertainty measures are particularly apt for theories that stress the role of firm-level risks in economic fluctuations (e.g., Christiano et al., 2014). The VIX measures are obviously more apt for theories that link asset-pricing behavior to economic fluctuations. The EPU measures are highly relevant for theories that link asset-pricing to political decision-making in reaction to macroeconomic developments (e.g., Pastor and Veronesi, 2012). The newspaper-based and Twitter-based measures are perhaps more closely aligned with the perceptions of households and salience of news. All of the uncertainty measures we consider are potentially useful in testing and implementing theories about investment and consumption under uncertainty. Indeed, many of them have been used to that end in previous studies.¹⁶

Finally, we should point out that ongoing high levels of uncertainty do not bode well for a full and rapid economic recovery. Elevated uncertainty generally makes firms and consumers cautious, retarding investment, hiring and expenditures on consumer durables. See, for example, Bernanke (1983), Dixit and Pindyck (1994), Abel and Eberly (1996) and Bertola, Guiso and Pistaferri (2005). Given the scale of recent job losses and the collapse in investment, a strong and rapid recovery would require a huge surge in new activity, which sustained high levels of uncertainty (unprecedented in recent history) will discourage.

¹⁶ See Bloom (2014) and Baker et al. (2016) for references.

References

- Abel, Andrew and Janice Eberly, 1996. "Optimal investment with costly reversibility," *Review of Economic Studies*, 63, no. 4, 581–593.
- Ahir, Hites, Nicholas Bloom and Davide Furceri, 2019. "The World Uncertainty Index," Stanford mimeo.
- Alfaro, Laura, Anusha Chari, Andrew Greenland and Peter K. Shott, 2020. "Aggregate and Firm-Level Stock Returns during Pandemics, in Real Time," working paper, 2 April.
- Altig, David, Jose Maria Barrero, Nick Bloom, Steven J. Davis, Brent Meyer, Emil Mihaylov and Nick Parker, 2020b. "Firms Expect Working from Home to Triple," Technical Report, Federal Reserve Bank of Atlanta, 28 May.
- Altig, David, Jose Maria Barrero, Nick Bloom, Steven J. Davis, Brent Meyer and Nick Parker, 2020c. "Surveying Business Uncertainty" NBER Working Paper 25956. Revised, March 2020. Forthcoming, *Journal of Econometrics*.
- Anderson, Roy M., Hans Heesterbeek, Don Klinkenberg, and T. Dierdre Hollingsworth, 2020. "How will country-based mitigation measures influence the course of the covid-19 epidemic?" *The Lancet*, 395, no. 10228 (March).
- Atkeson, Andrew, 2020a. "How Deadly Is Covid-19? Understanding the Difficulties with Estimation of Fatality Rate," working paper, 31 March 2020.
- Atkeson, Andrew, 2020b. "What Will Be the Economic Impact of COVID-19 in the US? Rough Estimates of Disease Scenarios," NBER Working Paper 26867, March.
- Baker, Scott, Nicholas Bloom and Steven J. Davis, 2016. "Measuring Economic Policy Uncertainty," *Quarterly Journal of Economics*, November.
- Baker, Scott Baker, Nicholas Bloom, Steven J. Davis and Kyle Kost, 2019. "Policy News and Equity Market Volatility," NBER working paper 25720.
- Baker, Scott R., Nicholas Bloom, Steven J. Davis, Kyle Kost, Marco Sammon, and Tasaneeya Viratyosin, 2020. "The Unprecedented Stock Market Reaction to COVID-19." Forthcoming, *Review of Asset Pricing Studies*.
- Baker, Scott Baker, Nicholas Bloom, Steven J. Davis and Thomas Renault, 2020. "Economic Uncertainty Measures Derived from Twitter," working paper, June.
- Baker, Scott, Nicholas Bloom, Steven J. Davis and Stephen Terry, 2020. "COVID-Induced Economic Uncertainty," NBER Working Paper No. 26983.
- Barrero, Jose, Nicholas Bloom and Steven J. Davis, 2020. "COVID-19 Is Also a Reallocation Shock," forthcoming, *Brookings Papers on Economic Activity*.
- Barrero, Jose, Nicholas Bloom and Ian Wright, 2017. "Short and long run uncertainty," NBER Working Paper 23676.
- Barro, Robert J., Jose F. Ursua and Joanna Weng, 2020. "The Coronavirus and the Great Influenza Pandemic: Lessons from the 'Spanish Flu' for the Coronavirus's Potential Effects on Mortality and Economic Activity," NBER Working Paper 26866, revised April 2020.
- Bendavid, Eran and Jay Bhattacharya, 2020. "Is Coronavirus as Deadly as They Say?" *Wall Street Journal*, 24 March.
- Bernanke, Ben, 1983. "Irreversibility, uncertainty, and cyclical investment," *Quarterly Journal of Economics*, 98, no. 1, 85–106.
- Bertola, Giuseppe, Luigi Guiso, and Luigi Pistaferri, 2005. "Uncertainty and consumer durables adjustment," *Review of Economic Studies*, 72, no. 4, 973–1007.

- Bloom, Nicholas “Fluctuations in Uncertainty, 2014. *Journal of Economic Perspectives*, Spring 2014.
- Bloom, Nicholas, Scarlet Chen, Phil Bunn, Paul Mizen, Pawel Smietanka and Greg Thwaites (2019), “The impact of Brexit on UK firms,” NBER Working Paper 26218, September.
- Christiano, Lawrence J., Roberto Motto and Massimo Rostagno, 2014. “Risk Shocks,” *American Economic Review*, 104, no. 1, 27-65.
- Correia, Sergio, Stephen Luck and Emil Verner, 2020. “Pandemics Depress the Economy, Public Health Interventions Do Not: Evidence from the 1918 Flu,” working paper, 10 April.
- Croushore, Dean and Tom Stark, 2019. “Fifty Years of the Survey of Professional Forecasters,” *Economic Insights*, Federal Reserve Bank of Philadelphia.
- Dewatripont, Mathias, Michel Goldman, Eric Muraille and Jean-Philippe Platteau, 2020. “Rapidly Identifying Workers Who Are Immune to COVID-19 and Virus-Free Is a Priority for Restarting the Economy,” *VOX CEPR Policy Portal*, 23 March.
- Dew-Becker, Ian and Stefano Giglio, 2020. “Cross-sectional uncertainty and the business cycle: Evidence from 40 years of options data,” working paper.
- Dixit, Avinash and Robert Pindyck (1994). *Investment under uncertainty*. Princeton: Princeton University Press.
- Eichenbaum, Martin S., Sergio Rebelo and Mathias Trabandt, 2020. “The Macroeconomics of Epidemics,” NBER Working Paper 26882, March.
- Fauci, Anthony S., H. Clifford Lane and Robert R. Redfield, 2020. “Covid-19 – Navigating the Uncharted,” *New England Journal of Medicine*, 26 March. DOI: 10.1056/NEJMe2002387.
- Ferguson, Neil et al., 2020. “Impact of Non-Pharmaceutical Interventions to Reduce Covid-19 Mortality and Healthcare Demand,” Imperial College COVID-19 Response Team.
- Ferguson, Niall, 2020. “1918, 1957, 2020: Big Pandemics and their Economic, Social and Political Consequences,” working paper, 20 May.
- Glezen, W. Paul, 1996. “Emerging Infections: Pandemic Influenza,” *Epidemiologic Review*, 18, no. 1, 64-76.
- Guerreri, Veronica, Guido Lorenzoni, Ludwig Straub and Ivan Werning, 2020. “Macroeconomic Implications of COVID-19: Can Negative Supply Shocks Cause Demand Shortages?” working paper, 2 April.
- Hamilton, James, 2018. “Why You Should Never Use the Hodrick-Prescott Filter,” *The Review of Economic and Statistics*, Vol. 100, Issue 5 (December).
- Hassan, Tarek A., Laurence van Lent, Stephan Hollander and Ahmed Tahou, 2020, “Firm-Level Exposure to Epidemic Diseases: Covid-19, SARS, and H1N1,” mimeo.
- Jorda, Ocar, Sanjay R. Singh and Alan M. Taylor, 2020. “Longer-Run Economic Consequences of Pandemics,” *Covid Economics: Vetted and Real-Time Papers*, 1, 3 April.
- Jurado, Kyle, Sydney Ludvigson and Serena Ng, 2015. “Measuring Uncertainty,” *American Economic Review*, 105, no. 3 (March).
- Leduc, Sylvain and Zheng Liu, 2020. “The Uncertainty Channel of the Coronavirus,” *Economic Letters*, Federal Reserve Bank of San Francisco, 30 March.
- Li, Ruiyun, Sen Pei, Bin Chen, Yimeng Song, Tao Zhang, Wan Yang and Jeffrey Shaman, 2020. “Substantial Undocumented Infection Facilitates the Rapid Dissemination of Novel Coronavirus (SARS-CoV2),” *Science*, 16 March. DOI: 10.1126/science.abb3221.

- Linton, N.M. et al., 2020. "Incubation period and other epidemiological characteristics of 2019 novel Coronavirus infections with right truncation: A statistical analysis of publicly available case data," *Journal of Clinical Medicine* 9, no. 2 (17 February).
- Pastor, Lubos and Pietro Veronesi, 2012. "Uncertainty about Government Policy and Stock Prices," *Journal of Finance*, 67, no. 4, 1219-1264.
- Romer, Paul and Rajiv Shah, 2020. "Testing Is Our Way Out," *Wall Street Journal*, 3 April.
- Stock, James H., 2020a. "Data Gaps and the Policy Response to the Novel Coronavirus," NBER Working Paper 26902, March,
- Stock, James H., 2020b. "Random Testing Is Urgently Needed," 23 March.
- Toda, Alexis Akira, 2020. "Susceptible-Infected-Recovered (SIR) Dynamics of Covid-19 and Economic Impact," *Covid Economics: Vetted and Real-Time Papers*, 1, 3 April.
- Vogel, Gretchen, 2020. "New blood tests for antibodies could show true scale of coronavirus pandemic," *Science*, 19 March.

Table 1: Measures of Uncertainty for the COVID-19 Crisis

Measure	Value in January 2020	% Jump Jan 2020 to Peak	Date of COVID-19 Peak Value	Source
VIX 1-Month implied volatility, US	13.3	497	March 16	www.cboe.com/vix
VIX 24-Month implied volatility, US	16.2	108	March 18	Dew-Becker and Giglio (2020)
News Economic Policy Uncertainty, US	110.1	683	May 26	www.economicuncertainty.com
Twitter Economic Uncertainty , US	139.8	594	April 22-28	Baker, Bloom, Davis and Renault (2020)
Firm Subjective Sales Uncertainty, US	2.7	154	April 2020	www.frbatlanta.org/research/surveys/business-uncertainty
Firm Subjective Sales Uncertainty, UK	4.3	91	April 2020	www.decisionmakerpanel.com
Macro Forecaster disagreement, US	0.3	755	2020q2	www.philadelphiafed.org/research-and-data/real-time-center/survey-of-professional-forecasters/data-files/rgdp
Macro Forecaster disagreement, UK	0.5	1960	2020q2	www.bankofengland.co.uk/report/2020/monetary-policy-report-financial-stability-report-may-2020
Model-Based Macro Uncertainty	0.8	36	March 2020	https://www.sydneyludvigson.com/macro-and-financial-uncertainty-indexes

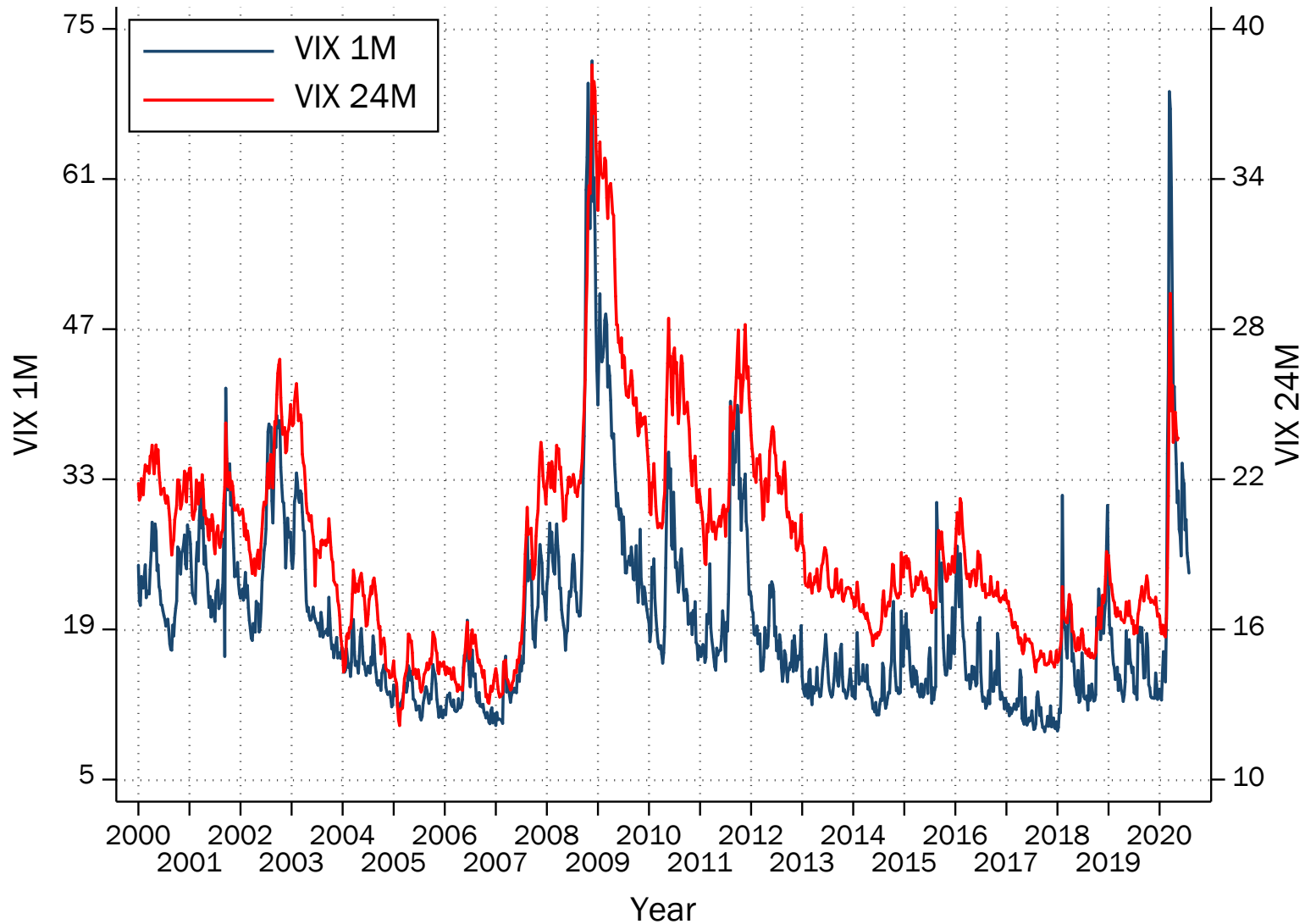
Notes: The VIX is the implied volatility (over the next month and over the next 24 months) on the S&P500 index from the Chicago Board of Options Exchange. Economic Policy Uncertainty index values constructed from the daily data as described in Baker, Bloom and Davis (2016). Subjective sales growth uncertainty is the activity-weighted average of the standard deviation of each firm’s subjective forecast distribution over its own future sales growth rate from the current quarter to four quarters hence. See Altig et al., 2020b). US data are from the Survey of Business Uncertainty, UK data are from the Decision Maker Panel Survey. Forecast disagreement is measured as the standard deviation across forecasters of one-year-ahead annual real GDP growth rate forecasts. US data are from the Survey of Professional Forecasters conducted by the Philadelphia Fed. UK data are from the Survey of External Forecasters conducted by the Bank of England. Model-Based Macro Uncertainty constructed from hundreds of time series, as described in Jurado, Ludvigson and Ng (2015).

Appendix

To assess the impact of uncertainty shocks on real economic outcomes, we fit VARs to monthly US data and adopt a Cholesky ordering as follows: uncertainty measure; log(S&P500 stock market index, as measured by the closing value on the last day of the previous month); the effective Federal Funds Rate; log(manufacturing employment), seasonally adjusted; and log(industrial production), seasonally adjusted. The ordering and specification follow Baker, Bloom, and Davis (2016). We detrend all variables using the method of Hamilton (2018), with $p=36$ and $h=12$.

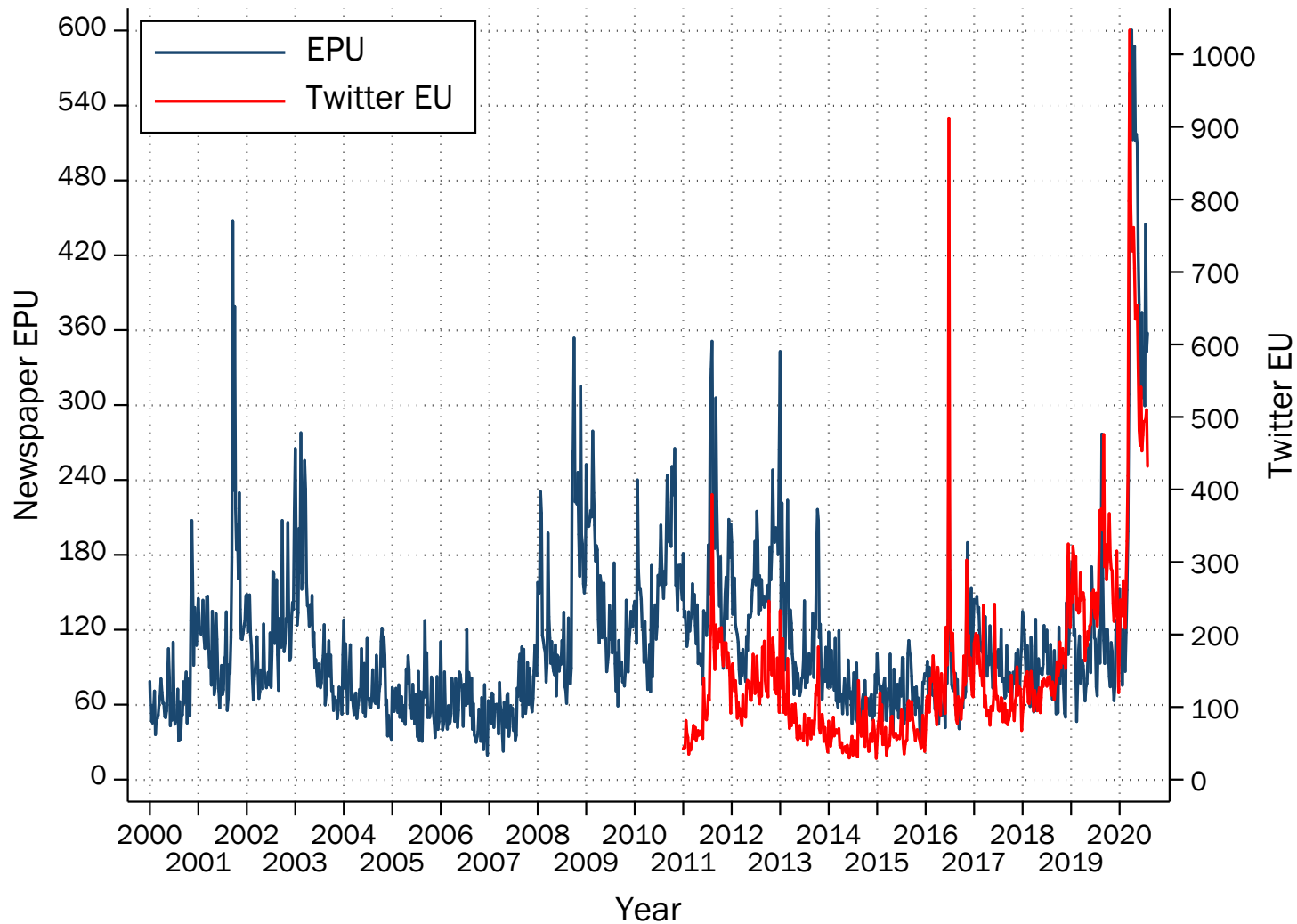
We use four uncertainty measures: implied stock market volatility, as measured by the one-month VIX (October 1966 to June 2020); the model-based macro uncertainty measure of Jurado, Ludvigson and Ng (October 1966 to April 2020); disagreement about US GDP growth rates at a one-year forecast horizon in the Philly Fed's Survey of Professional Forecasters (August 1974 to May 2020); and the Baker-Bloom-Davis newspaper-based measure of economic policy uncertainty (April 1989 to Jun 2020). We linearly interpolate the once-per-quarter forecast disagreement values to create a series at monthly frequency.

Figure 1: VIX, Implied Stock Returns Volatility, Weekly Since 2000



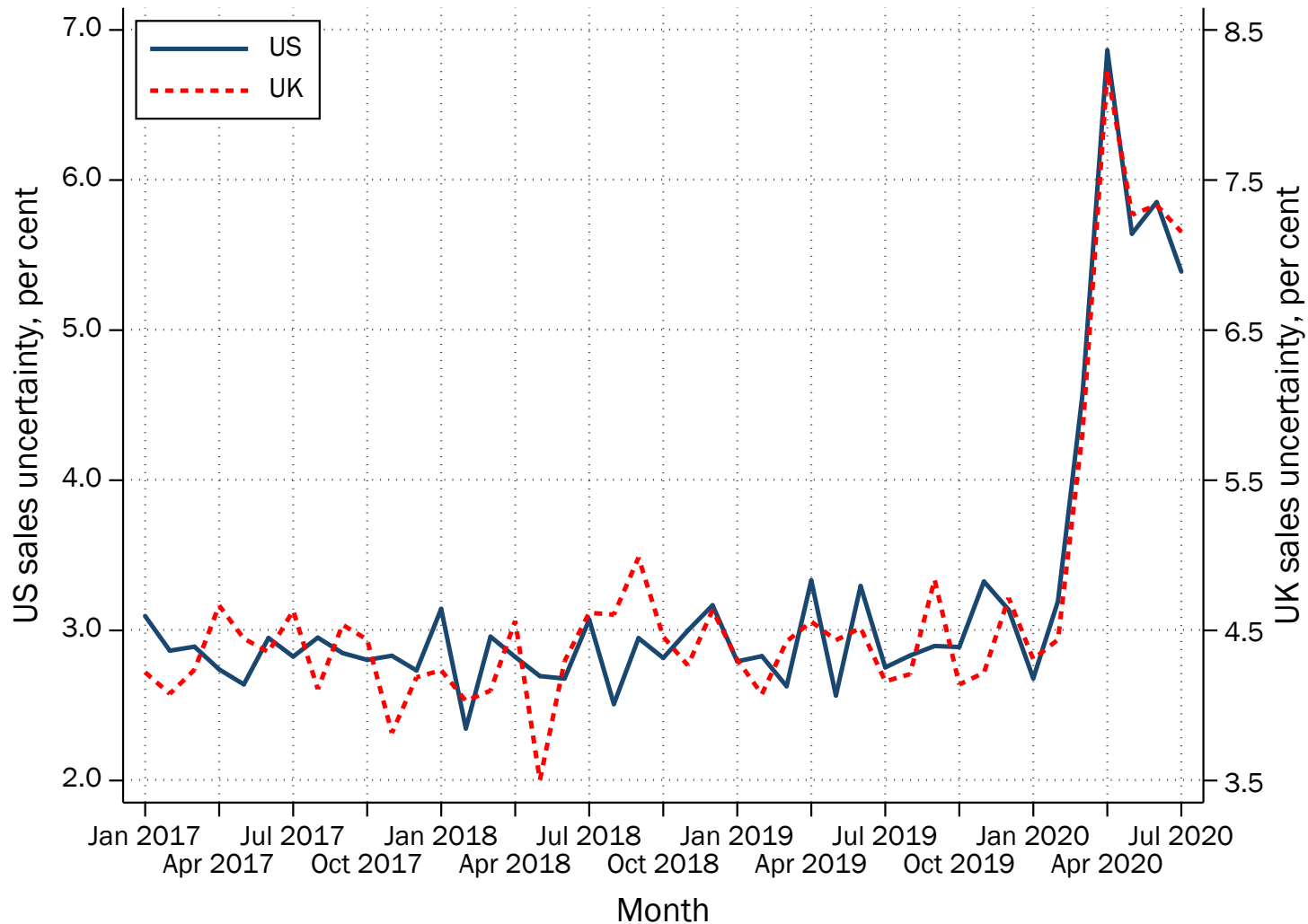
Notes: Weekly implied volatility over the next month on the S&P500 index from the Chicago Board of Options Exchange, expressed in annualized units. We plot data from 3 January 2000 to 4 August 2020 (18 May 2020 for VIX 24M). Values downloaded from <https://fred.stlouisfed.org/series/VIXCLS>. Weekly implied volatility over the next 24 months downloaded from Wharton Research Data Services. Latest data kindly provided by Ian L. Dew-Backer.

Figure 2: U.S. Economic Policy Uncertainty Index and Twitter Economic Uncertainty Index, Weekly Since 2000



Notes: Weekly values for EPU and Twitter EU using data downloaded from www.policyuncertainty.com/. See Baker, Bloom and Davis (2016) and Baker, Bloom, Davis and Renault (2020) for details of index construction. We plot data from 1 January 2000 to 4 August 2020 (2 August for Twitter EU).

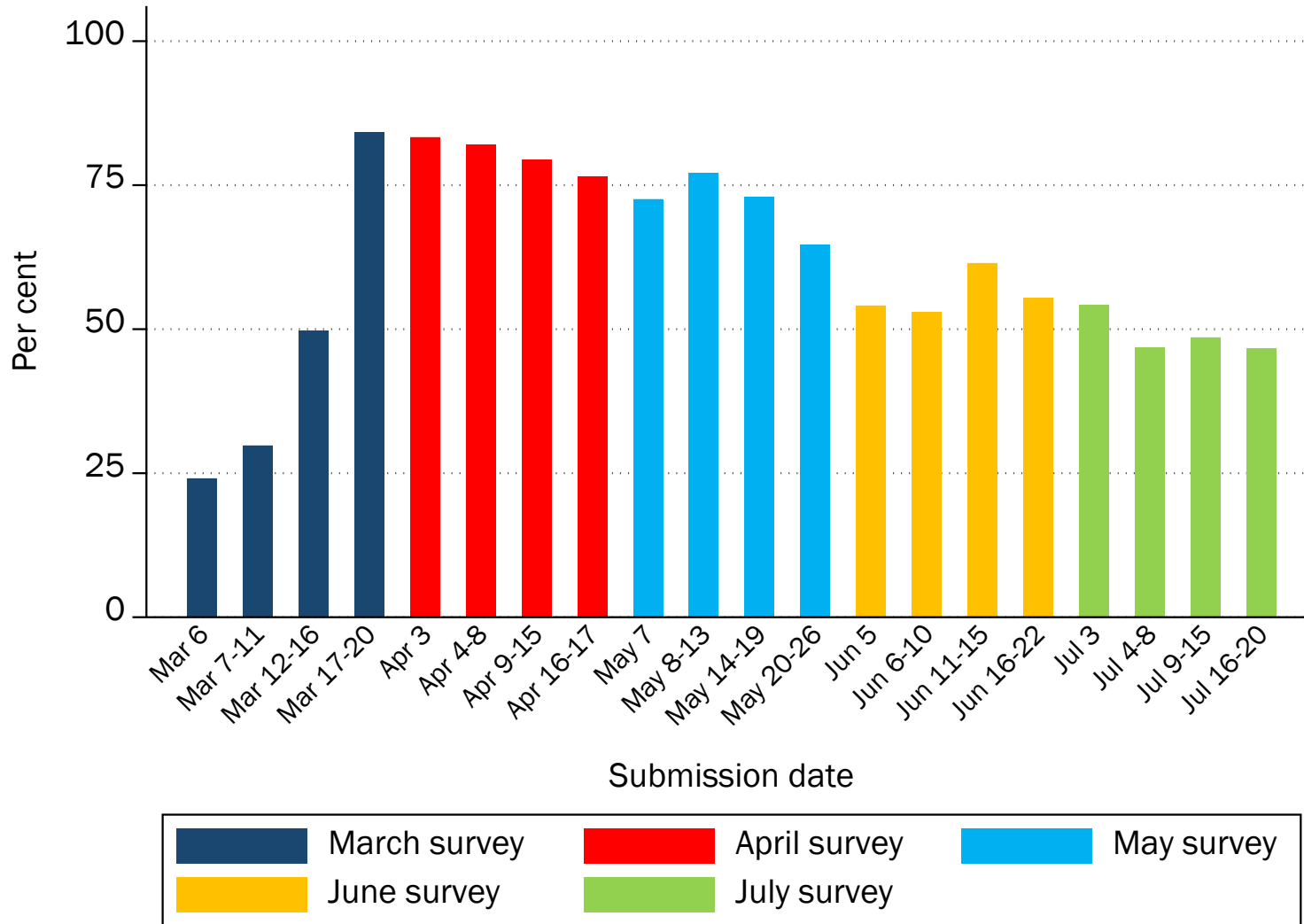
Figure 3: Firm-Level Subjective Sales Uncertainty, Monthly from 2017



Notes: Subjective uncertainty about the growth rate of sales at a four-quarter look-ahead horizon. US data form the Survey of Business Uncertainty at www.frbatlanta.org/research/surveys/business-uncertainty (Altig et al., 2020c). UK data from the Decision Maker Panel Survey at www.decisionmakerpanel.com (Bloom et al., 2019).

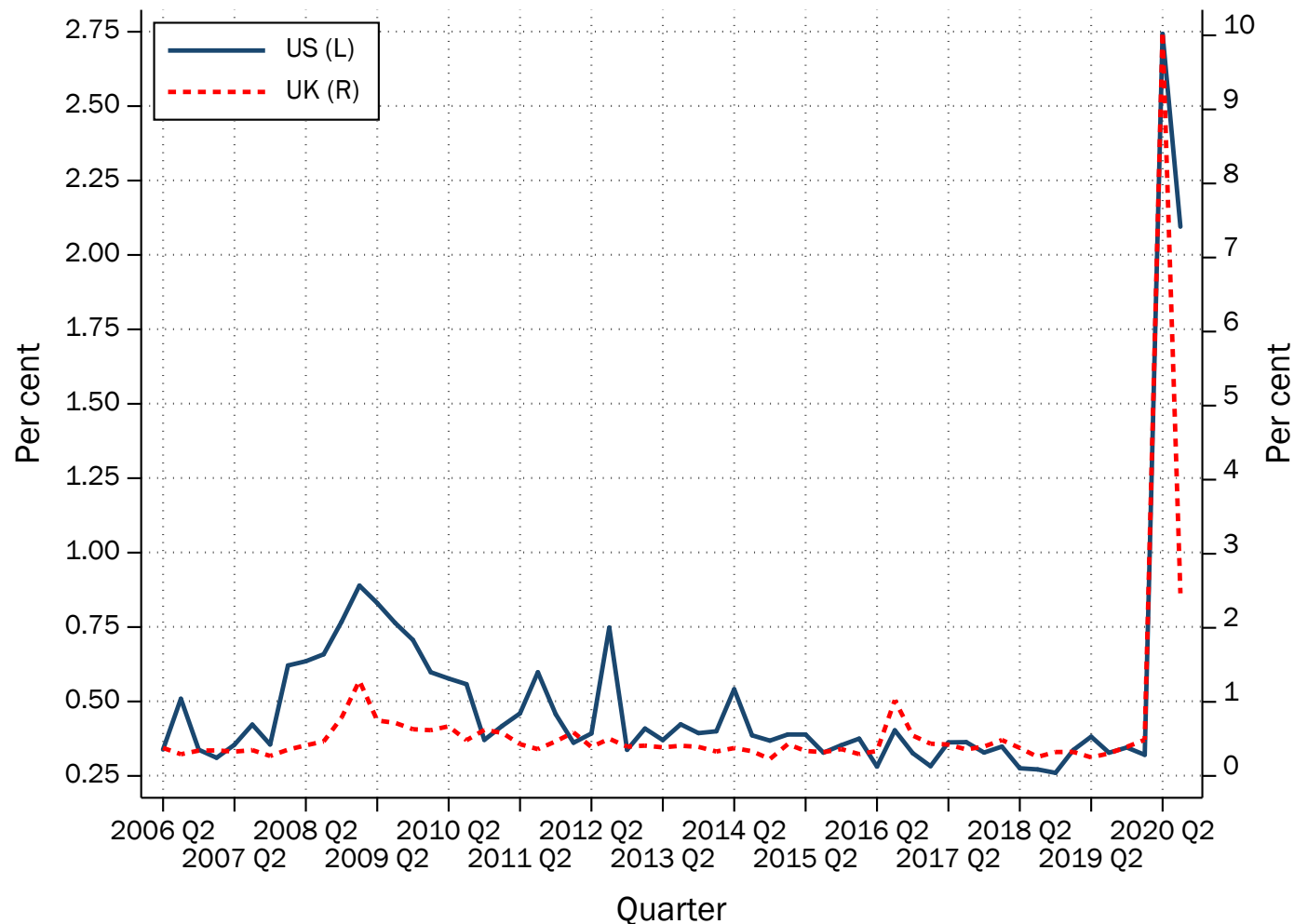
Figure 4: COVID-Induced Uncertainty Rose Rapidly in March 2020

% firms reporting Covid-19 as their top source of uncertainty



Notes: Decision Maker Panel Survey (www.decisionmakerpanel.com) conducted by the Bank of England, Nottingham University and Stanford University and described in Bloom et al. (2019). 21

Figure 5: Cross-sectional dispersion of GDP growth forecasts



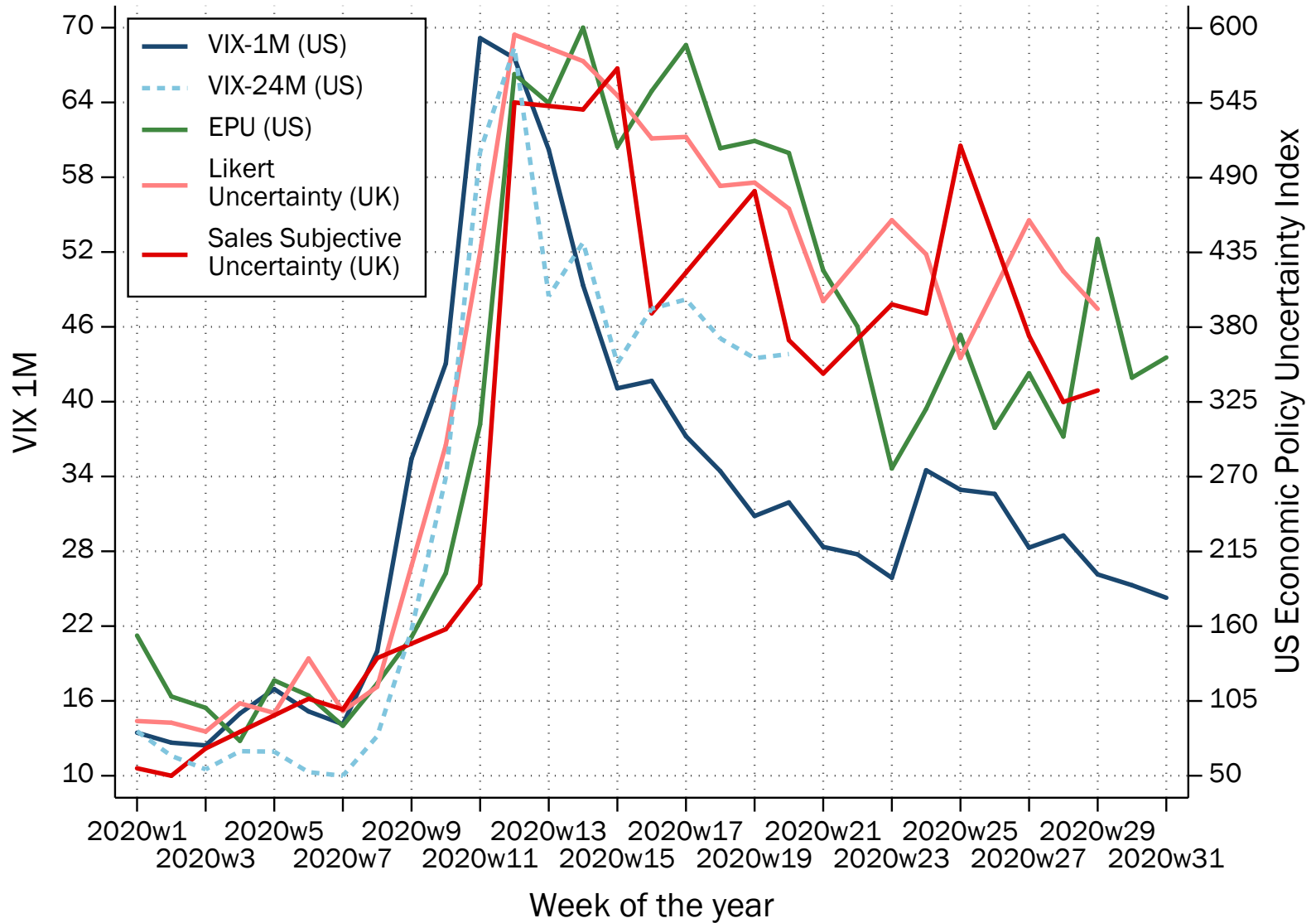
Notes: Chart shows standard deviation of one-year-ahead annual real GDP growth forecasts. US data are from the Survey of Professional Forecasters conducted by the Philadelphia Fed (www.philadelphiafed.org/research-and-data/real-time-center/survey-of-professional-forecasters). The deadline for submitting responses to the SPF survey is usually in the first half of February, May, August, and November (see www.philadelphiafed.org/media/research-and-data/real-time-center/survey-of-professional-forecasters/spf-release-dates.txt). The submission deadline for the latest survey was 12 May 2020. UK data are from the Survey of External Forecasters conducted by the Bank of England (www.bankofengland.co.uk/monetary-policy-report/2020/january-2020/other-forecasters-expectations). The SEF is in the field for two weeks one month ahead of the Bank of England's publication of the Monetary Policy Report. This is usually the second half of January, April, July, and October. The latest SEF survey ended on 24 April 2020.

Figure 6: Model-based macro uncertainty



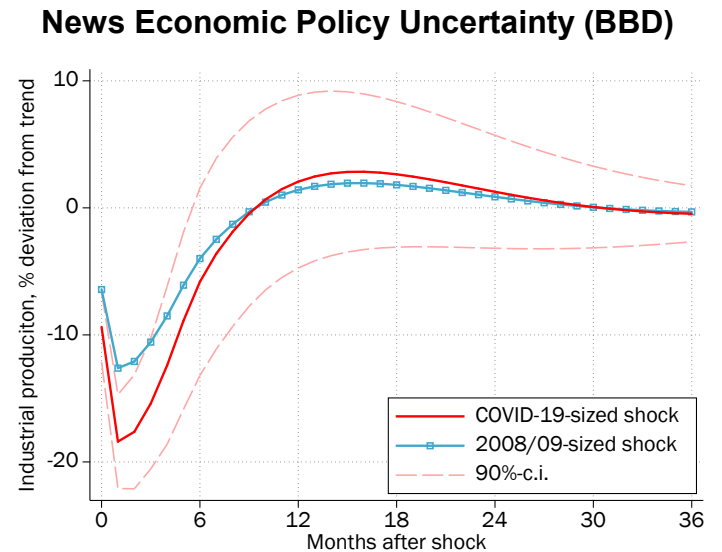
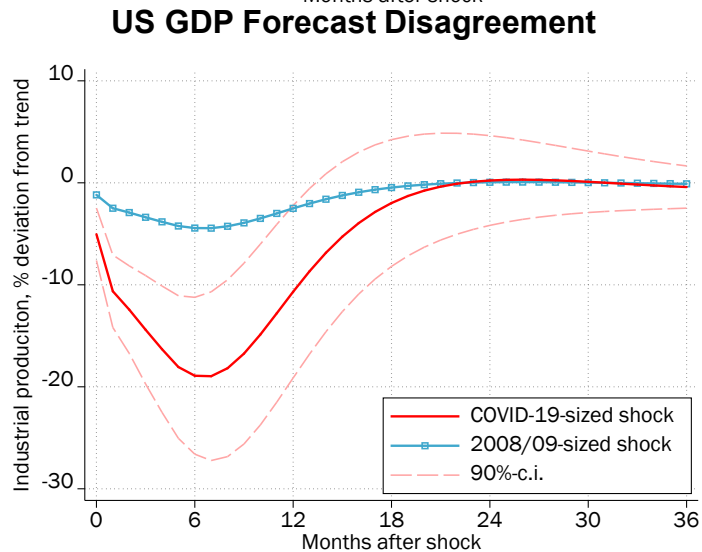
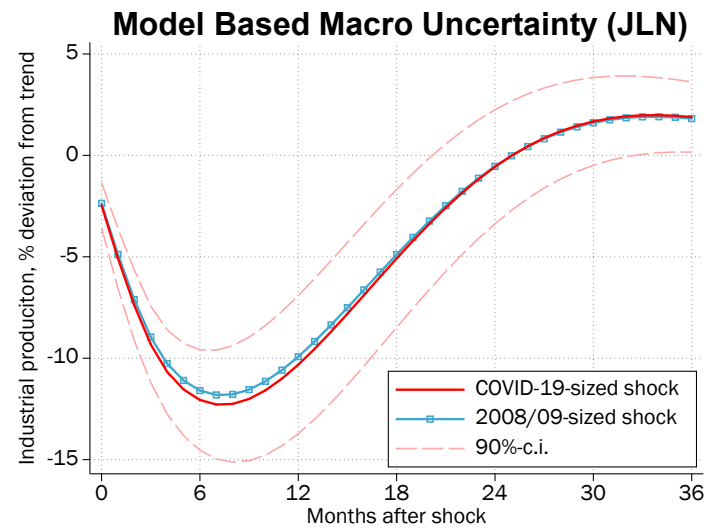
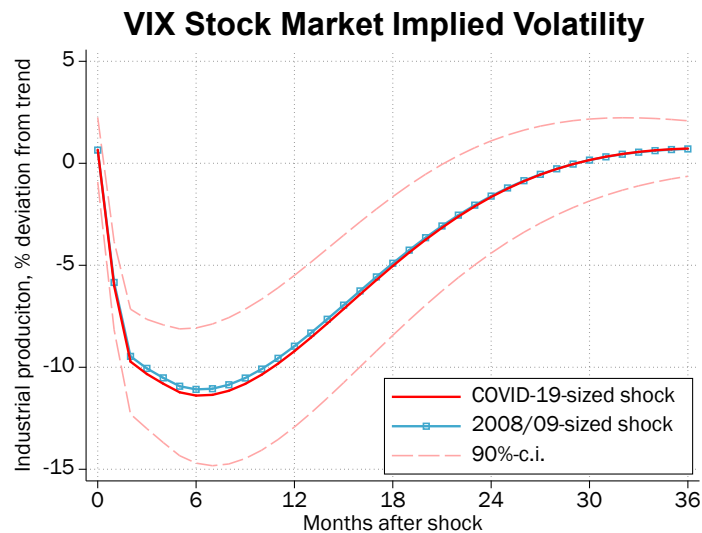
Notes: One-month-ahead macro uncertainty for 1960:07-2020:04, as computed by Jurado, Ludvigson, and Ng (2015) and available at www.sydneyludvigson.com/macro-and-financial-uncertainty-indexes.

Figure 7: High frequency measures of uncertainty during 2020



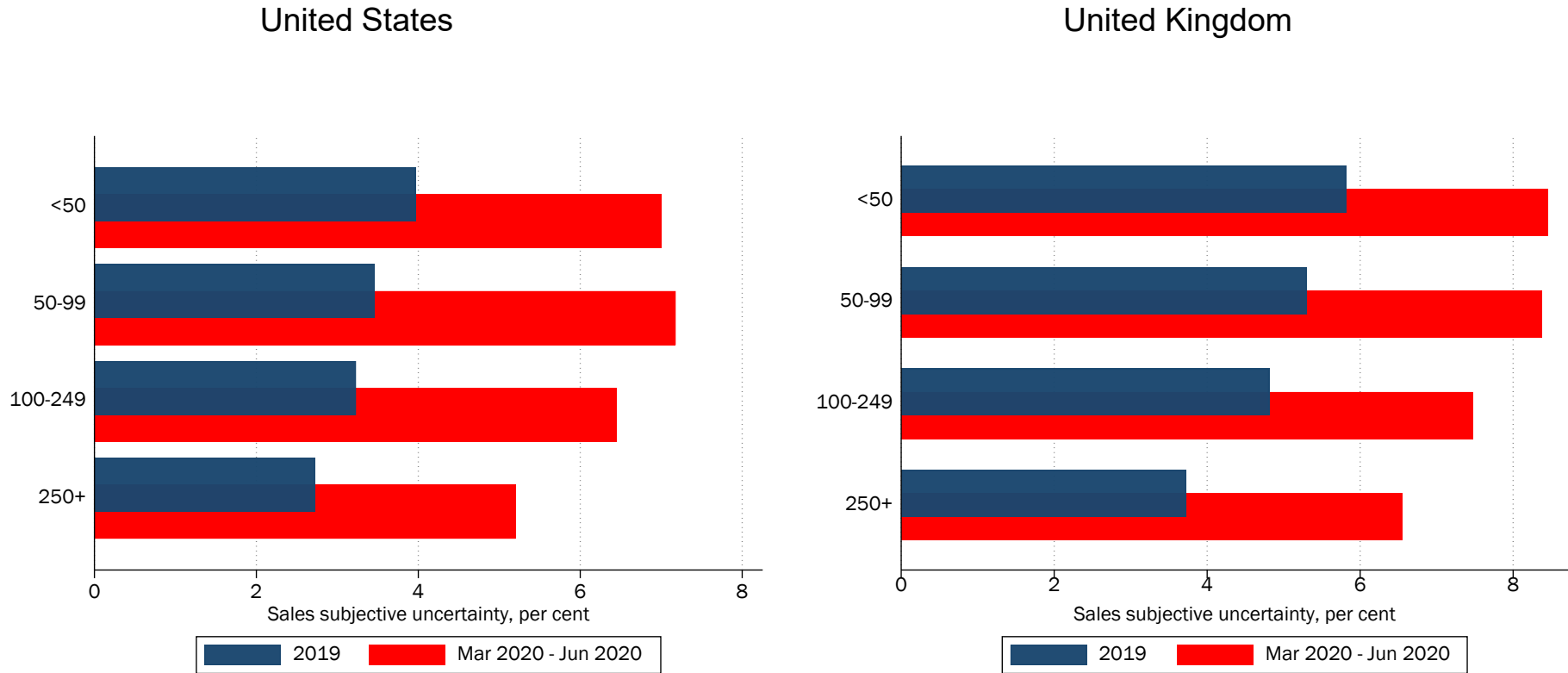
Notes: Decision Maker Panel Survey conducted by the Bank of England, Nottingham University and Stanford University and Bloom et al. (2019) and www.decisionmakerpanel.com. Values linearly interpolated when the DMP survey was not in the field. Values of the Likert Uncertainty measure were extrapolated using information about firms' sales expectations and uncertainty for the first five weeks. VIX-24M, Likert Uncertainty, and Sales Subjective Uncertainty's axes are hidden.

Figure 8: Impact of uncertainty on US output



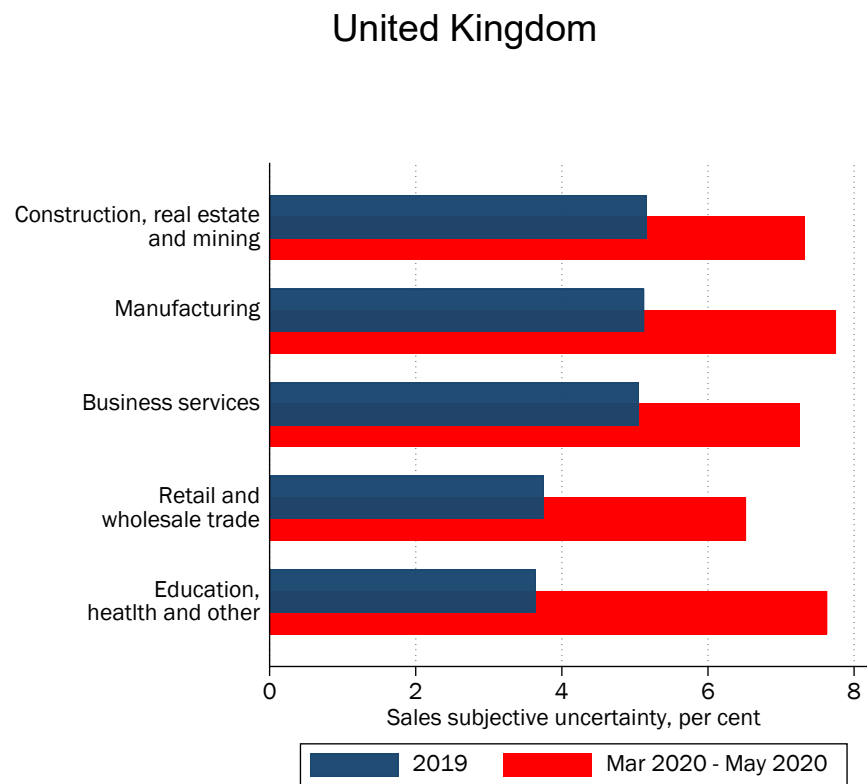
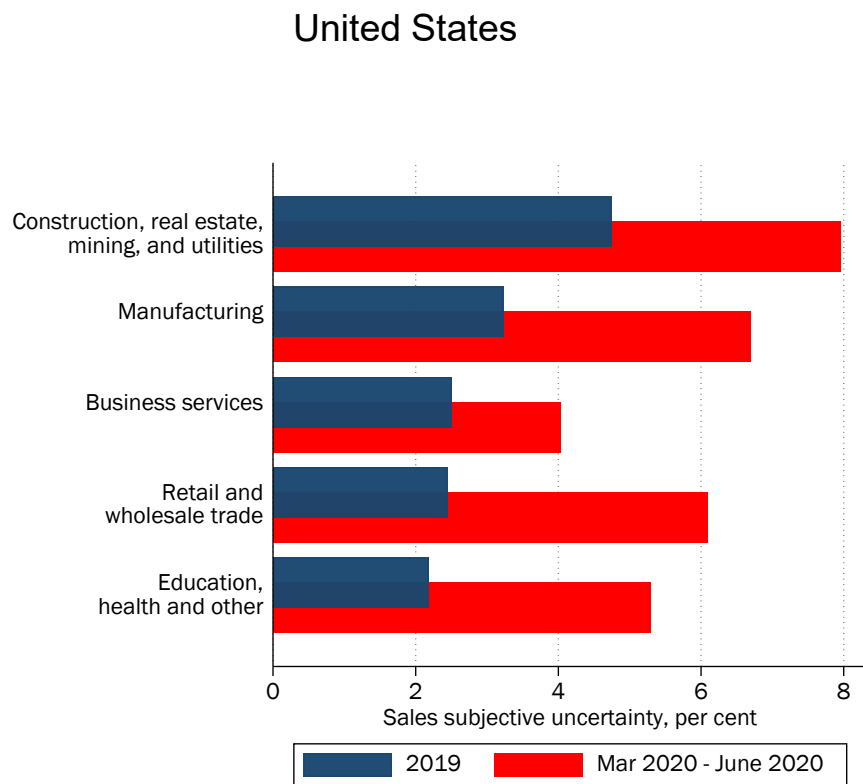
Note: The charts show VAR-estimated impulse response functions for industrial production to four uncertainty innovations equal to the increase from January 2020 to their 2020 peaks (red lines), with 90 percent confidence bands, or to their 2008/09 peak (blue lines). We detrend following Hamilton (with $p=36$, $h=12$) and include three lags of each variable. We identify innovations using a Cholesky ordering as follows: uncertainty, $\log(\text{S\&P 500 index})$, effective federal reserve funds rate, $\log(\text{manufacturing employment})$, and $\log(\text{industrial production})$. We fit models to monthly data from October 1966 to June 2020 (VIX), October 1966 to April 2020 (macro uncertainty), August 1974 to May 2020 (forecaster disagreement), and April 1989 to June 2020 (economic policy uncertainty).

Figure A1: Subjective sales growth rate uncertainty by firm size



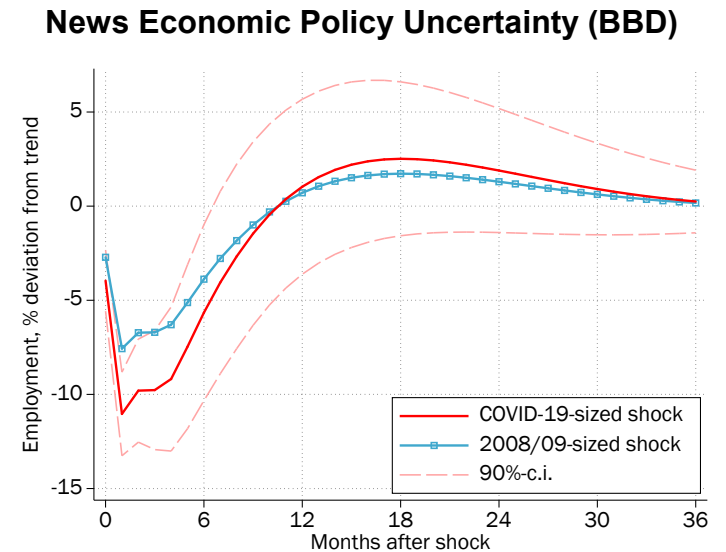
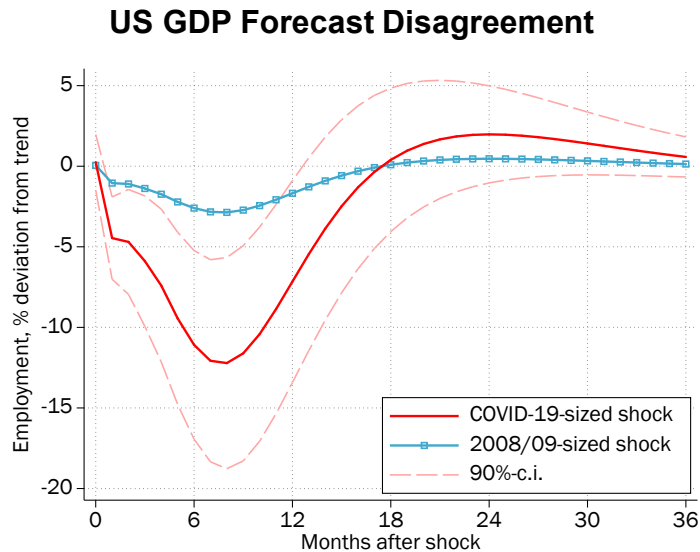
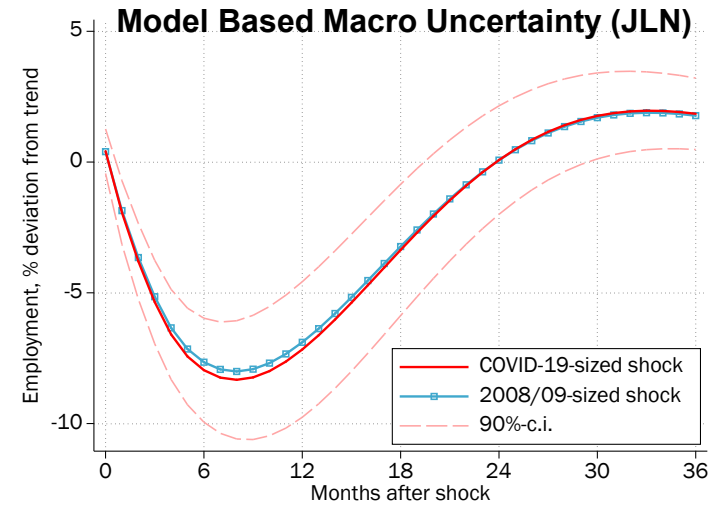
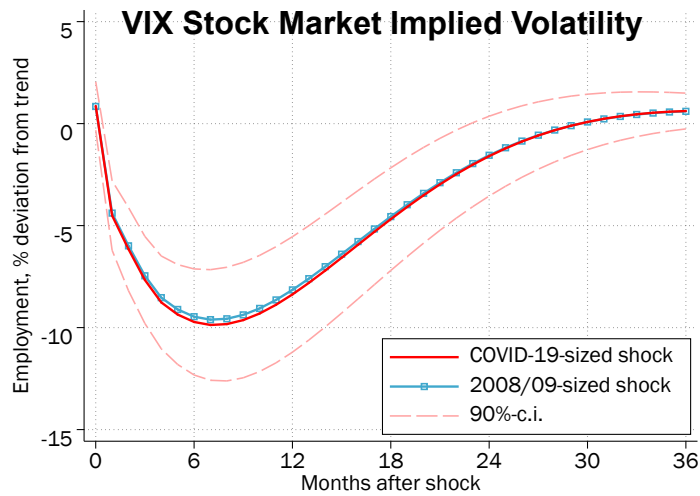
Notes: Subjective uncertainty measured for the growth rate of 4 quarters ahead firm level sales expectations (details in Altig et al. 2020c). US data from the Survey of Business Uncertainty conducted by the Federal Reserve Bank of Atlanta, Stanford University, and the University of Chicago Booth School of Business (<https://www.frbatlanta.org/research/surveys/business-uncertainty>). UK data from the Decision Maker Panel Survey conducted by the Bank of England, Nottingham University and Stanford University (see Bloom et al. (2019) and www.decisionmakerpanel.com).

Figure A2: Subjective sales growth rate uncertainty by industry



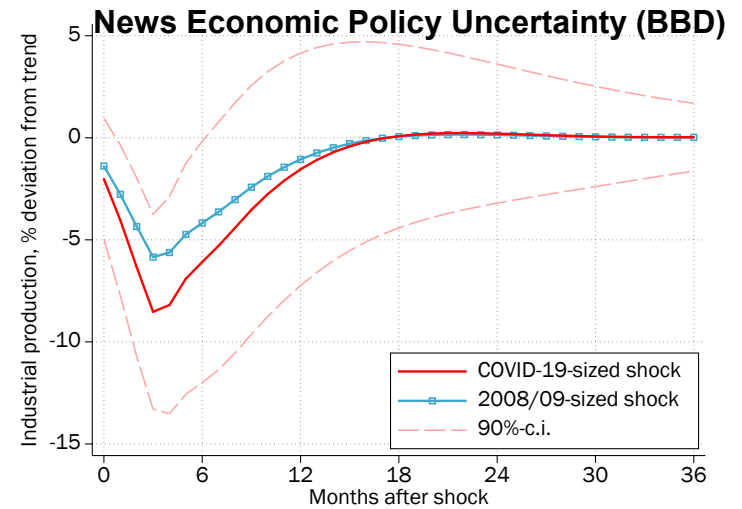
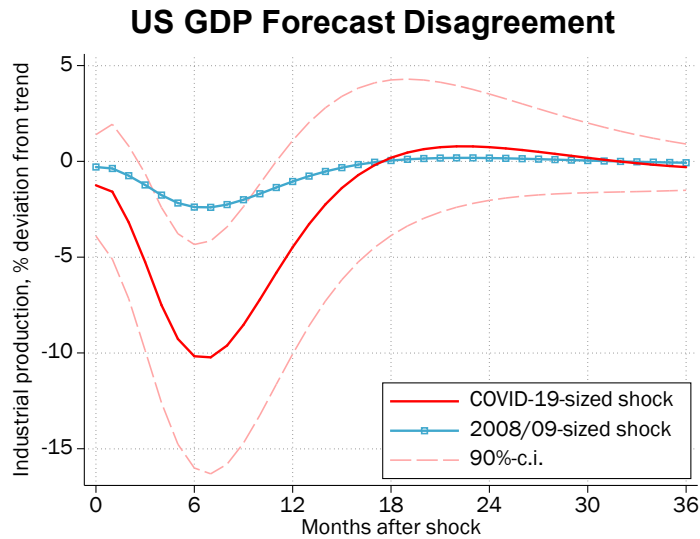
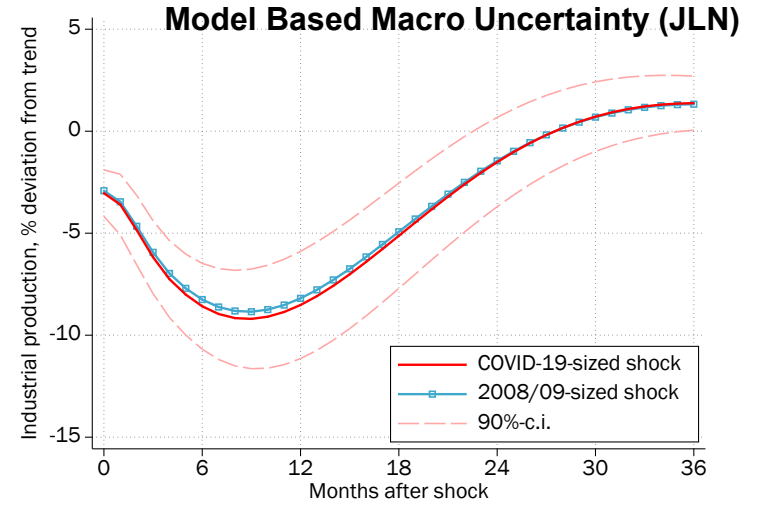
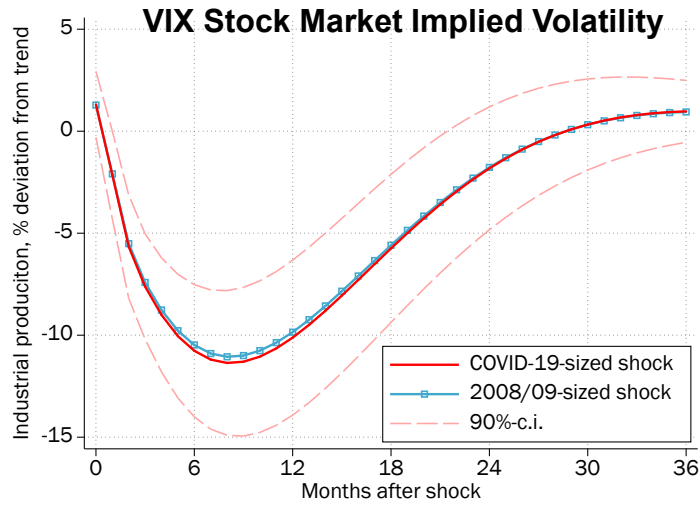
Notes: Subjective uncertainty measured for the growth rate of 4 quarters ahead firm level sales expectations (details in Altig et al. 2020). US data form the Survey of Business Uncertainty conducted by the Federal Reserve Bank of Atlanta, Stanford University, and the University of Chicago Booth School of Business (<https://www.frbatlanta.org/research/surveys/business-uncertainty>). UK data from the Decision Maker Panel Survey conducted by the Bank of England, Nottingham University and Stanford University (see Bloom et al. (2019) and www.decisionmakerpanel.com).

Figure A3: Impact of uncertainty shocks on employment



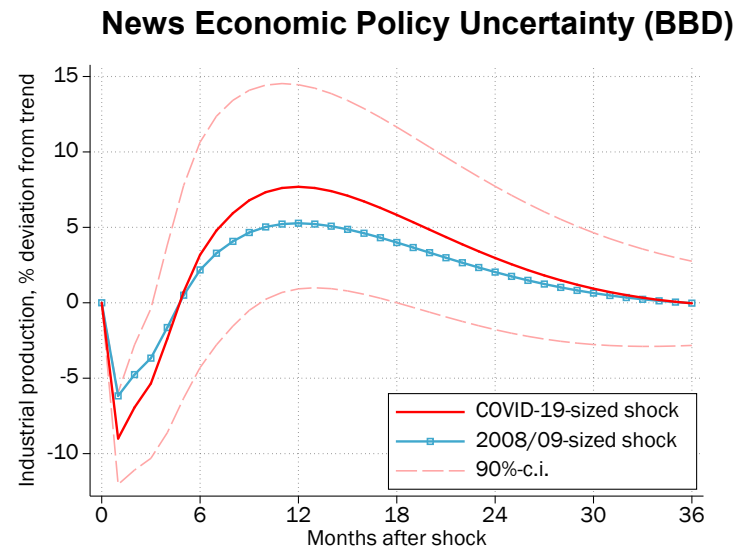
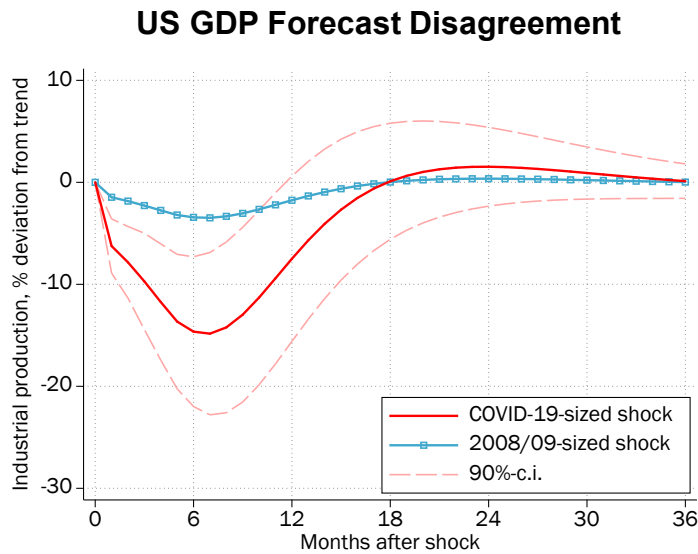
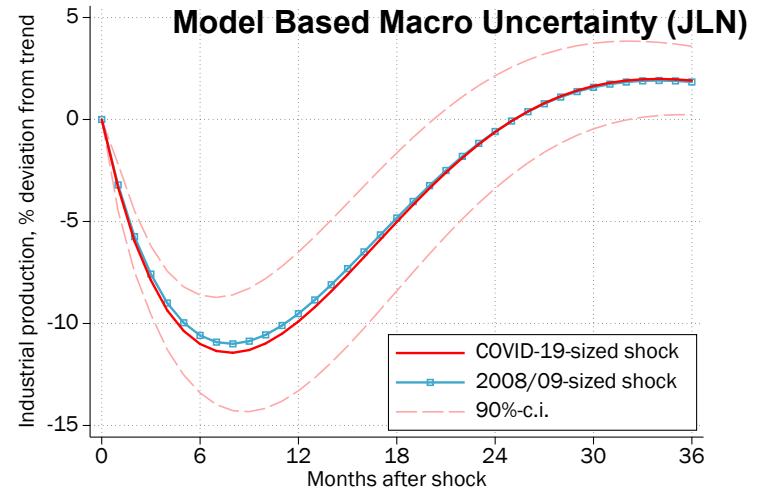
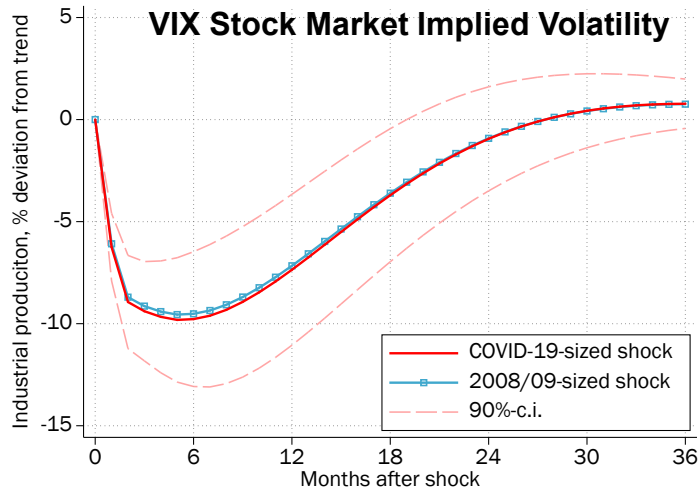
Note: The charts show VAR-estimated impulse response functions for employment to four uncertainty innovations equal to the increase from January 2020 to their 2020 peaks (red lines), with 90 percent confidence bands, or to their 2008/09 peak (blue lines). We detrend following Hamilton (with $p=36$, $h=12$) and include three lags of each variable. We identify innovations using a Cholesky ordering as follows: uncertainty, $\log(\text{S\&P 500 index})$, effective federal reserve funds rate, $\log(\text{manufacturing employment})$, and $\log(\text{industrial production})$. We fit models to monthly data from October 1966 to June 2020 (VIX), October 1966 to April 2020 (macro uncertainty), August 1974 to May 2020 (forecaster disagreement), and April 1989 to June 2020 (economic policy uncertainty).

Figure A4: Impact of uncertainty on output using pre-COVID data



Note: The charts show VAR-estimated impulse response functions for industrial production to four uncertainty innovations equal to the increase from January 2020 to their 2020 peaks (red lines), with 90 percent confidence bands, or to their 2008/09 peak (blue lines). We use the same detrending method, specification, identification assumptions, and data as in Figure 8 in the main text, except for ending the sample period in December 2019.

Figure A5: Impact of uncertainty on output – reversed ordering



Note: The charts show VAR-estimated impulse response functions for industrial production to four uncertainty innovations equal to the increase from January 2020 to their 2020 peaks (red lines), with 90 percent confidence bands, or to their 2008/09 peak (blue lines). We use the same detrending method, specification, and data as in Figure 8 in the main text, except for a different identification assumptions, with variables ordered as follows: log(industrial production), log(manufacturing employment), effective federal reserve funds rate, log(S&P 500 index), and uncertainty.