Economic Uncertainty and the Recovery

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Abstract: Economic uncertainty jumped in reaction to the COVID-19 pandemic, with most indicators reaching their highest values on record. Alongside this rise in uncertainty has been an increase in downside tail-risk reported by firms. This uncertainty has played three roles. First, amplifying the drop in economic activity early in the pandemic; second slowing the subsequent recovery; and finally reducing the impact of policy as uncertainty tends to make firms more cautious in responding to changes in business conditions. As such, the incredibly high levels of uncertainty are a major impediment to a rapid recovery. We also discuss three other factors exacerbating the situation: the need for massive reallocation as COVID-19 permanently reshapes the economy; the rise in working from home which is impeding firm hiring; and the ongoing medical uncertainty over extent and duration of the pandemic. Collectively, these conditions are generating powerful headwinds against a rapid recovery from the COVID-19 recession.

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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 medical path of the virus, the associated economic slowdown, the responses from policymakers, consumers, and businesses.[1]

This paper starts by examining a few leading measures of economic uncertainty before and during the COVID-19 pandemic, building on Altig et al. (2020b). Our focus is on *forward-looking* uncertainty measures that are available in near real-time. These measures show a massive increase in uncertainty across the board upon the arrival of the pandemic. Indicators based on newspaper articles, forecaster disagreements and business surveys of subjective uncertainty have all surged to all-time highs. Using our newspaper indicators, we show that two components – fiscal policy and health policy uncertainty – have seen particularly large rises during the pandemic.

We also use two new large panel firm surveys, the UK Decision Maker Panel and the US Survey of Business Uncertainty to study the distributions of firm-level subjective expected outcomes. These survey data highlight how the pandemic has induced a particularly large fear of negative tail-risk outcomes. For example, in the US survey, the typical firm reported that its 10^{th} percentile outcome –a plausible worst-case scenario – *before* the pandemic was 0% annual sales growth. During the pandemic, the 10^{th} percentile fell to a -15% sales decline, highlighting how firms are now concerned with the potential for extremely large contractions.

[1] On uncertainty about key parameters in epidemiological models of Covid-19 transmission and mortality, see Atkeson (2020a), Bendavid and Bhattacharya (2020), Fauci et al. (2020) and Li et al. (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, Rebelo and Trabant (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 potential medium- and long-term macroeconomic consequences, see Barrero, Bloom and Davis (2020), Barro, Ursua and Weng (2020) and Jorda, Singh and Taylor (2020).

2. Measuring COVID-19 Uncertainty

There is a wide range of measures of uncertainty,[2] but in this paper we focus on three measures that are forward-looking and available real-time or with limited delay.

Text-Based Uncertainty Measures: Figure 1 plots the US Economic Policy Uncertainty Index of Baker, Bloom and Davis (2016). The daily version of this index reflects the frequency of newspaper articles with one or more terms about "economics," "policy" and "uncertainty" in roughly 1,000 daily US newspapers. It is normalized such that its mean value over the period from 1985 to 2010 is 100, so values above 100 reflect higher-than-average uncertainty. The weekly index plotted in Figure 1 surges to almost 600 in March 2020 before falling back to around 400 through July 2020, levels higher than anything seen historically, looking back as far as 1985. 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. This rise is also related to concerns over the pandemic, with over 90% of the articles about economic policy uncertainty in March 2020 mentioning "COVID," "Coronavirus," "pandemic" or other terms related to infectious diseases.

We also examine the Twitter-based Economic Uncertainty (TEU) index, constructed by scraping all tweets worldwide that contain both "economic" and "uncertainty" (or variants of each term) from 1 January 2010 to present, which yields about 200,000 tweets.[3] The index then computes the frequency of tweets concerning "economic" and "uncertainty" (including variants of each term), and is normalized to 100 from 2010 to 2015. This is also shown weekly in Figure 1, spiking to all-time high levels of around 1000 during the COVID-19 pandemic (and exceeding its notable spike in June 2016 after the Brexit vote).

In summary, both text measures above suggest that uncertainty surged to many times it normal level during the pandemic, and both record their highest levels since their series began.

In Figure 2 we dig deeper into the the rise in the overall economic policy uncertainty (EPU) index, analyzing what the underlying policy categories accounting for the spike in the overall

[2] See, for example, the various measures in Fernandez-Villaverde et al. (2011), Jurado, Ludvigson and Ng (2015), Leduc and Liu (2016), Scotti (2016), Dew-Becker et al. (2017), Bachmann et al. (2018), Caldara and Iacoviello (2018), and the broad reviews in Cascaldi-Garcia et al. (2020) and Rogers and Xu (2019)
[3] See Baker, Bloom, Davis and Renault (2020) for details, and the data on http://www.policyuncertainty.com/twitter_uncert.html

series. We focus on four key categories – fiscal policy, monetary policy, health policy and trade policy. The category indices count the number newspaper articles that mention our core EPU index terms plus category-specific terms. For example, to be counted in the health-policy series the article has to include the standard EPU terms plus any of "health care" or "Medicaid" or "Medicare" or "health insurance" or "prescription drugs" etc. To be in the fiscal policy category, the article has to, again, mention the standard EPU terms and also mention any of "government spending" or "federal budget" or "budget battle" or "balanced budget" etc.[4]

As we can see in Figure 2, the pandemic surge in policy uncertainty has been driven in particular by fiscal policy and health policy. This is not surprising – the CARES act and other fiscal stimulus packages have received considerable attention in the media, as has the impact of COVID-19 on the health system. More interestingly, monetary policy uncertainty has risen but not nearly as dramatically, suggesting it has contributed relatively less to overall uncertainty during the current crisis.[5] This is notable given this spanned a period of extraordinary stress in financial markets, including the turmoil in the Treasury market in February and March. Our interpretation of this relatively low level of monetary policy uncertainty is this reflects the rapid action of the Fed to maintain liquidity in financial markets and stave off the crisis. Finally, we also include the trade-policy uncertainty index in Figure 2 given its role in recent rises in the EPU index during 2018 and 2019. In 2020, trade policy appears to not to have played any significant role (to date) in driving overall economic policy uncertainty.

Forecaster Disagreement: There is a long history of using forecaster disagreement measures to proxy for uncertainty, and also a long history of disagreement about their suitability for that purpose.[6] 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 use the standard-deviation of one-year-ahead GDP growth rate forecasts for the US and UK from the Survey of Professional Forecasters (SPF) and the Survey of External Forecasters (SEF)

[4] The full list of category terms is here: http://www.policyuncertainty.com/categorical_terms.html
[5] Husted, Rogers and Bo (2019) also generate a newspaper-based index of monetary policy uncertainty, which also does not surge during the 2020 pandemic.
[6] See, for example, Bomberger (1996) and Rich and Tracy (2020) for evidence showing a strong and weak link between forecast disagreement and uncertainty respectively.

respectively. There are, on average, 41 forecasters per survey response period in the US and 23 in the UK.

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, an eight-fold increase. UK forecast disagreement rose from 0.49 percentage points to 10.1, an astounding twenty-fold increase. These surges align with the large increase in the macro uncertainty index generated by the methodology of Jurado, Ludvigson and Ng (2015), which reached an all-time high in April 2020.[7]

Subjective Uncertainty Measures Computed from Business Expectation Surveys: We examine subjective sales uncertainty measures from the US Survey of Business Uncertainty (SBU) and the UK monthly Decision Maker Panel (DMP).[8] These panel surveys recruit participants by phone from population databases that cover nearly all eligible public and private companies with 10 or more employees (about 300,000 in the US and 50,000 in the UK). The SBU has around 400 respondents per month, and the DMP has around 3,000. The core questions in both surveys 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. (See Figure A1 for the sales questions from each survey.). By calculating each firm's subjective standard deviation over 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 the survey-based time-series measures of sales growth uncertainty for the United States and the United Kingdom. Both measures point to pronounced increases in uncertainty in March 2020 and April 2020, before moderating slightly after May 2020. Pandemic uncertainty is clearly well above any previous peaks in their (short) histories, which is particularly notable in the UK given its recent experience with the Brexit process. As described in detail in Altig et al. (2020a) these firm-level growth expectations are highly predictive of realized growth rates, and firm-level subjective uncertainty predicts the magnitudes of future forecast errors and future forecast revisions.

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[7] See https://www.sydneyludvigson.com/macro-and-financial-uncertainty-indexes
[8] See www.frbatlanta.org/research/surveys/business-uncertainty and http://decisionmakerpanel.com/

To better visualize the widening of firms' subjective distributions, Figure 4 plots several percentiles of the distributions of expected sales growth, pooling across all respondents in each of the US Survey of Business Uncertainty and the UK Decision Maker Panel. For each firm in month *t* we use the five mass points and probabilities is provides in the survey to calculate a probability distribution for its four-quarter-ahead expected sales growth. We then take the employment weighted average across all firms' probability distributions in month *t* to generate a subjective distribution for the representative firm's future sales growth. We then plot the 10th, 25th, 50th, 75th and 90th percentiles of this distribution.

Figure 4 shows the COVID-19 pandemic has had three effects. First, the central tendency of future sales growth has fallen, as indicated by the fall in the median (50th percentile) of the future sales growth distribution. Second, uncertainty (second moment) about future sales growth has risen, demonstrated by the widening gap between the higher (e.g. 90th) and lower (e.g. 10th) percentiles (and corroborating the patterns in Figure 3). Third, left tail-risk (subjective skewness) of sales growth has dropped (become more negative), as highlighted by the far greater drop in the lower 10th percentile. Before the pandemic the distribution of future sales growth appears positively skewed –the distance between the 90th and 50th percentiles is higher than the distance between the 50th and the 10th. During the pandemic we see the opposite, with large drops in the 10th percentile of the distribution in both the US and UK. This highlights increased tail-risk accompanying the pandemic recession – namely, large numbers of firms have extremely negative worst-case outcome forecasts. If we take the 10th percentile outcome as a plausible estimate of firms' "worst case" scenario, this has dropped for the typical firm from 0% growth in the US and -5% in the UK pre-pandemic to -15% in the US and -20% in the UK during the pandemic.[9] These are extremely large movements in the left-tail worst-case outcomes, reflecting the surge in tail-risk perceived by firms during the pandemic recession, dwarfing the impact of other uncertainty shocks like the ongoing Brexit process or the US-China trade dispute.

A long-literature on tail-risk and skewness suggests these risks can also be extremely damaging to firm-level investment and hiring, as firms are typically not (fully) insured against these events.[10]

[9] The UK forecasts are more pessimistic potentially because of the added tail-risk due to the ongoing Brexit process.
[10] See for example, Rietz (1988) and Barro (2006) for early work on macro skewness and Salgado, Guvenen and Bloom (2020) for a survey of more recent work on macro and micro-skewness.

As such, the impact of the pandemic could be more damaging than implied by traditional measures of uncertainty due to the added impact of the large increase in left-tail risk.

Stock Market Volatility: Figure 5 plots the VIX, the 1-month implied volatility of the S&P 500, and a common financial measure of uncertainty.[11] The VIX spiked to almost 70 on a weekly basis in March 2020 and reached an all-time daily closing high of 82.7 on March 16th. But then it fell back rapidly as the stock-market started to recover in late March, and by August 2020 was between 20 to 25, near its pre-pandemic levels of around 15. This behavior contrasts with those of real measures of uncertainty like the US or UK firm subjective uncertainty from Figures 3 and 4 or the economic policy uncertainty index, which have remained substantially elevated through July 2020. Firms continue to see incredibly high levels of uncertainty, presumably driven by uncertainty about the progress of the virus, the associated policy responses, and the virus's impact on the economy. Similarly, the persistently high EPU index reflects the extensive ongoing discussion of economic uncertainty in the media. The drop in the VIX highlights the divergence between "Wall Street" vs "Main Street" in respect to the second moment (i.e. uncertainty), shadowing a similar divergence in the first moment (i.e. a resurgent stock-market nearing all-time highs in mid-August while the real economy remains depressed). As such, while the VIX has classically been a popular measure of uncertainty, that many (ourselves included) have used in prior research, during the pandemic it appears to be a less suitable indicator for contemporaneous uncertainty in the real "main-street" economy.[12]

3. The Impact of Uncertainty

There are three primary channels through which uncertainty could delay the recovery from the pandemic recession. First, uncertainty acts through risk-aversion to raise discount rates; second uncertainty acts through real-options to reduce investment, hiring and consumption; and third, the same real-options can make firms and consumers less responsive to fiscal and monetary stimulus.

[11] See, for example, Bloom (2009) or Leduc and Liu (2020).
[12] One possible reason is the S&P500 is becoming increasingly concentrated on hi-tech firms, which is now approaching 30% of its valuation, which has been performing well during the pandemic. Another possible reason is the S&P500 is more long-run focused, pricing in an eventual recovery (see, for example, Abel and Eberly's (2012) discussion of the impact of long-horizon news on current stock valuations).

All three channels highlight both the damaging effect of uncertainty on the recovery and the potential benefits of reducing macro and micro uncertainty though stable and predictable policy.

Risk Aversion and Risk Premia: Economists since Keynes and Tobin have long pointed out how investors need to be compensated for higher risk. Hence, the COVID-19 induced surge in uncertainty, which effectively raises risk, will increase risk premia and raise the cost of finance (see also Landier and Thesmar 2020). Uncertainty also increases the probability that borrowers might default, by increasing the probability of left-tail default outcomes, and thus resulting in more resources devoted to paying costs associated with bankruptcy. This role of uncertainty in raising borrowing costs has repeatedly been shown to reduce micro and macro growth, as emphasized in papers on the impact of uncertainty in the presence of financial constraints (e.g. Gilchrist, Sim and Zakrasjek, 2014; Christiano, Motto and Rostagno, 2014 and Arellano, Bai and Kehoe, 2019).

Pandemic-related uncertainty may also impact firms through the incentives of their chief executive officers. Most top corporate executives do not have not well-diversified portfolios: both their personal financial assets and their human capital are disproportionately tied up in their firm. Indeed, Panousi and Papanikolaou (2012) show in a panel of US firms that investment drops when uncertainty is higher, and particularly so for firms where the chief executive officer holds extensive equity in the firm and so is highly exposed to firm-level risk. We believe this effect will be particularly pronounced in 2020 due to the large increase in negative tail risk under COVID-19.

The Delay Effect of Real Options: A second body of literature on uncertainty focuses on "real options" (e.g. Bernanke 1983; Brennan and Schwartz 1985; McDonald and Siegel 1986, Abel and Eberly 1994, and Dixit and Pindyck 1994). The idea is that firms can look at their investment choices as a series of options: for example, a restaurant chain that owns an empty plot of land has the option to build a new store on the plot. If the restaurant becomes uncertain about the future – for example, because it is unsure to what extent consumers will return to indoor dining vs. home-delivery – it may prefer to wait. If post-pandemic consumers do return to indoor dining, the restaurant chain can develop the site with high internal dining capacity. If instead, consumer preferences continue to favor home-delivery (and take-out), it can develop the restaurant with less internal space but better vehicle access. In the language of real options, the option value of delay is high for the restaurant chain when uncertainty is high. As a result, uncertainty makes firms cautious about actions like investment and hiring, which may be expensive to reverse due to adjustment costs.

Investment adjustment costs have both a physical element (equipment may get damaged in installation and removal) and a financial element (the used-good discount on resale). However, real-options effects are not universal. They arise only when decisions cannot be easily reversed; after all, reversible actions do not lead to the loss of an option. Thus, firms may be happy to hire part-time employees even when uncertainty is extremely high. They can easily lay-off these employees if conditions deteriorate. As such, the extremely high levels of pandemic uncertainty may lead to a rise in the share of part-time hiring.

Real-options effects can be exacerbated in the presence of financial constraints because firms also have an incentive to hoard cash (Gilchrist, Sims and Zakrasjek, 2010, Alfaro, Bloom and Lin 2019). These "cash-options" can amplify the impact of real options, highlighting the importance of continuing to maintain the stability of the financial system through-out the pandemic crisis. Price stickiness can also augment the impact of uncertainty shocks since firms are unable to rapidly adjust prices to changing conditions (e.g. Fernandez-Villaverde et al. 2015 and Basu and Bundick 2017), highlighting the importance of also maintaining stable inflation.

Turning from investment to consumption, there is an analogous channel for uncertainty to cause postponed consumption (e.g. Romer 1990, Eberly 1994 or Alfaro and Park 2019). When consumers make the decision to buy durables like housing, cars, and furniture, they can usually delay purchases relatively easily. For example, people may be thinking about moving to another house, but they could either move this year or wait until next year. This option value of waiting will be much more valuable when income uncertainty is higher. If, for example, you are unsure about whether you will keep you job until the end of this year it makes sense to wait until this is decided before undertaking an expensive house move. Delaying purchases of non-durable goods like food and entertainment is harder, so the real-options effects of uncertainty on non-durable consumption will be lower.

So overall, the literature suggests the real-options impact of COVID-19 uncertainty will strongly reduce investment, hiring and durable consumption by US firms and consumers. Figure 6 from Baker, Bloom and Terry (2020) shows one estimate of this impact for investment, plotting empirical and model-based estimates of the uncertainty impact of the COVID-19 shock on US

GDP. The impact is large at between 2% to 4% of GDP, although it is clearly not the primary driver of the 11% cumulative drop in US GDP to date relative to 2019Q4.

Finally, we note that to the extent that the pandemic drop in GDP was driven by supply (rather than demand) constraints, the marginal impact of uncertainty could be muted. However, this is a complex question as is not clear how much supply or demand are driving the pandemic because of network effects (e.g. Guerrieri, Lorenzoni, Straub and Werning 2020), and because sustained increases in uncertainty can themselves lower supply by lowering investment and hiring.

The Cautionary Effect of Real Options and the Impact on Policy: The real-options impact of uncertainty also has an additional channel that could delay the recovery, namely by blunting the impact of stimulus policy. Uncertainty typically makes firms and consumers less sensitive to changes in business conditions, and monetary and fiscal stimulus are no exception. Since agents become more cautious, they respond less strongly to a given change in demand or prices. For example, while the investment elasticity with respect to interest rates might be 0.5 when uncertainty is low, it could fall to 0.25 during an uncertainty shock.[13] This has been shown for both firms (e.g. Guiso and Parigi 1999 and Bloom, Bond and Van Reenen 2007) and consumers (e.g. Foote, Hurst and Leahy 2000 and Bertola, Guiso and Pistaferri 2005). This research suggests the response to any given policy response is likely to be lower because of high COVID-19 uncertainty. The same logic also highlights the benefits of policies that can reduce uncertainty – for example, by reducing systemic financial risks or providing transparent long-run policy guidance.

4. Other factors delaying the recovery

In closing we want to highlight three other factors we have been examining that are likely to further complicate the recovery.

Reallocation: The pandemic has exacted a staggering economic toll on the US and countries around the world. Yet, as much of the economy shut down, many firms expanded in response to

[13] In formal economic models this often takes the form of widening S-s bands. Within the bands, consumers or firms don't respond to changing conditions. They adjust only when they are outside the bends. There is a lower density of consumers or firms near the boundary of the bands when uncertainty is high (particularly if uncertainty has recently increased) because higher uncertainty expands the Ss bands. Stimulus then becomes less effective because there are fewer agents it can push into the adjustment region.

pandemic-induced demand shifts. As Bender and Dalton (2020) put it in the *Wall Street Journal*, "The coronavirus pandemic is forcing the fastest reallocation of labor since World War II, with companies and governments mobilizing an army of idle workers into new activities that are urgently needed." That is, COVID-19 is a major reallocation shock.

This heterogeneous impact is illustrated in Figure 7 showing the distribution of responses from a survey of 2,380 US firms in April 2020 to a question about the expected impact of the pandemic on their next 3 months and 12 months sales.[14] The mean impacts are strongly negative (-30% for 3 months and -13% for 12 months), with 13% reporting a 100% sales drop in their 3-month predictions due to business closures. But 15% of firms report positive 3-month sales change expectations and 22% report positive 12-month sales changes expectations. This heterogeneity in outcomes takes places across industries – hi-tech is seeing surging demand while accommodation, travel and entertainment are seeing large declines. Much of the heterogeneity also takes place within industries – for example, commercial versus private flights (commercial flights were down 65% in July 2020 while private flights were only 16% down[15]) or eat-in versus home delivery restaurant meals.

Figure 8 plots the evolution of one overall measure of reallocation from Barrero, Bloom and Davis (2020), namely the expected absolute gross-change in sales across all firms less the net total change.[16] This statistic is the forward-looking analog to the backward-looking measures of excess job reallocation examined in Dunne, Roberts and Samuelson (1989), Davis and Haltiwanger (1992) and many later studies. It calculates how much sales levels are expected to change across firms less the change needed for the overall expected expansion/contraction. Figure 8 shows that expected sales reallocation jumped an incredible 600% after the arrival of the pandemic.

This massive movement of sales, and thus capital and labor, across firms and industries will likely compound the challenges induced by high uncertainty. Firms are not just facing massive macro uncertainty, policy and medical uncertainty. They are also facing permanent shifts in

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[14] See Bloom, Fletcher and Yeh (2020) for full survey details.

[15] https://www.wsj.com/articles/business-jets-are-flying-again-their-manufacturers-arent-11594982514

[16] Formally this is defined as follows, noting that $\mathrm{E}_t g_{i,t+12}$ is the t-period expected growth of employment in firm *i* until period *t+12*:

$$\mathrm{E}_t X_{t+12}^{\text{jobs}} = \sum_{i \in S_t^-} \left(\frac{z_{it}}{Z_t}\right) |\, \mathrm{E}_t g_{i,t+12} \,| + \sum_{i \in S_t^+} \left(\frac{z_{it}}{Z_t}\right) |\, \mathrm{E}_t g_{i,t+12} \,| - \left| \sum_i \left(\frac{z_{it}}{Z_t}\right) \mathrm{E}_t g_{i,t+12} \right|.$$

demand and industry structures, many of which are hard to predict given the uncertainty over the course of the virus and its impact on consumer preferences.

Working From Home: A second compounding shift is the enormous increase in employees working from home. Data from the 2018 Bureau of Labor Statistics American Time Use Survey[17] reveals that before COVID-19 around 5% of working days were spent by US employees at home. The majority of these days were accounted for by employees who took occasional days to work from home. Only 2% of work-from-days came from employees who were full-time home-based workers. Figure 9 (left-panel) highlights how this pattern has radically changed under COVID. The figure reports the results from two 2,500 person surveys over May-July 2020 of individuals aged 20-64 in the US who earned over $20,000 in 2019 (so are likely to have been employed full-time in 2020 if not for the pandemic). We see that 39% of employees now report working from home, and most are doing so full time. This has important implications for hiring since employees and firms in interviews we carried out mention the challenges with onboarding and training new employees remotely. We also see this in the right-panel of Figure 9 where 46% of employees report that working from home has made it "substantially harder" to hire new employees at their firm. For example, one respondent, a home-based new hire, reported struggling to learn even basic work behavior, such as the typical start and end time for her team, and the length of coffee and lunch breaks, citing her inability to observe colleagues in person.

Ongoing Medical Uncertainty: Finally, the COVID-19 pandemic contains an additional element of uncertainty which goes beyond our experience in examining prior uncertainty shocks, which is the medical side. There is extremely wide-ranging uncertainty, from uncertainty about when a vaccine or effective treatment will be discovered, to when it will be widely available, to how effective it will be and who will even take the vaccine given pockets of anti-vax sentiment.[18]

Fed Chairman Jerome Powell noted on July 28th, 2020, "*the path forward for the economy is extraordinarily uncertain and will depend in large part on our success in containing the virus*". Figure 10 provides one measure of this medical, based on the frequency of discussions of the word "uncertainty" in the context of infectious diseases in the Economic Intelligence Unit's (EIU)

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[17] See https://www.bls.gov/news.release/flex2.t01.htm.

[18] See, for example, the discussion over the potential lack of uptake of a new vaccine due to anti-vaccine sentiment, which could prevent vaccination rates reaching the levels necessary to generate herd immunity to the SARS-Cov-2 virus https://www.ft.com/content/89b90830-b301-4712-9655-49a1b5d94eee

quarterly country reports. The EIU provides quarterly reports for over 140 countries which they construct and edit in a harmonized way, and which can be used as a text source for creating country and global uncertainty indices. Ahir, Bloom and Furceri (2019) take this data and search for the overall frequency of the word "uncertainty" in the context of infectious disease terms, and average this across all countries, to construct the World Pandemic Uncertainty Index plotted quarterly in Figure 10. This index reached its highest level in 2020Q2, surpassing its prior-peak in 2020Q1, reflecting the extreme ongoing uncertainty. Until this medical uncertainty abates it is hard for the broader policy and economic uncertainty to recede, highlighting the uncertainty over even the duration of the current pandemic.

5. Conclusions

Economic uncertainty jumped in reaction to the COVID-19 pandemic, with most indicators reaching their highest values on record. Using newspaper indicators of uncertainty we find that two components – fiscal policy and health policy uncertainty – have seen particularly large rises during the pandemic.

Alongside this rise in uncertainty, there has been an increase in downside tail-risk reported by firms. In pre-pandemic times the 10th percentile of US firms' subjective forecasts was for zero sales growth. During the pandemic the 10th percentile has dropped to -15%, highlighting how firms are concerned over the potential for extremely large contractions.

This high uncertainty will have increased the risk premium for investing and increased the value of "real options" to wait, leading firms to delay investing and hiring. Uncertainty, thus, will have amplified the negative shock caused by the pandemic on impact, and is also likely to slow the rate of recovery. In addition, uncertainty tends to reduce the impact of stimulus policy as it makes firms more cautious in their responses to changes in business conditions. As such, the incredibly high levels of uncertainty are a major impediment to a rapid recovery.

We conclude by focusing on three other factors exacerbating the situation. First, we point to the need for massive reallocation as COVID-19 reshapes the economy in the near- and longer-term, which is forcing huge increases in cross-firm and industry movements of capital and labor, and making the general environment yet more volatile and uncertain. Second, we document the rise in working from home, which survey evidence suggests is impeding hiring due to the difficulties related to onboarding and training new employees fully remotely. Finally, uncertainty over the medical extent, severity and duration of the pandemic are creating enduring uncertainty over the economic and political consequences the pandemic. These conditions are collectively generating additional headwinds in the ability to enact a rapid recovery from the COVID-19 recession.

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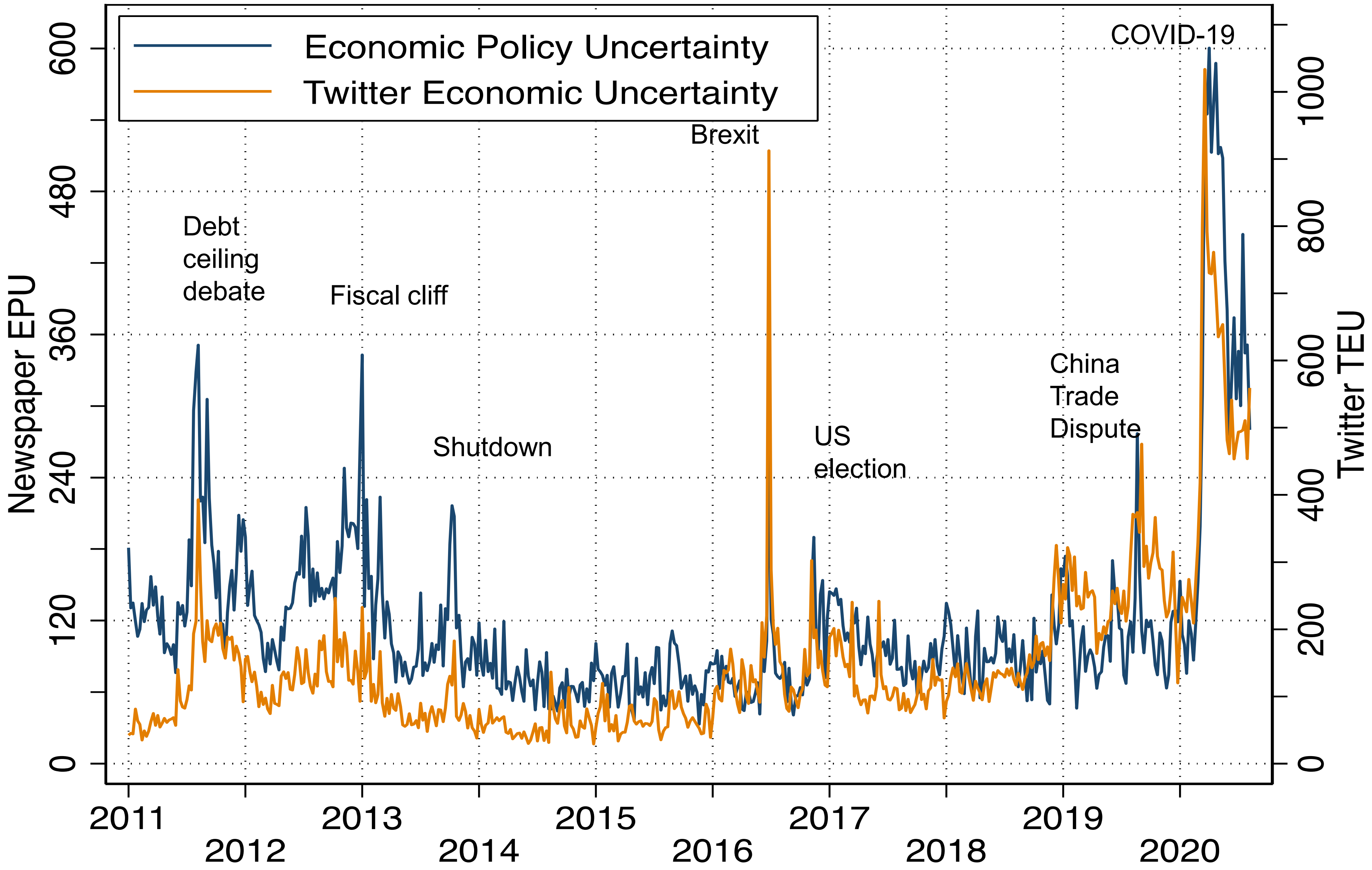
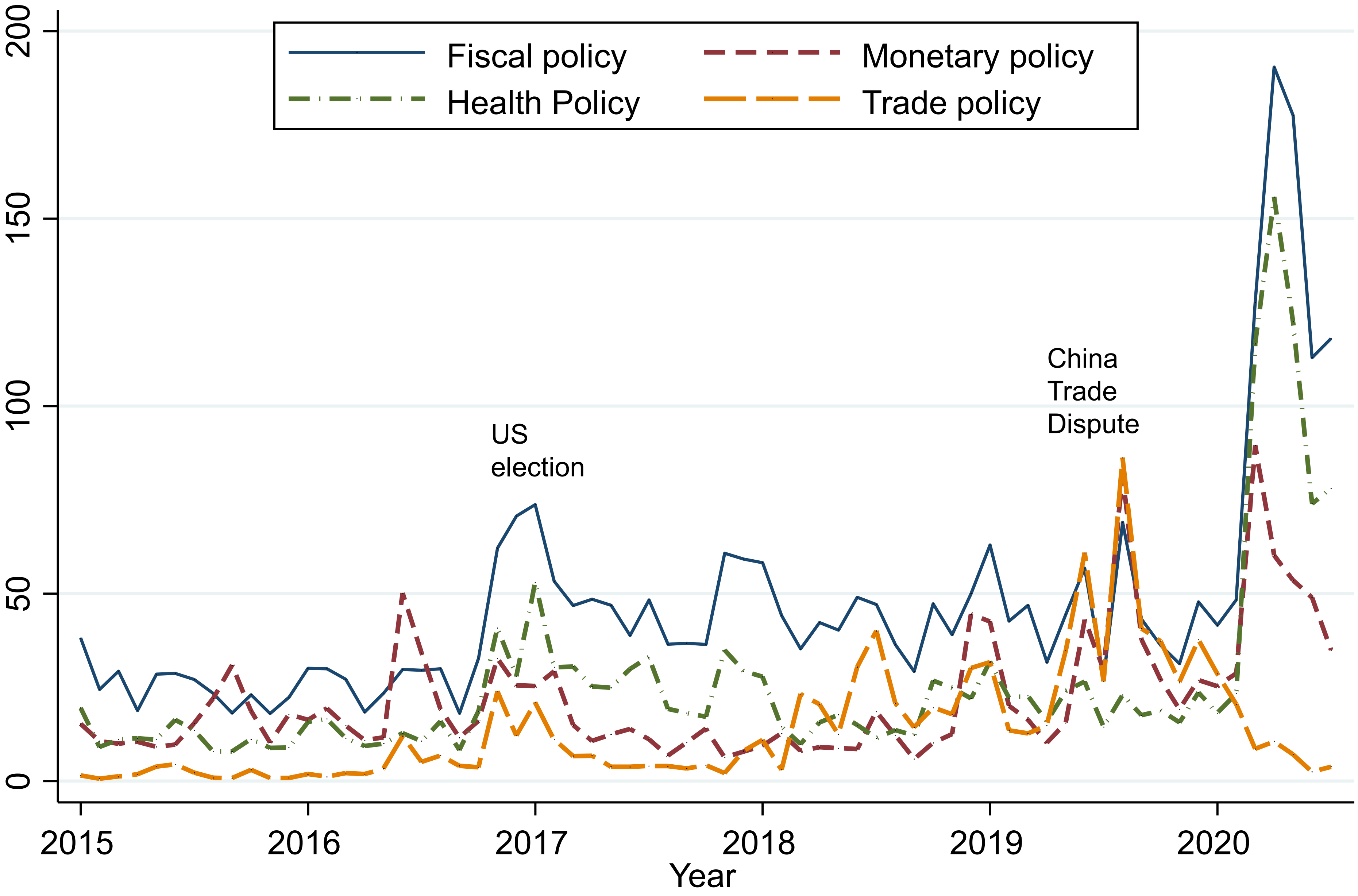
Figure 1: Newspaper and Twitter text uncertainty measures hit all-time highs during the pandemic



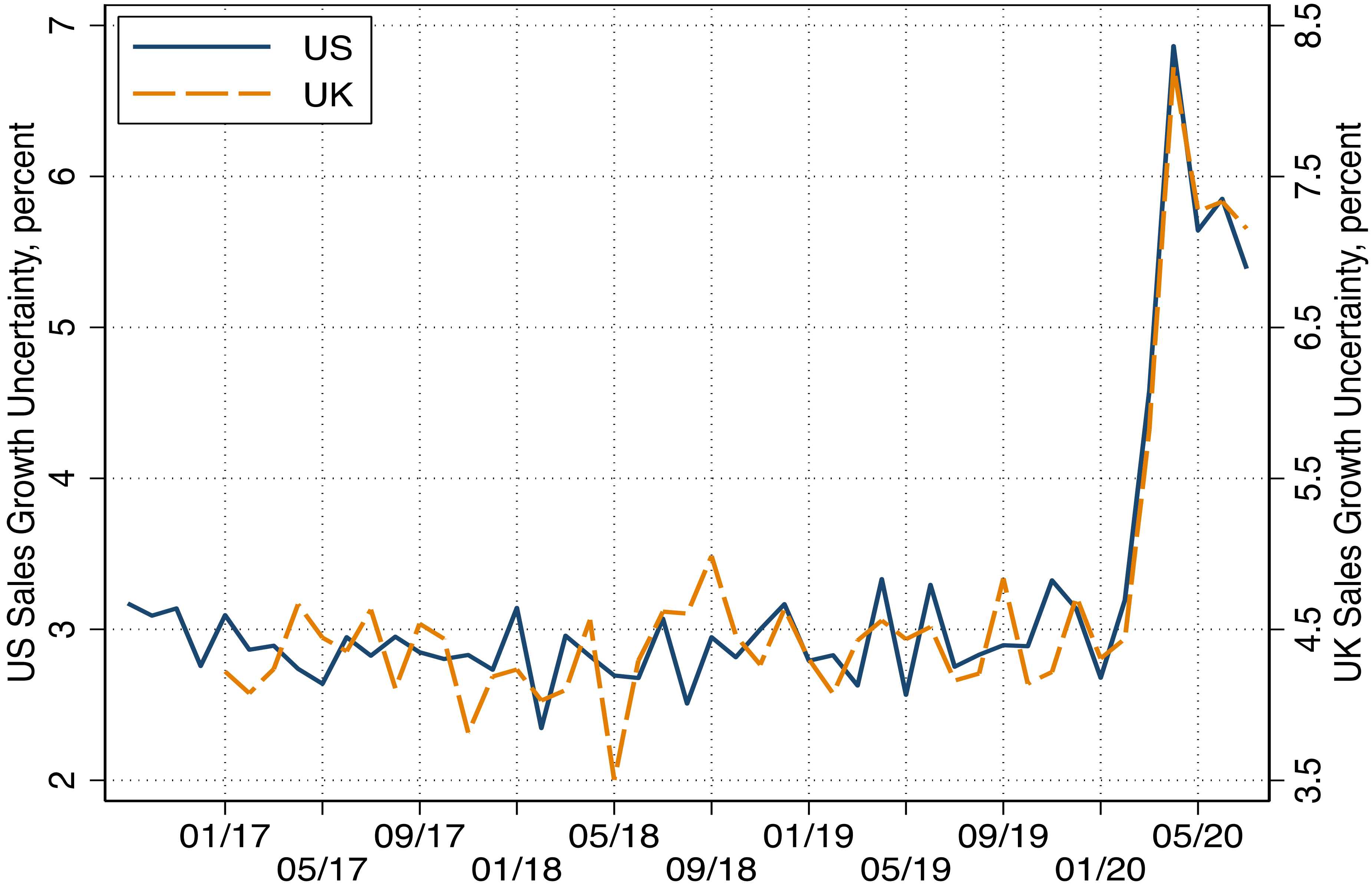
Notes: Weekly values for Economic Policy Uncertainty (EPU) index and Twitter Economic Uncertainty (TEU) index from www.policyuncertainty.com. See Baker, Bloom and Davis (2016) for details of EPU index construction and Baker, Bloom, Davis and Renault (2020) for details of the TEU index construction, with data at http://www.policyuncertainty.com. We plot data from 1 January 2011 to 12 August

Figure 2: The COVID surge in policy uncertainty is mainly driven by fiscal and health news



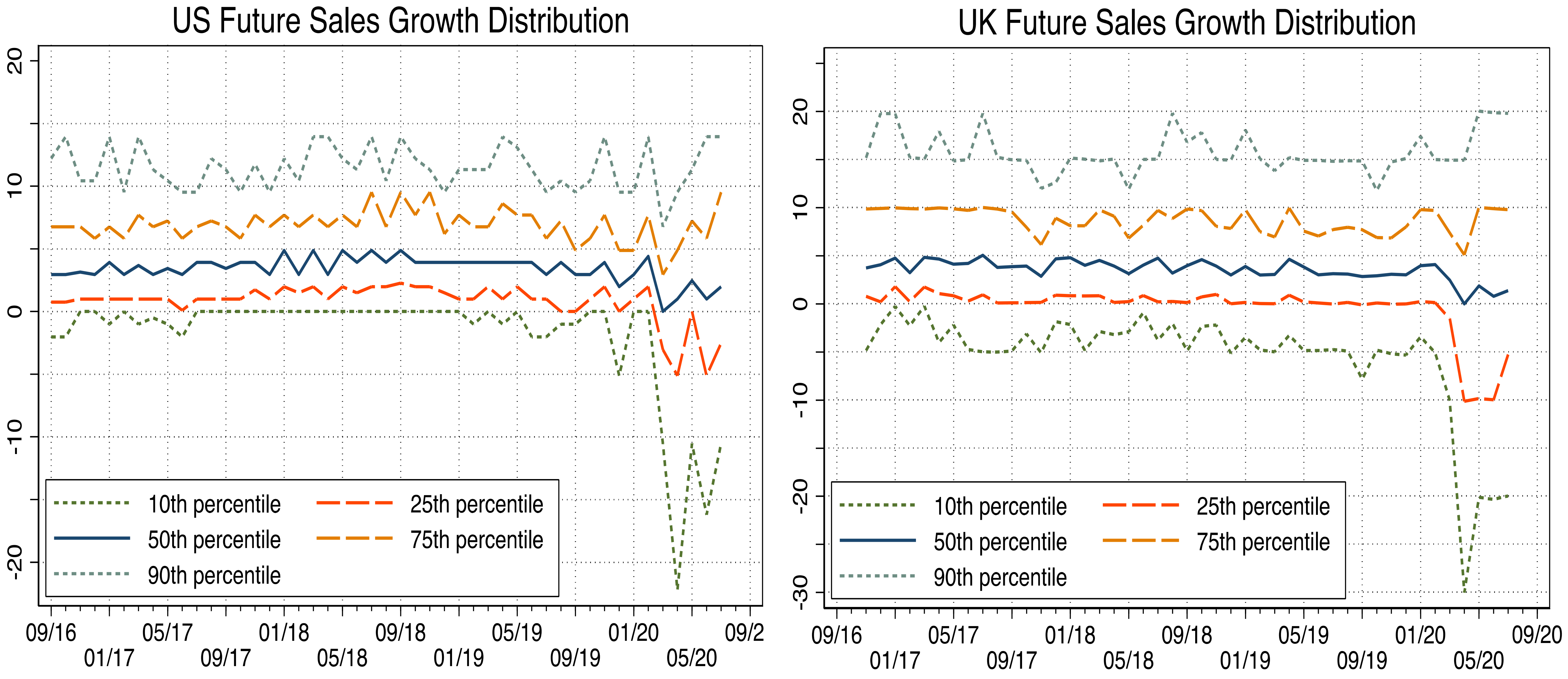
Notes: Weekly values for Economic Policy Uncertainty (EPU) index categories from www.policyuncertainty.com. See Baker, Bloom and Davis (2016) for details of EPU index construction. We plot data from 1 January 2015 to 30 July, with categories showing large rises in 2020 or 2019 plotted. Note that the average of the four plotted categories from 1985-2019 is as follows: Fiscal Policy=45.7, Health=17.7, Monetary Policy=27.1, and Trade Policy=5.7. This highlights how the rise in health policy in 2020 and trade policy in 2019 are particularly striking given their otherwise relatively low level.

Figure 3: Firm subjective sales uncertainty doubled during the pandemic, and has remained high



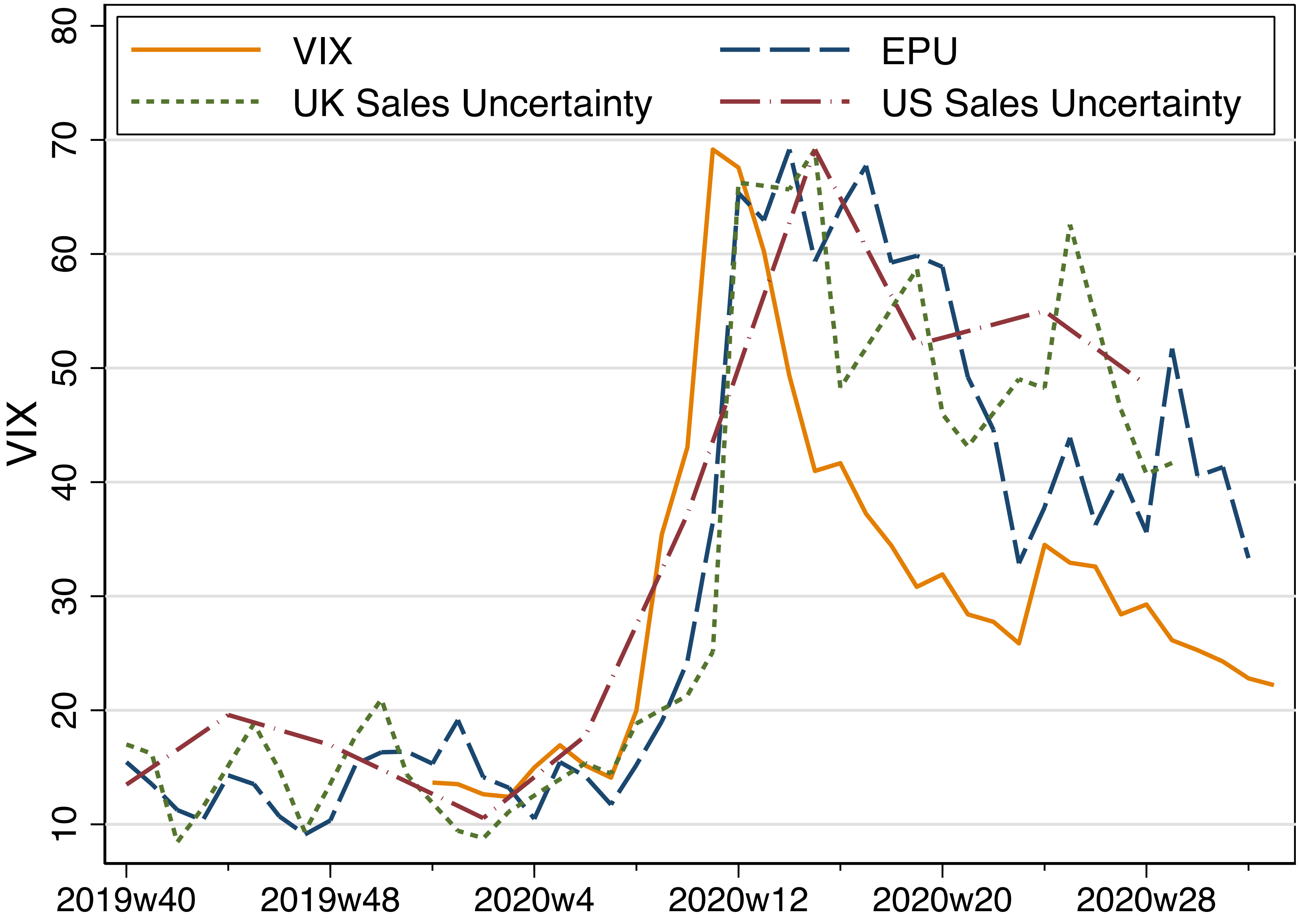
Notes: Source Altig et al. (2020). Subjective uncertainty measured for the growth rate of 4 quarters ahead firm level sales expectations (details in Altig et al. 2020). US data from the Survey of Business Uncertainty conducted by the Federal Reserve Bank of Atlanta, Stanford University, and the University of Chicago Booth School of Business (https://www.frbatlanta.org/sbu). 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 4: The pandemic generated extensive downside tail-risk for firms



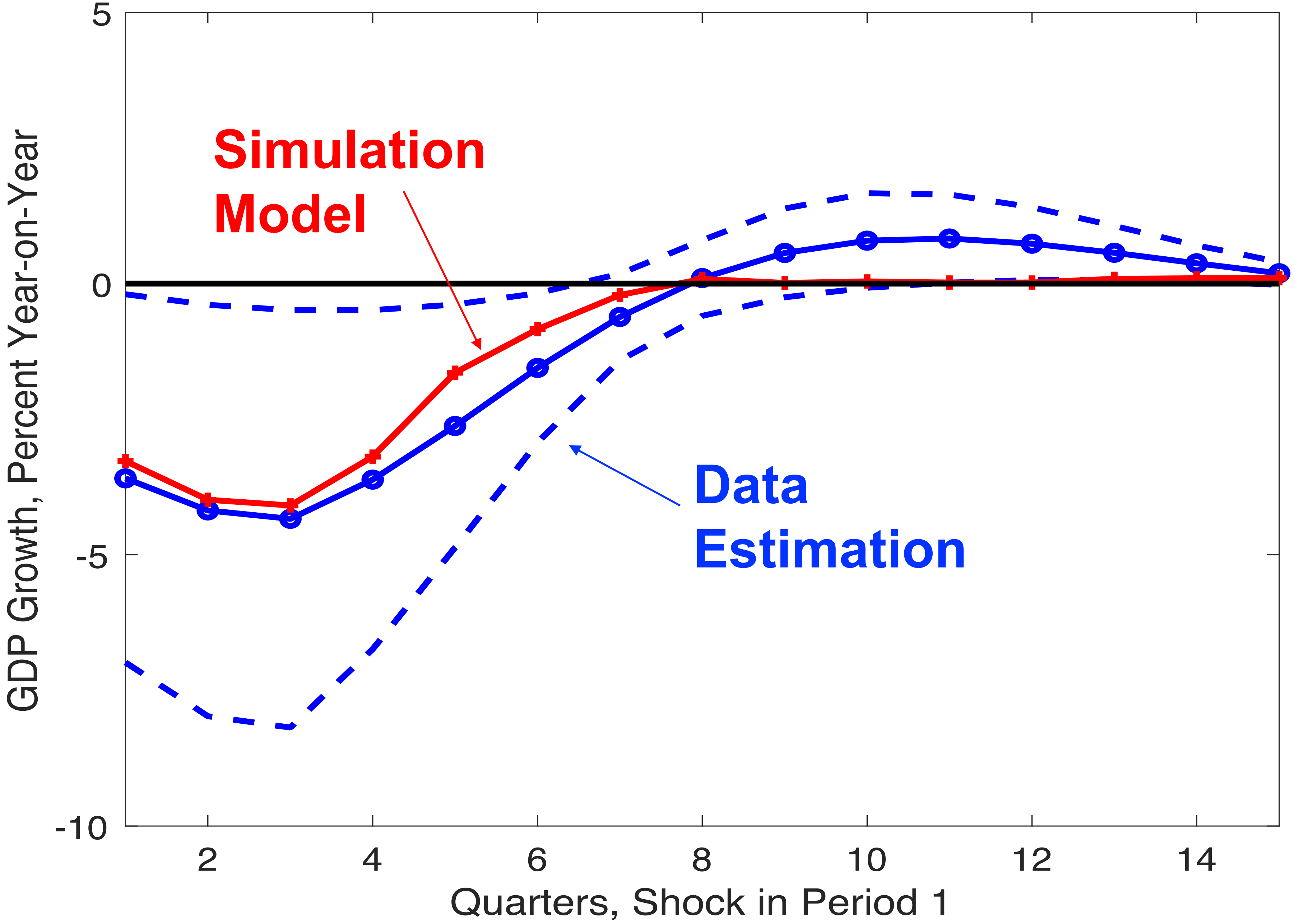
Notes: Each graph displays quantiles of the aggregate distribution of firm's distributional expectations of future sales growth, looking ahead at a four-quarter horizon. In each month, we aggregate individual firms' five-point subjective distributions by weighting a given firm's five support points by their probabilities and then weigh the support points for each firm by its employment. US data are 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/sbu) (see Altig et al. 2020). 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 5: “Wall Street” financial uncertainty has fallen more than “Main Street” output uncertainty



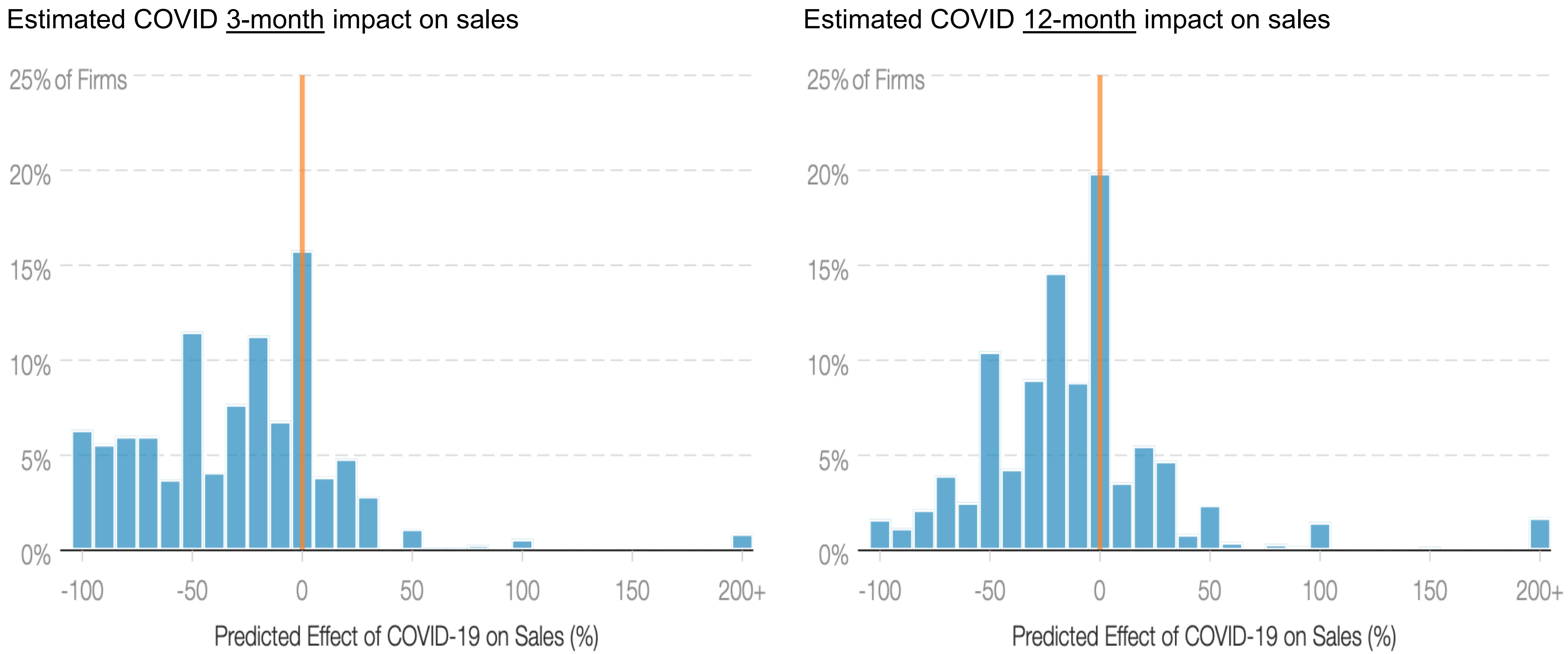
Notes: The VIX (Source: CBOE via Yahoo! Finance) and EPU (Source: www.policyuncertainty.com) series are simple averages of daily values in each week. The UK Sales Uncertainty data comes from the Decision Maker Panel survey conducted by the Bank of England, Nottingham University and Stanford University. Because of the large sample of almost 3000 firms per month this has been broken down into a weekly survey based on reporting periods. See Bloom et al. (2019) and www.decisionmakerpanel.com for details. The US Sales Uncertainty data comes 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/sbu). This has been plotted monthly as the smaller sample does not permit an accurate weekly survey. For plotting, we re-scale the EPU and UK and US Sales Uncertainty indices to have the same mean pre-pandemic (i.e. in weeks 1 to 7) and the same peak as the VIX.

Figure 6: Estimates suggest the pandemic uncertainty reduced GDP by around 2% to 4%



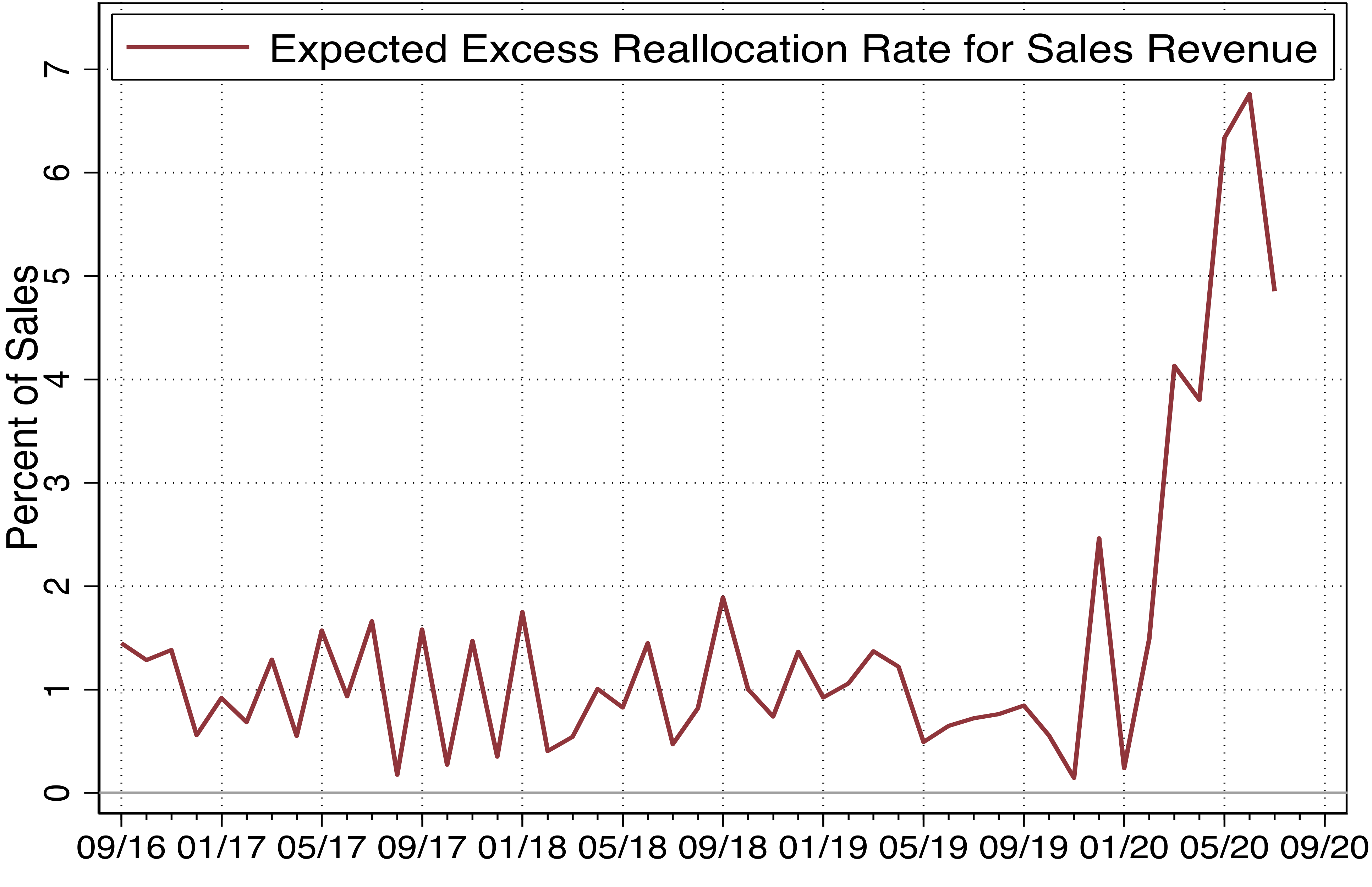
Notes: Source: Baker, Bloom and Terry (2020). The "Data Estimation" figure shows the response of GDP growth to a COVID-19 calibrated innovation in uncertainty. The parameters are estimated from a disaster instrumental variable VAR estimation. The estimation sample is a panel of about 4,400 nation-quarters spanning around 40 nations from 1987Q1-2017Q3. GDP growth in period t is the percentage growth from quarter t-4 to t. The estimated VAR includes time + country effects, country dummies, 3 lags, with GDP growth, stock returns, and the stock return uncertainty index. The instruments include natural disasters, coups, revolutions, & terrorist attacks. 90% empirical block bootstrapped bands plotted. The "simulation model" estimates the impact of a COVID-19 calibrated uncertainty shock in a general equilibrium model of firms with capital and labor adjustment costs model calibrated to US data.

Figure 7: The Pandemic has a heterogeneous impact on firms



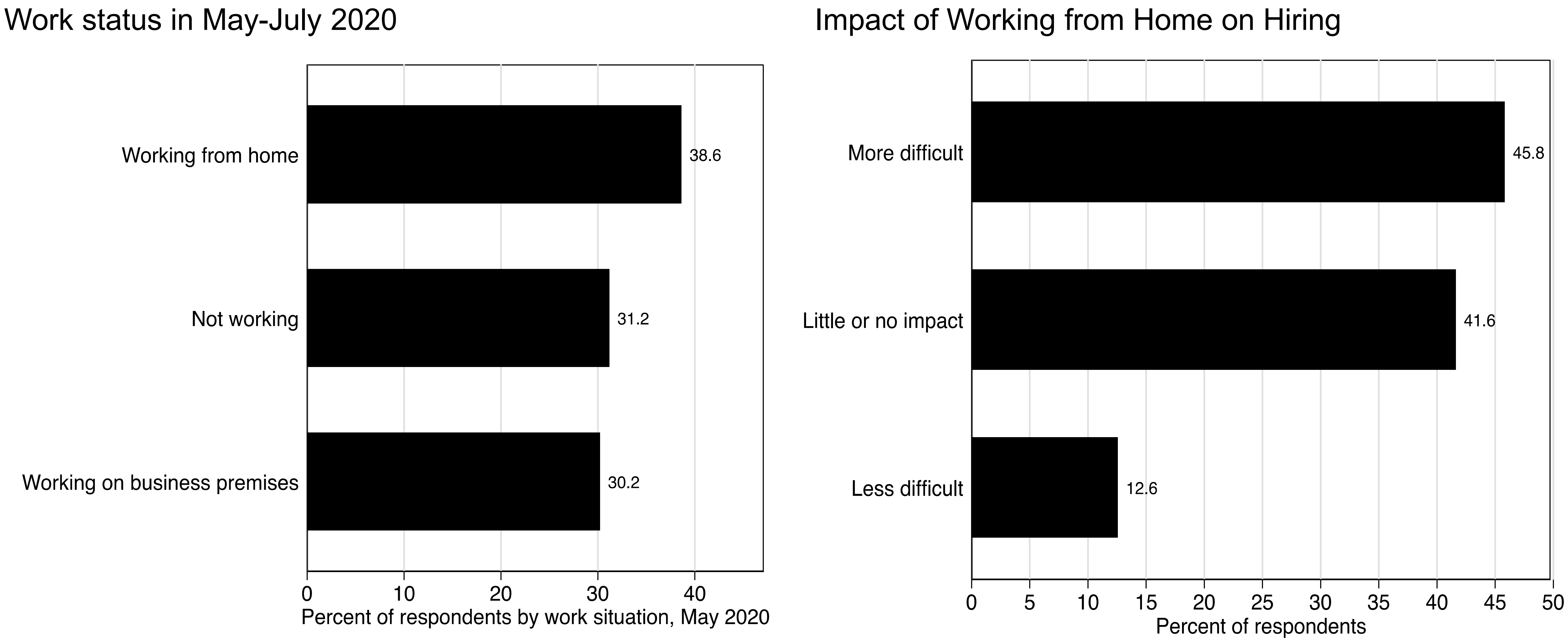
Notes: Source Stanford-Stripe survey of 2,380 smaller US firms using the Stripe.com payments system (see Bloom, Fletcher and Yeh 2020). These are almost entirely privately held smaller firms, with a mean of 9 employees and $350,000 annual sales, spread across the US and all industrial groups. The figure plots the histogram of the responses to two questions: *"By what percentage will COVID-19 impact your firms in the next three months*" on the left and "*By what percentage will COVID-19 impact your firms in the next twelve months"* on the right.

Figure 8: The Pandemic is inducing a large increase in cross firm and industry reallocation



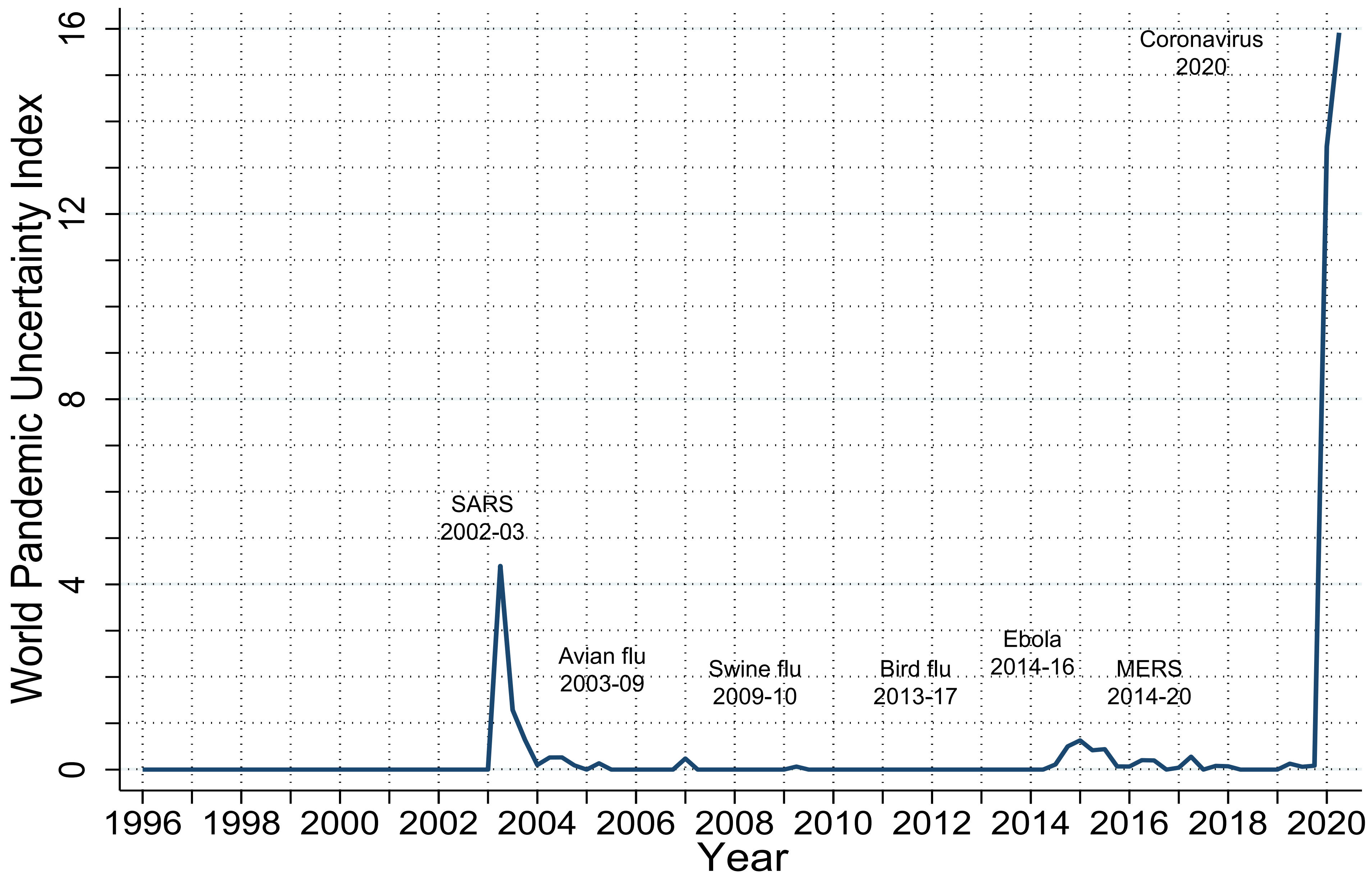
Notes: Source Barrero, Bloom and Davis (2020). The expected excess reallocation rate for sales revenue measures the rate at which sales revenue will move from one firm to another over the next four quarters, after accounting for aggregate sales revenue growth. This is computed as the activity-weighted average of the absolute (gross) value of individual firms' expected sales revenue growth, *less* the absolute value of the activity-weighted average sales revenue growth. The underlying data are 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/sbu.

Figure 9: The large increase in working from home is making it harder to hire



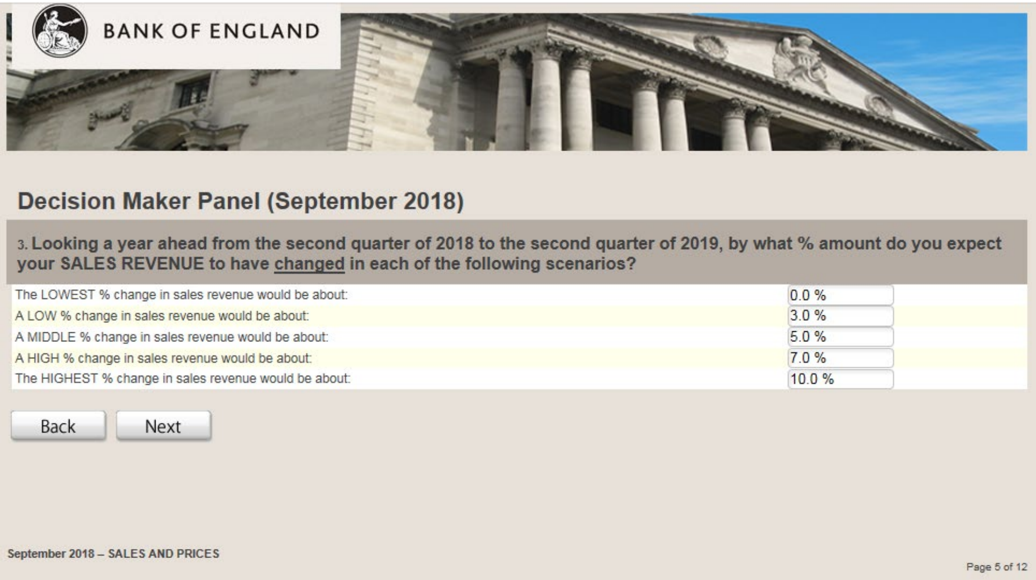
Notes: Source Barrero, Bloom and Davis (2020). On the left we show responses to the question "*Currently (this week) what is your work status?*". On the right, we show responses to the question "*What impact has working from home had on the ability to make new full-time hires in your employer's business?*" Data are from two surveys of 2,500 US residents aged 20 to 64, who earned more than $20,000 per year in 2019 carried out between May 21-29 and June 30 to July 9 by QuestionPro on behalf of Stanford University. Sample reweighted to match current CPS by income, industry, and state.

Figure 10: COVID uncertainty remains extremely high around the world



Notes: Data are from the World Uncertainty Index website's World Pandemic Uncertainty Index (WPUI), which measures discussions about pandemics at the global and country level in the Economist Intelligence Unit's approximately 140 country reports which are produced quarterly (or monthly for some larger countries, although we use only the quarterly updates for consistency). The underlying data are at https://worlduncertaintyindex.com/data/ (see Ahir, Bloom and Furceri, 2020)

Appendix Figure A1: The UK and US Firms Surveys: Sales Outcomes and Probability Questions


BANK OF ENGLAND

Decision Maker Panel (September 2018)

3. Looking a year ahead from the second quarter of 2018 to the second quarter of 2019, by what % amount do you expect your SALES REVENUE to have changed in each of the following scenarios?

The LOWEST % change in sales revenue would be about:	0.0 %
A LOW % change in sales revenue would be about:	3.0 %
A MIDDLE % change in sales revenue would be about:	5.0 %
A HIGH % change in sales revenue would be about:	7.0 %
The HIGHEST % change in sales revenue would be about:	10.0 %

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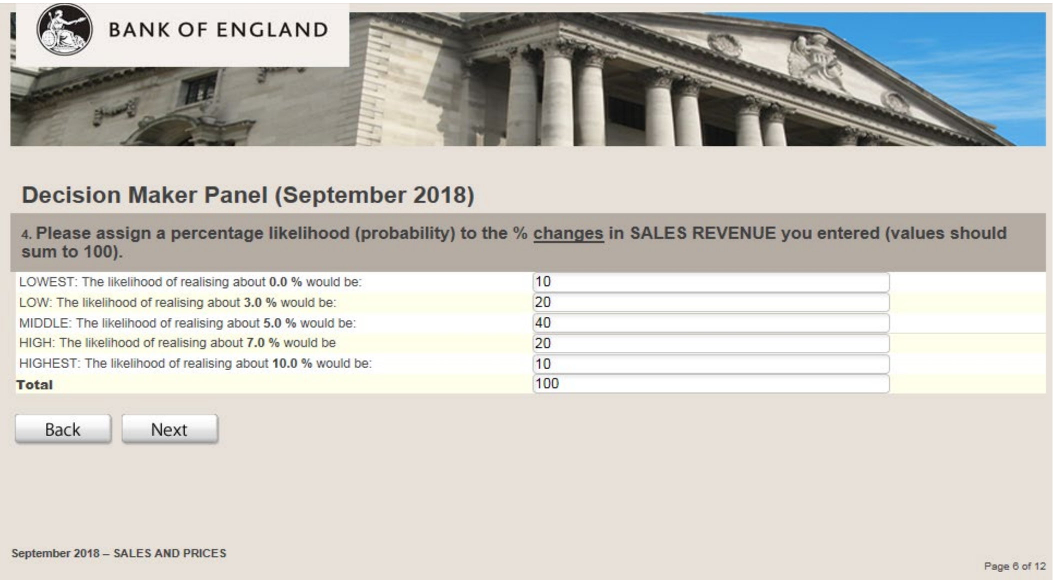
BANK OF ENGLAND

Decision Maker Panel (September 2018)

4. Please assign a percentage likelihood (probability) to the % changes in SALES REVENUE you entered (values should sum to 100).

LOWEST: The likelihood of realising about **0.0 %** would be:	10
LOW: The likelihood of realising about **3.0 %** would be:	20
MIDDLE: The likelihood of realising about **5.0 %** would be:	40
HIGH: The likelihood of realising about **7.0 %** would be	20
HIGHEST: The likelihood of realising about **10.0 %** would be:	10
Total	100

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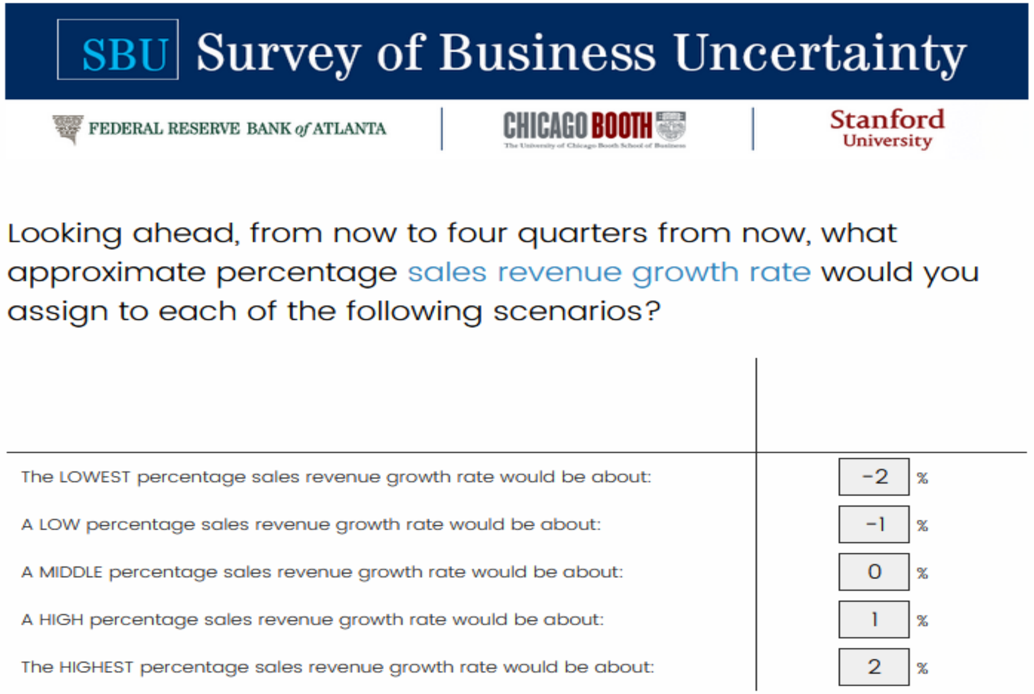
SBU Survey of Business Uncertainty

FEDERAL RESERVE BANK of ATLANTA | CHICAGO BOOTH | Stanford University

Looking ahead, from now to four quarters from now, what approximate percentage sales revenue growth rate would you assign to each of the following scenarios?

The LOWEST percentage sales revenue growth rate would be about:	-2 %
A LOW percentage sales revenue growth rate would be about:	-1 %
A MIDDLE percentage sales revenue growth rate would be about:	0 %
A HIGH percentage sales revenue growth rate would be about:	1 %
The HIGHEST percentage sales revenue growth rate would be about:	2 %


SBU Survey of Business Uncertainty

FEDERAL RESERVE BANK of ATLANTA | CHICAGO BOOTH | Stanford University

Please assign a percentage likelihood to the sales revenue growth rates you entered. (Values should sum to 100%)

LOWEST: The likelihood of realizing a **-2%** sales revenue growth rate would be:	15 %
LOW: The likelihood of realizing a **-1%** sales revenue growth rate would be:	25 %
MIDDLE: The likelihood of realizing a **0%** sales revenue growth rate would be:	30 %
HIGH: The likelihood of realizing a **1%** sales revenue growth rate would be:	25 %
HIGHEST: The likelihood of realizing a **2%** sales revenue growth rate would be:	5 %
Total	100 %

Notes: The top row shows the questions about the scenarios and then probabilities from the UK Decision Maker panel and the bottom row the same questions from the US Survey of Business Uncertainty. In both surveys these questions are preceded by questions about current and year ago sales levels.