Economics

Discussion Paper

Series

EDP-2013

THE COVID-INDUCED UNCERTAINTY SHOCKS

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December 2020

Economics

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Abstract

Using a statistical identification, we extract a Covid-induced shock by exploiting large daily jumps in financial markets caused by news about the pandemic. This shock depresses economic and financial indicators, increases risk and uncertainty measures, has sizeable distributional effects, and hits most harshly those industries relying on face-to-face interactions. Impulse response function analysis across several identification strategies leads us to interpret the statistical Covid-induced shock as a structural uncertainty shock.

Keywords: COVID 19, Uncertainty Shocks, Heteroskedasticity, Daily SVAR.

JEL codes: D80, E17, E32, E66, L50.

*We thank Nick Bloom, Efrem Castelnuovo, Michele Ca Zorzi, Massimo Ferrari, Georgios Georgiadis, Ekaterina Kazak, Alastair Hall, Anh Nguyen, David Peel, Carlo Reggiani, William Tayler, Mike Tsionas and Chris Wallace and seminar participants at the European Central Bank, University of Manchester and Lancaster University for useful comments and discussions. Errors are our own.

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1 Introduction

Understanding and measuring the causal effects of the Covid pandemic is a primary goal for economists and policy-makers alike. However, this has proven to be a daunting task both from an empirical as well as from a theoretical point of view. From an empirical point of view, during the first wave of the pandemic, there were many co-founding factors happening contemporaneously, such as changes in expectations, policy interventions, sudden increases in uncertainty. This makes isolating causal effects of the pandemic very problematic. At the same time, the overall pandemic is not easily reconcilable with standard macroeconomic fundamentals, thus making it difficult to analyse it under the lens of off-the-shelf general equilibrium models. We address these issues and make two contributions. First, we exploit unexpected news and announcements related to the pandemic to extract a *Covid-induced* shock and estimate its short-run recessionary effects. Second, we propose an interpretation of Covid-induced shocks as structural uncertainty shocks. We analyse US daily data and cover the period between the 13th of January and the 29th of July 2020.

The Covid-induced shock is extracted with a statistical procedure within a VAR, by combining a daily dataset of economic indicators, see Chetty et al. (2020), with the information content around days with large jumps in financial markets directly caused by Covid-related news and announcements, as reported by Baker et al. (2020) and major national newspapers.[1] In particular, we show that around these event days, the volatility of the system is higher than during non-event days, and that this difference can be attributed to a single, orthogonal shock, the 'Covid-induced' shock. This procedure is commonly known in the applied-macroeconomic literature as identification by heteroskedasticity, see Rigobon (2003), Wright (2012) and Gürkaynak et al. (2020).

At its core, we exploit the lumpy nature of relevant news and announcements about the pandemic as a source of statistical identification. Our key identifying assumption is that during our selected dates, the Covid-induced shocks are heteroskedastic, with a particularly high variance, while other contemporaneous shocks are not. As such, this

[1] Daily economic data used in our empirical exercise are from the Economic Tracker, available at tracktherecovery.org.

identification method allows for the possibility that other shocks occur on the same days beside the Covid-induced shock, as long as their variances are unchanged in these and other days.[2]

Based on this approach, our paper's main empirical insights consist in showing that during the pandemic, a Covid-induced shock has: i) significant contractionary effects on economic and financial aggregates; and ii) important distributional and sectoral effects. At the aggregate level, we show that an unexpected Covid-induced shock that contracts the S&P 500 Index by 1 percent, depresses standard economic indicators such as employment (-0.5 pc), private expenditure (-0.6 pc) and small business revenues (-0.6). Furthermore, we find that the same shock increases risk and uncertainty measures such as the VIX index (+5 pc), the Economic Policy index (+ 2.5 pc), TED (+2 bp) and BAA (+3.2 bp) spreads, and it depresses the global stock price index MSCI (-1 pc).

At the distributional level, we show that a Covid-induced shock reduces employment of poor households twice as much as that of rich households, i.e. -0.51 pc vs. -0.23 pc, respectively. Differently, the contraction in private expenditure is almost 40 percent higher for rich households (-0.50 pc) relative to poor ones (-0.35 pc). Moreover, as expected, we find that industries that rely heavily on face-to-face interactions, such as 'entertainment and hospitality', suffer a reduction in revenues that is around three times larger than the reduction in revenues experienced by industries which can operate remotely, such as business services.

Next, we provide evidence that our statistically identified Covid-induced shock can be interpreted as a structural uncertainty shock. This link between statistical and structural analysis is important because it allows to study the dynamics of the current pandemic under the lens of standard economic fundamentals. Our structural interpretation can also be useful for modelling and calibrating large general equilibrium models of the pandemic, such as the augmented SIR models, which are particularly insightful for macroeconomic as well as for microeconomic policy counterfactuals. All in all, we believe that our link

[2]Furthermore, unlike for monetary policy events, announcements about the pandemic are not fixed at a schedule time and most likely are scattered during the event days. For this reason it is unfeasible to create a few-minute window in stock price movements around a specific announcement and use it as instrument in a Proxy-SVAR fashion.

between Covid and uncertainty is reasonable for at least two reasons. First, the current Covid pandemic is increasing massively uncertainty about most, if not all, aspects of our lives. This makes it natural to link the pandemic news to uncertainty, as reported in the survey evidence of Dietrich et al. (2020), Coibion et al. (2020a), Binder (2020), Fetzer et al. (2020), and subsequent contributions.[3] Second, inspection of Covid-induced impulse response functions, i.e. large impact increase in VIX index, hump-shaped recessionary effects and increase in risk factors, clearly remind those of an uncertainty shock.

To assess our conjecture, we estimate a structural uncertainty shock on the whole sample under consideration by adopting three popular (and somewhat complementary) identification methods, i.e. Penalty Function as in Caldara et al. (2016), Cholesky as in Altig et al. (2020) and Sign-Restriction as in Uhlig (2005). Even though these identification schemes are completely different from our statistical identification, we find that the Covid-induced shocks and the structural uncertainty shocks generate qualitatively and quantitatively comparable dynamic responses of key financial and economic indicators. This holds both for the aggregate variables as well as for the distributional ones. Interestingly, we reach the same results when we control for potential overlapping information between first-moment shocks, such as agents confidence, and our measure of uncertainty. As such, our findings lead us to the conclusion that is reasonable to interpret the Covid-induced shock as structural uncertainty shock, that we label as *Covid-Induced Uncertainty* (CIU) shock.

Relation to the literature. Our paper relates to two strands of the emerging literature on the economic consequences of the Covid pandemic. First, we provide causal empirical evidence about the short-run effects of news and announcements about the pandemic. On this, our paper closely relates to the literature that employs high-frequency data to measure the economic repercussions brought by the Covid pandemic. At the aggregate level, Baek et al. (2020) measure the labour market effects of Stay-at-Home orders in the US and

[3] There is unprecedented uncertainty about the health consequences and the mortality of the virus; the ability and resources of healthcare systems to manage this exceptional emergency; the speed and effectiveness of a safe and reliable vaccine; social distancing, market lock-downs, and school closures; the depth and persistence of the economic downturn; and the speed and effectiveness of economic policies interventions; to name a few.

find that it caused around a quarter of all unemployment insurance claims between mid-March and beginning of April 2020. Using a newly compiled weekly economic indicator, Lewis et al. (2020) find that the pandemic had already a significant contractionary effect on the US economy in the early weeks of the outbreak. Coibion et al. (2020a,b) use a repeated large-scale household survey and analyse the recessionary effects of the pandemic and lockdowns on employment, consumption and macroeconomic expectations. At the distributional level, Chetty et al. (2020) uses a newly built daily dataset of economic indicators for the US and find that the pandemic outbreak had a stronger impact on the employment of the poor and the consumption expenditure of the rich. Hacioglu et al. (2020) find similar results in a weekly dataset of the UK.

We depart from this literature as we estimate the short-run causal effects of Covid by exploiting large jumps in the stock markets that we combine with daily economic indicators of the pandemic. As such we can rely on standard high-frequency time-series techniques, and analyse both the aggregate as well the distributional short-run effects of the pandemic.

Second, we contribute to the literature that interprets the current pandemic under the lens of structural uncertainty shocks. Baker et al. (2020), Ludvigson et al. (2020), Cox et al. (2020), Dietrich et al. (2020), Caggiano et al. (2020) and subsequent contributions. The closest contributions to our paper can be found in Baker et al. (2020) and Altig et al. (2020). These papers calibrate the size of the uncertainty shock on the jumps of the VIX index observed during the pandemic, and then they back out the contractionary effects of CIU shocks either in a post-80s quarterly model of economic disasters (Baker et al., 2020) or in a post-60s monthly Cholesky-VAR (Altig et al., 2020).

We differ from these papers on two important aspects. First of all, we estimate a SVAR at daily frequency, on a sample of the pandemic (Jan-July 2020). This approach can isolate a precise quantitative understanding of the transmission mechanism of CIU shocks and, crucially, draw a formal link (at least at the empirical level) between Covid related news and announcements, and uncertainty shocks. This link is generally treated as an ex-ante assumption by the cited literature. Finally, our approach can also help to avoid potential issues of structural breaks in the data post January 2020, see Lenza and Primiceri (2020).

However our method comes at the cost of analysing a restricted number of variables (those available at daily level). Furthermore, our inference is valid just for the sample under consideration, i.e. Jan-Jul 2020. As such our results only cover the short-run effects of a CIU shock. In this sense, data availability allows us to provide an important, unique and high frequency, yet partial, perspective about the economic effects of uncertainty shocks during the pandemic.

Second, we also analyse non-trivial distributional effects of CIU. In this sense, our paper can shed light on how the increase in uncertainty, in particular at the onset of the outbreak, has exposed various parts of the US economy differently. Interestingly, our results are broadly consistent with the descriptive evidence of Chetty et al. (2020) for the US and of Hacioglu et al. (2020) for the UK. From this, our structural analysis suggests that uncertainty might be a pivotal element in understanding the dynamics of aggregate as well as distributional indicators during the first wave of the Covid pandemic.

The remaining of the paper is the following. Section 2 describes the statistical technique used in the paper to extract our Covid-induced shock. Section 3 gives a brief description of our dataset. Section 4 reports our empirical results for the Covid-induced shock, both at the aggregate and distributional levels, while Section 5 presents our link between the statistical Covid-induced shock and the structural uncertainty shock. Finally, Section 6 concludes.

2 The Covid-Induced Shock

Here we outline the empirical model used to extract our Covid-induced shock. We estimate a VAR at daily frequency by combining heteroskedasticity identification a la Rigobon (2003), Wright (2012) and subsequent contributions, with standard Bayesian techniques, see also Miescu and Mumtaz (2020). The description of the latter can be found in Appendix A.

The starting point of our analysis is a reduced-form VAR of order P, written as:

$$Y_t = X_t \beta + \mu_t, \tag{1}$$

where Y_t is $1 \times N$ matrix of endogenous variables, $X_t = [X_{t-1}, .., X_{t-P}, 1]$ is a $1 \times (NP + 1)$

matrix of regressors, and β is a $(NP+1) \times N$ matrix of coefficients. Finally μ_t is a $1 \times N$ vector of reduced-form residuals. Identification of meaningful shocks amounts to finding a mapping Γ between the prediction errors μ_t and a vector of mutually orthogonal shocks ϵ_t, i.e.

$$\boldsymbol{\Gamma}\epsilon_t = \mu_t, \tag{2}$$

where $\boldsymbol{\Gamma}$ is a $N \times N$ non-singular matrix of coefficients that satisfy $E(\mu_t \mu_t') = \boldsymbol{\Gamma}\boldsymbol{\Gamma}'$. The identification of our Covid-induced shock within the vector ϵ_t exploits the following two testable assumptions: i) the volatility of the system on those days in the sample (event days) when large jumps ($\geq$ 2.5 pc) of the S&P 500 index are due to news and announcements about the pandemic is different, i.e. higher, than in other days (non-event days); and ii) that the difference in volatility between event and non-event days is explained by one single orthogonal shock. We label this shock as *Covid-induced* shock.

In a nutshell, the identification exploits the lumpy and unpredictable nature of important events related to the Covid pandemic, so that the days on which they happen, are random dates on the calendar. If this is true, the variance of all other orthogonal shocks in vector ϵ_t should be the same on these and other days. Crucially, the conditional variance of the other shocks can vary from day to day, as long as their average variance is the same on event and non-event days.

Then, by defining Σ_H and Σ_L as the variance-covariance matrices of the reduced form errors on events and non-events days and σ_H^2 and σ_L^2 as the variances of the Covid-induced shocks on event and non event days, respectively, we can transform equation (2) as

$$\Sigma_H - \Sigma_L = \Gamma_1 \Gamma_1' \left(\sigma_H^2 - \sigma_L^2\right). \tag{3}$$

This enables us to recollect the vector Γ_1, which suffices to identify our Covid-induced shock.[4] Given we are not interested in identifying any other orthogonal shock, we do not need to impose any further structure on Γ.[5]

[4]Given that $\Gamma_1\Gamma_1'$ and $(\sigma_H^2 - \sigma_N^2)$ are not separately identified, we can impose the normalisation $\sigma_H^2 - \sigma_L^2 = 1$ without loss of generality. Furthermore, our notation implies that the Covid-induced shock is ordered first, but this is just for notational convenience, since the ordering of variables is irrelevant.

[5]Note that the estimated coefficients in Γ_1 are still consistent in the case that heteroskedasticity is misspecified in the model, see Rigobon (2003) for further details.

From a statistical point of view, we proceed as follows. We estimate the parameters of our VAR via standard Bayesian techniques. Then, we compute within the same iteration, the sample variance-covariance matrices of the VAR residuals on event, i.e. $\hat{\Sigma}_H$, and non-event days, i.e. $\hat{\Sigma}_L$. Finally, we estimate the vector $\hat{\Gamma}_1$ of parameters corresponding to our Covid-induced shock, as a standard minimum distance problem, i.e.

$$\Gamma_1 = \arg\min_{\Gamma_1} \left[vech\left(\hat{\Sigma}_H - \hat{\Sigma}_L\right) - vech\left(\Gamma_1 \Gamma_1'\right) \right]' \left[\hat{V}_L + \hat{V}_H\right]^{-1} \times \left[vech\left(\hat{\Sigma}_H - \hat{\Sigma}_L\right) - vech\left(\Gamma_1 \Gamma_1'\right) \right], \tag{4}$$

where $\hat{V}_H$ and $\hat{V}_L$ are the sample estimates of the variance-covariance matrices of $vech(\hat{\Sigma}_H)$ and $vech(\hat{\Sigma}_L)$, respectively.

3 The Data

This section describes in details the data used in our econometric exercise. We work at daily frequency and our sample covers the period 14/1/2020 to 26/07/2020. Our data come from three distinct sources. First of all, we collect readily available daily financial data such as the S&P 500 index, the VIX index *et cetera*. Second, we use publicly available daily data on a set of economic indicators such as employment and private spending at the granular level, constructed via anonymized data from private companies, see Chetty et al. (2020) for further details. Third, we select the list of day/events necessary for our identification by exploiting the newspaper-based dataset presented in Baker et al. (2020), which covers our data sample.[6]

In the original dataset, the authors examine next-day newspaper explanations for each daily movement in the U.S. stock market greater than 2.5 percent and classify the journalist's explanation of the sudden stock market movements into sixteen categories. The underline observation is that large stock market jumps always attract media coverage in major newspapers on the very same night or on the following day. Then we classify as event days, the episodes in Baker et al. (2020) dataset within our sample that have as a pri-

[6]While daily data about economic indicators are available up until the end of October 2020, the data classification of events in Baker et al. (2020) ends at the end of July 2020.

mary cause news and announcements about the Covid pandemic.[7] In order to improve our identification, we remove those days when important policy or macroeconomic announcements were made (such as 3*rd* of March and 29*th* of April) and events without a clear classification. In this way we isolate seventeen event days between Januray and July 2020. The list of events can be found in Table 1.

Table 1 – Description of the events used for identification.

Date	S&P 500 Jump	Primary cause from Baker et al. (2020)
24/02/2020	-0.034	Covid
25/02/2020	-0.030	Covid
27/02/2020	-0.044	Covid
03/03/2020	-0.028	Covid
05/03/2020	-0.034	Covid
11/03/2020	-0.049	Covid
12/03/2020	-0.095	Covid
16/03/2020	-0.120	Covid
18/03/2020	-0.052	Covid
01/04/2020	-0.044	Covid
06/04/2020	0.070	Covid
08/04/2020	0.034	Covid
14/04/2020	0.031	Covid
17/04/2020	0.027	Covid
18/05/2020	0.032	Covid
11/06/2020	-0.059	Covid
24/06/2020	-0.026	Covid

4 The Empirical Evidence

This section presents the results about the Covid-induced shocks. First, we describe our benchmark econometric model and discuss a number of issues related to the validity of our identification. Second, we present a set of estimated impulse response functions (IRFs) to Covid-induced shocks for aggregate, distributional and industry-level variables.

[7]Further complementary explanation about the stock market events can be found in `stockmarketjumps.com`.

The Benchmarck Model. Our econometric specification consists of a five-variable VAR, comprising of financial and economic indicators, i.e.

$$X_t = \left[ln\left(VIX_t\right), ln\left(S\&P500_t\right), R_t, ln\left(C_t\right), ln\left(Emp_t\right)\right], \tag{5}$$

where $ln\left(VIX_t\right)$ is the (log of) VIX index, a popular financial indicator, commonly used as a proxy for forward looking economic uncertainty, e.g. Bloom (2009). $ln\left(S\&P500_t\right)$ is the (log of) the S&P 500 Index, the main US stock market indicator. It is meant to capture a number of first-order effects, given its forward-looking nature and the amount of information it contains. (R_t) is the 1-Year Treasury Constant Maturity Rate (DSG1). As argued by Gertler and Karadi (2015), this variable is an appropriate proxy for monetary policy when the Federal Fund Rate is stuck at zero, as in the sample under consideration. $ln(C_t)$ is the (log of) private expenditure and is the most common economic indicator to capture aggregate demand conditions. It is reported as the seasonally adjusted credit/debit card spending relative to January 4th 2020. Finally, $ln(Emp_t)$ is the (log of) employment level and it is meant to capture labour market conditions. Despite its daily frequency, our benchmark VAR includes variables typically used in applied works, e.g. Baker et al. (2016). The sample is consistently kept between 14/01/2020-26/07/2020, and the lag structure is equal to ten, i.e. two working weeks.[8]

Validation of our identification. Our identification strategy is based on two requirements. First, we require that event and non-event days are different with respect to their variance-covariance matrix of reduced-form residuals, that is $\Sigma_H \neq \Sigma_L$. This is essential to achieve identification as it signals heteroskedasticity on event days. We verify this requirement by computing for each saved draw in the Gibbs-sampler, the statistical distance

$$\hat{\Pi}_1 = vech\left(\hat{\Sigma}_H - \hat{\Sigma}_L\right) vech\left(\hat{\Sigma}_H - \hat{\Sigma}_L\right)'. \tag{6}$$

If the two variance-covariance matrices are not statistically different, we should obtain posterior distributions concentrated around zero. Figure 1 (left-quadrant) shows that this

[8] We experimented with different lag structures, and results do not change, see Appendix B, Figure B.2.

is not the case, as the Kernel distribution is not centered at zero. This brings favourable evidence to our identification assumption.

Second, we want that the difference in the variance-variance matrices can be factored in the form of $\Gamma_1\Gamma_1^{'}$, i.e. $\Sigma_H - \Sigma_L = \Gamma_1\Gamma_1^{'}$. This indicates that the difference in the variance-covariance matrices between event and non-event days can be explained by one orthogonal shock, the Covid-induced shock. We verify this requirement by computing, for each saved draw, the statistical distance

$$\hat{\Pi}_2 = \left[vech\left(\hat{\Sigma}_H - \hat{\Sigma}_L\right) - vech\left(\hat{\Gamma}_1\hat{\Gamma}_1^{'}\right)\right]^{'}\left[vech\left(\hat{\Sigma}_H - \hat{\Sigma}_L\right) - vech\left(\hat{\Gamma}_1\hat{\Gamma}_1^{'}\right)\right]. \tag{7}$$

The identification assumption is verified if the posterior distribution of Π_2 is concen-

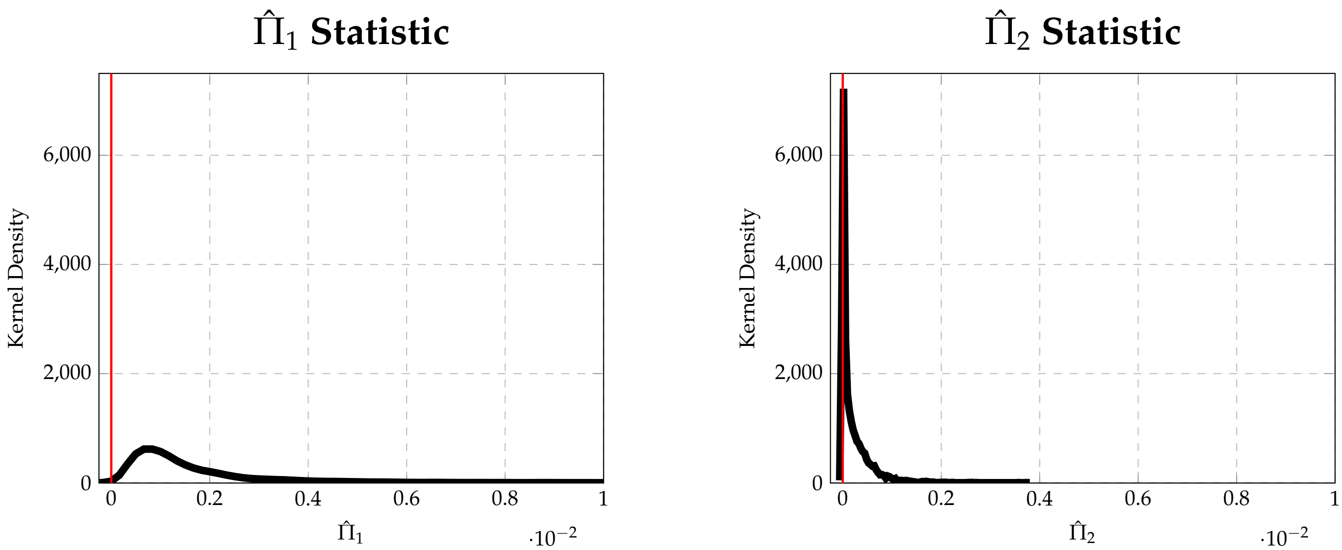

Figure 1 – Kernel density functions calculated on 5000 posterior draws of the statistics $\hat{\Pi}_1$, see equation (6), and $\hat{\Pi}_2$, see equation (7).

trated around zero, which Figure 1 (right-quadrant) suggests to be the case.

As in Wright (2012), we can also test our two identification hypotheses via a standard Wald test (a slight statistical abuse under our Bayesian approach). In this case, for the first hypothesis, i.e. that the system is more volatile on event days, we test the null that $\Sigma_H = \Sigma_L$. For this, we use the posterior median from the statistic

$$\hat{\Omega}_1 = \left[vech\left(\hat{\Sigma}_H - \hat{\Sigma}_L\right)\right]^{'}\left[\hat{V}_L + \hat{V}_H\right]^{-1}\left[vech\left(\hat{\Sigma}_H - \hat{\Sigma}_L\right)\right], \tag{8}$$

while for the second requirement, i.e. that the difference in volatility between event and non-event days can be attributed to a single orthogonal shock, we test the null that $\Sigma_H -$

$\Sigma_L = \Gamma_1\Gamma_1'$. For this, we use the posterior median of the statistic

$$\hat{\Omega}_2 = \left[vech\left(\hat{\Sigma}_H - \hat{\Sigma}_L\right) - vech\left(\hat{\Gamma}_1\hat{\Gamma}_1'\right)\right]' \left[\hat{V}_L + \hat{V}_H\right]^{-1} \left[vech\left(\hat{\Sigma}_H - \hat{\Sigma}_L\right) - vech\left(\hat{\Gamma}_1\hat{\Gamma}_1'\right)\right]. \tag{9}$$

Our identification is validated if we reject the first hypothesis and accept the second. In our baseline VAR, we find $\hat{\Omega}_1 = 31.9$ (p-value = 0.006) and $\hat{\Omega}_2 = 16.5$ (p-value = 0.38), so we reject the first hypothesis and accept the second, as desired. As such we bring further support for our identification scheme and for the presence of a single orthogonal shock explaining the difference in volatility between event and non-event days.[9]

IRFs of Aggregate Variables. Now we turn our attention to the analysis of the impulse response functions (IRFs). For each observable, we report the response of its posterior median and the 68 and 90 credibility intervals to a Covid-induced shock that lowers the S&P 500 index by 1 percent.[10]

The Covid-induced shock has a prolonged contractionary effect on the financial markets as the S&P 500 index remains below its trend for around 40 working days (8 weeks). In the same fashion, the VIX index jumps on impact by around 5 percent and remains above its trend for about seven weeks (35 working days). The peak response in these two variables happen on impact and clearly reflects the forward-looking nature of financial markets. In Appendix B, Figure B.3, we show that world stock prices, i.e. the MSCI index, display a similar response to the S&P 500 index, reflecting the co-movement in the international financial variables, see Miranda-Agrippino and Rey (2020).[11] Along the same line, in Appendix B, Figure B.3, we find that a Covid-induced shock increases significantly two standard measures of risk, the TED and the BAA spreads, whose peak effects happen two weeks after the shock and is around 2 and around 3 basis points, for TED and BAA spreads, respectively.[12] Finally, in order to measure the effects of our Covid-induced

[9] In Appendix B, Figure B.1, we also run a placebo-style exercise and show that if we randomise the event dates, our Covid-induced shock is not identified. This result further supports our choice of events in a sample characterised by turbulent behaviour of the financial markets.

[10] While we also report the 90 percent credibility set, it is important to stress that the standard significance level within Bayesian settings is 68 percent, see Sims and Zha (1999).

[11] For these extended variables, we plot the response of the observables added singularly one-by-one to the benchmark model in (5).

[12] The TED spread is the difference between the three-month Treasury bill and the three-month LIBOR

shock on agents' expectations and confidence, in Appendix B, Figure B.3, we present results from VARs that include the Sentiment Index, a recent text-based measure of daily economic sentiment from economic and financial newspaper articles, see Shapiro et al. (2020). This index has been shown to correlate with a number of standard consumers' confidence measures available at lower frequencies, such as the Michigan Consumer Sentiment Index. We find that a Covid-induced shock has a negative effect on agents' sentiment, with a peak effect of around 0.5 pc three weeks after the shock. Interestingly, the response of the Sentiment Index to Covid news and announcements is muted on impact.

The Covid-induced shock also generates a contraction in the 1-year treasury rate, which approximates monetary policy. The peak response of around 2 basis points happens shortly after two weeks from the shock. The short delay in the response of the interest rate reflects the prompt policy actions taken by the monetary authority, both with conventional and unconventional instruments, see Bahaj and Reis (2020) and Cox et al. (2020) among others, to news and announcements about the pandemic. In Appendix B, Figure B.3, we also show that the newspaper-based measure of economic policy uncertainty, the EPU index (see Baker et al., 2016), increases significantly with increases in Covid-induced shock. Interestingly, the peak effect on EPU happens slightly after the movements in the 1-year Treasury rate, probably signalling an increase in policy uncertainty around monetary policy interventions.

The last row of Figure 2 presents the response of private expenditure and employment to a Covid-induced shock. The main message is that these economic variables contract significantly in the short-run to news and announcement about the pandemic. Employment, one of the main economic indicators of the labour market, decreases, with a maximal effect of 0.42 percent and 90 percent credibility set [-0.83;-0.02]. On the household side, we find that the maximal effect on private expenditure is around 0.5 percent and 90 percent credibility set [-1.2;-0.02]. In Appendix B, Figure B.3, we show that, consistently with the results on expenditure and employment, a Covid-induced shock contracts small-business revenues by around 0.6 percent and small business opening by around 0.5

based in US dollars. Put it differently, the TED spread is the difference between the interest rate on short-term US government debt and the interest rate on interbank loans.

percent.

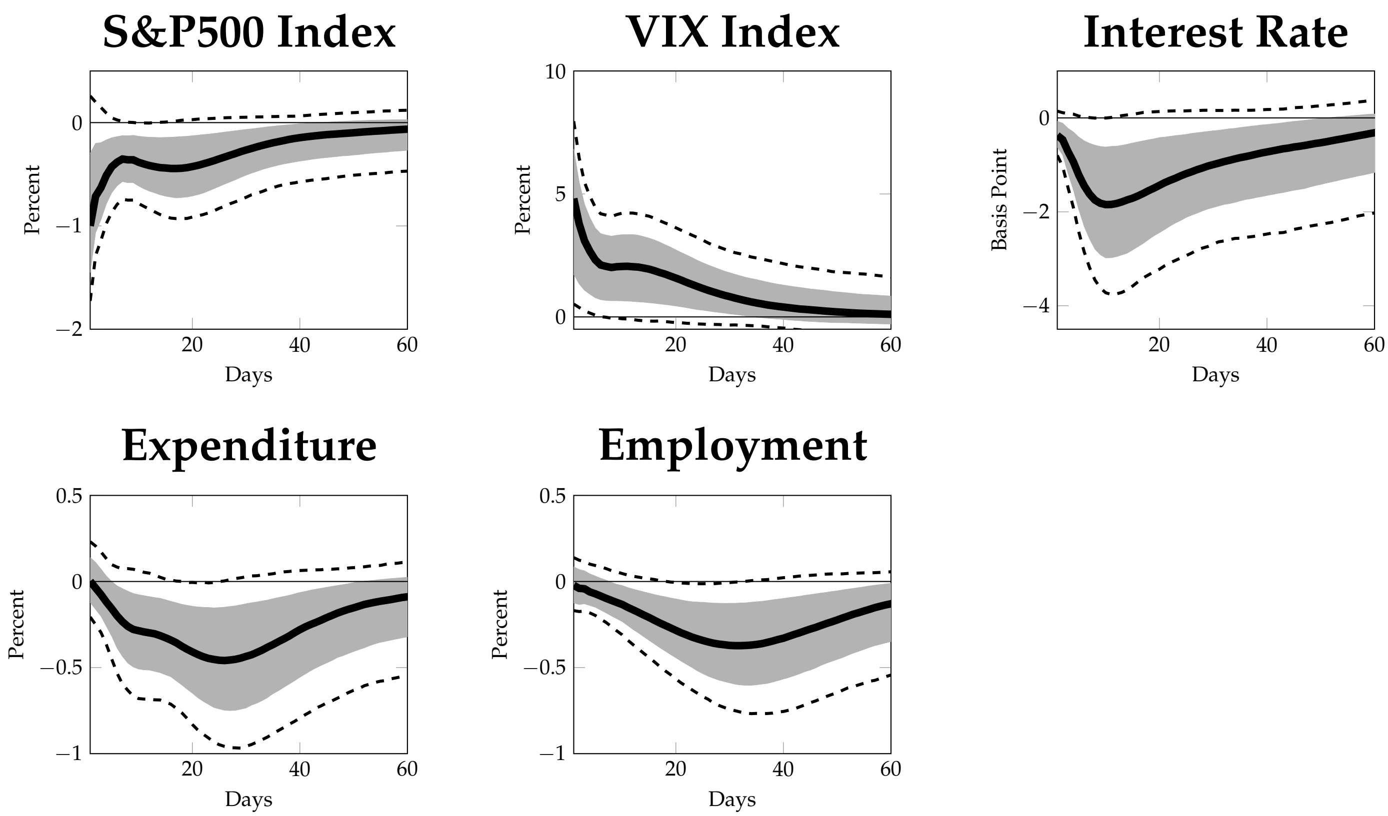

Figure 2 – IRFs to a Covid-induced shock lowering S&P 500 by 1 percent. Solid black line, median. Shaded areas and dotted lines are the 68 and 90 credibility sets, respectively.

These results are broadly consistent with the recessionary effects of the Covid pandemic typically found in the literature, e.g. Baek et al. (2020), Lewis et al. (2020) and Coibion et al. (2020a). Our key contribution lays in combining high-frequency data with an event-study identification scheme. In this way we can apply standard time-series techniques, and thus analyse the recessionary effects of news and announcements about the pandemic under the lens of VARs-the workhorse of empirical macroeconomics. This allows to study accurately the dynamic response of key economic and financial indicators and to recollect a precise transmission mechanism through IRFs analysis. It also enables us, by applying various identification schemes, to present a structural interpretation to the Covid-induced shock, see Section 5.

Results on Distributional/Sectoral Variables. Analysing the aggregate effects of a Covid-induced shock is important as it sheds light on the short-run consequences of the pandemic under a macroeconomic perspective. As such, the results presented in the previous section can be informative to policy-makers for the setting of sound short-run macroeconomic policies. However, as it is by now clear, the exposure to the pandemic is extremely heterogeneous across different parts of the economy, e.g. Belot et al. (2020), van Dorn et al. (2020), Coibion et al. (2020b) and Chetty et al. (2020). For instance, the strict lock-down hits very differently workers in manufacturing and in the service sectors, or business like Amazon vs. the local bookshop.

Along this line, in this Section we explore two forms of heterogeneity through which Covid-induced shocks could affect households behaviour and their welfare: first, along the income distribution, between richer and poorer areas; and second, across business sectors, such as business services, education and hospitality and expenditure categories, such as food services and transport. For the sake of brevity, we present the empirical findings in Table 2 where we include the peak effect of the median response along the IRFs, and the period when the peak effect materialises. Figure B.4, in Appendix B, reports the full set of IRFs for each observable in Table 2.

In order to be consistent among specifications, we proceed as follows. First, from the benchmark specification in (5), we keep three baseline variables, i.e.

$$[ln\left(VIX_t\right), ln\left(S\&P500_t\right), R_t.]$$

Then we add to this set, each variable in Table 2, one-by-one. This is done to avoid interference in the econometric specifications between aggregate expenditure and employment and their subcategories. Thus, it should be understood that all the results presented here come from a set of four-variable VARs. In all cases, the lag structure it kept at 10, as in the benchmark.

We start the analysis from the employment indicators. The main result is that employment in low income (bottom quartile) areas decreases more than twice as much as that in high income areas (top quartile), i.e. -0.58 vs -0.23 percent, respectively. Both responses are significant at 90 percent. There are at least two reasons that can explain this result.

First of all, some sectors are traditionally more populated by high-income workers, e.g. business services, and could continue to operate within the pandemic as they require less in-person contacts. This is also confirmed by the relative small loss of revenues by small-business operating in this sector (see Part B of the Table). Second, it is natural to expect that the employment status of high-income workers, being on average more skilled, is in general less exposed to business-cycle risk and fluctuations, a standard finding in macro/labour studies, see inter alia, Solon et al. (1994) and Bils et al. (2012).

On the expenditure side, we find that the peak contraction on spending in high-income areas is around 40 percent larger than in poorer areas, i.e. -0.50 vs. -0.35 percent, respectively. First of all, there is compelling evidence that households at the top of income distribution finance their consumption out of asset ownership (Lettau et al., 2019), whose returns decrease sharply in the face of a Covid-induced shock. This effect might be only mitigated by portfolio rebalancing found in the survey evidence presented in Coibion et al. (2020a). Second of all, it appears that the decrease in expenditure happened in categories where rich households spend traditionally more, such as food services and entrainment, see Part C of the Table. Conversely, categories where poor households spend relatively more, i.e. groceries, do not experience a reduction in the face of a Covid-induced shock. Interestingly, also the contractions of small-business revenues and openings follow the same pattern as the expenditure variable, and they appear more severely affected by Covid-induced shocks in rich rather than in poor areas.

Moving to the sectoral analysis in Part B of the Table, we find a clear, although not surprising, pattern. Industries that rely less on face-to-face and personal interactions suffer less from Covid-induced shocks relative to industries where the nature of the industry requires face-to-face interactions. For instance, the Professional and Business Service Industry (NAICS 60) recorded a smaller decrease in terms of employment, revenues and business opening than the Leisure and Hospitality Industry (NAICS 70). This is a specific feature of the pandemic and it differs sharply from the firm level-response at business cycle frequencies before January 2020, when the main discriminant factor was instead the firm's financial exposure, e.g. Gilchrist et al. (2014) and Alfaro et al. (2018).

Interestingly, our findings are consistent with the descriptive evidence provided by

Table 2 – Peak Effects on Distributional and Sectoral Variables. Asterisks * and ** mean 68 and 90 percent significance, respectively.

Part A: Distribution

Variable	**Peak Effect**	**Period** (in weeks)
Employment, Aggregate	-0.48**	6
Employment, High Income	-0.23**	5
Employment, Mid Income	-0.47**	6
Employment, Low Income	-0.58**	6
Expenditure, Aggregate	-0.45**	5
Expenditure, High Income	-0.50*	5
Expenditure, Mid Income	-0.42**	5
Expenditure, Low Income	-0.35**	6
Small Business Revenue, Aggregate	-0.60**	5
Small Business Revenue, High Income	-0.66*	5
Small Business Revenue, Mid Income	-0.60**	5
Small Business Revenue, Low Income	-0.52**	4
Small Business Openings, Aggregate	-0.50**	6
Small Business Openings, High Income	-0.53**	6
Small Business Openings, Mid Income	-0.48**	6
Small Business Openings, Low Income	-0.41**	6

Part B: Sectors

Variable	**Peak Effect**	**Period** (in weeks)
Employment,Trade, Transportation and Utilities	-0.40**	6
Employment, Professional and Business Services	-0.29*	6
Employment, Education and Health Services	-0.44**	6
Employment, Leisure and Hospitality	-1.10**	6
Revenues, Trade, Transportation and Utilities	-0.76**	6
Revenues, Professional and Business Services	-0.33**	5
Revenues, Education and Health Services	-8.25*	6
Revenues, Leisure and Hospitality	-1.29**	5
Business Openings,Trade, Transportation and Utilities	-0.89**	5
Business Openings, Professional and Business Services	-0.52**	2
Business Openings, Education and Health Services	-0.56**	5
Business Openings, Leisure and Hospitality	-0.61**	5

Part C: Expenditure Categories

Variable	**Peak Effect**	**Period** (in weeks)
Accomodation and Food Service	-1.23**	5
Arts, Entertainment, and Recreation	-1.31*	5
General Merchandise Stores	-9.12**	5
Grocery and Food Store	1.17	1
Health Care and Social Assistance	-1.15**	5
Transportation and Warehousing	-1.18**	5

Chetty et al. (2020) for the US, by Hacioglu et al. (2020) for the UK and subsequent contributions. Like us, these analyses find that the largest drop in earnings happens in poor household areas, while the biggest drop spending is recorded in rich areas. These papers also report, like us, that the effects of Covid-19 on business activities crucially depends on how a specific industry relies on face-to-face interactions. Along the same line, large surveys evidence presented in Coibion et al. (2020a) and Coibion et al. (2020b) find that expenditure categories that record the largest drop are those, such as entrainment and transport, where social distancing is more difficult.

5 A Structural Interpretation to Covid-Induced Shocks

What we have done so far is to analyse the transmission mechanism of a Covid-induced shock on a set of aggregate and distributional variables. The results obtained are important as they shed light on the short-run causal effects of news and announcements about the pandemic. Of course, one serious drawback of our analysis is that the identified shock does not have a clear structural interpretation, as its origin is purely statistical. For this reason, it is difficult to connect our Covid-induced shock to standard macroeconomic fundamentals. Here we show that our statistically identified shock can be interpreted as structural uncertainty shock, that we label as *Covid-Induced Uncertainty* (CIU) shock.

There are several pieces of evidence that point out to this interpretation. First, the current pandemic has brought about an unprecedented level of uncertainty about all aspects of our lives, thus it comes natural to link Covid-induced shocks to uncertainty shocks. Second, the IRFs of our Covid-induced shock, i.e. impact response of VIX and S&P 500 indexes, hump-shaped recessionary effects and increase in risk factors, closely resemble those of an uncertainty shock. Finally, the zero impact responses of the Sentiment Index and various credit market indicators (BAA and TED Spread) to our Covid-induced shock, lead us to exclude other potential first-order structural interpretations such as 'expectation' or 'financial' shock.

In order to check our conjecture, we proceed in a similar fashion of Kurmann and Otrok (2013). First, we identify a structural uncertainty shock from unexpected movements in the VIX index in model (5), via a Penalty Function (PF) approach as in Caldara et al. (2016). Second, we compare the IRFs of the extracted structural uncertainty shocks and those from the statistical Covid-Induced shock both on aggregate variables as well as on distributional ones.

The PF approach consists of estimating the elements of matrix Γ in (2) in order to maximize a criterion function, subject to a set of inequality constraints. We apply this method in an agnostic way by defining the uncertainty shock as the innovation that generates the largest increase on impact of the IRF of the VIX index. In this way, we can achieve identification with a minimal set of assumptions and without exploiting any event over the sample.

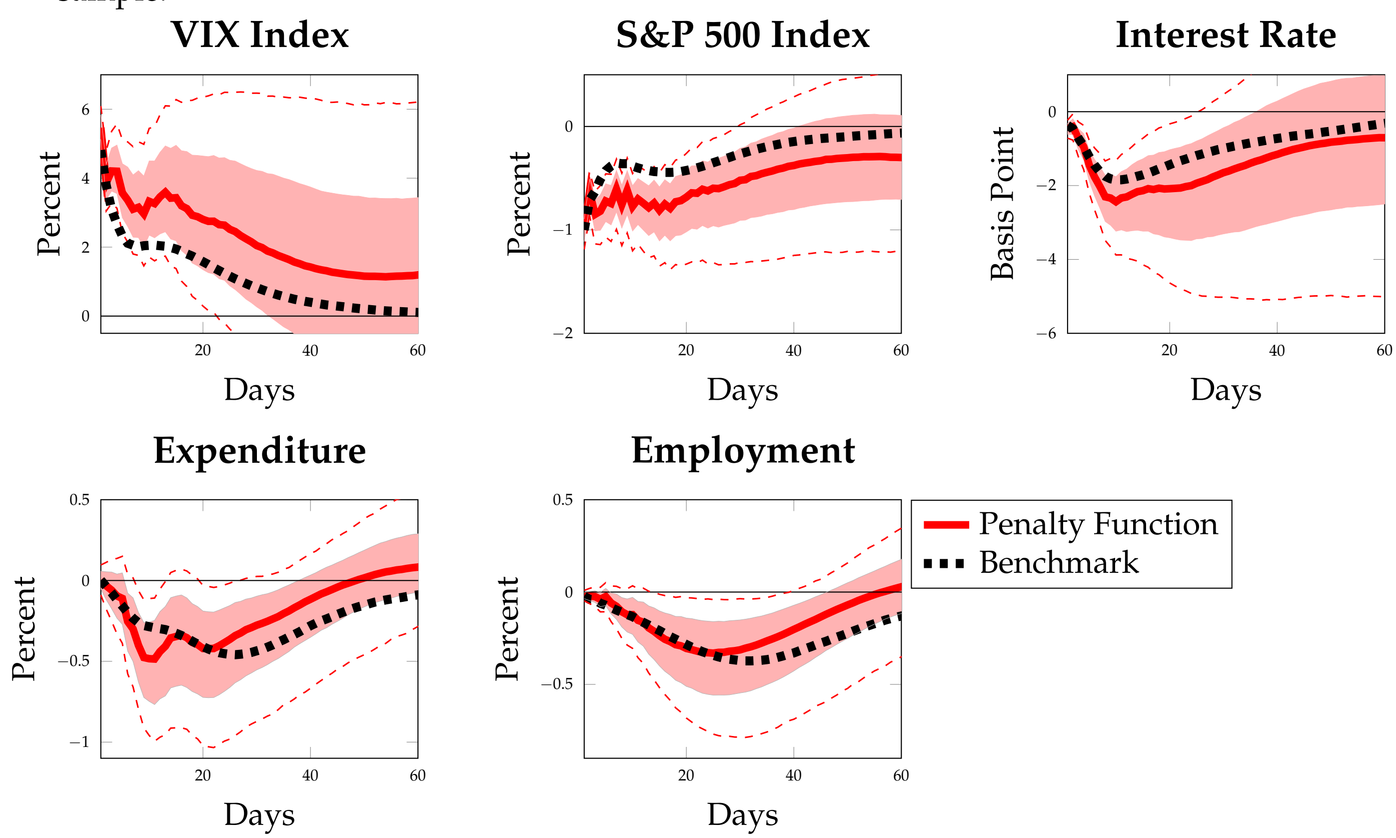

Figure 3 – IRFs to a Covid-induced uncertainty (CIU) shock lowering S&P 500 by 1 percent, PF structural identifications. Solid red lines identify the median for the PF identification, while shaded areas and broken lines represent the 68 and 90 percent credibility sets, respectively. Dashed black line, median response to the benchmark Covid-induced shock obtained with statistical identification.

Figure 3 reports the IRFs for the CIU shock with the PF identification scheme and the median from the statistical Covid-induced shock. Even though our PF identification scheme is completely different from the statistical approach used in the benchmark model of Section 2, we find that the Covid-induced shock and the structural uncertainty shock generate comparable dynamic responses of key financial and economic indicators. This is true for the median responses as well as for the credibility sets. From this, our results strongly suggest that our statistically identified Covid-induced shock can be interpreted as a structural uncertainty shock. Interestingly, we obtain the same correspondence between Covid-induced shock and uncertainty with distributional variables, see Figure C.2 in Appendix C. This further confirms our structural interpretation.

Additional Checks. In Appendix C, Figure C.1, we show that the same link between Covid-induced surprises and uncertainty holds with two other popular identification approaches. The first of these amounts to impose zero restrictions on the contemporaneous matrix Γ, i.e. Cholesky factorisation. With this approach, the ordering of the variables in the VAR matters for the underlying timing of the causality of the shocks, and as such, the Cholesky scheme is less general than the PF approach. On the ordering, we follow a large literature, e.g. Basu and Bundick (2017) and Altig et al. (2020), and identify the uncertainty shock by ordering the VIX index first. We thus assume that the VIX index does not respond on impact to any structural shock in the system other than to itself. Given the daily frequency of our empirical model, we believe that this timing assumption is reasonable and not too restrictive.

The second identification scheme is the Sign-Restriction, e.g. Uhlig (2005) and subsequent contributions. It consists of specifying the sign of the IRFs responses of some variables included in model (5). Given the nature of the shock that we aim to identify, we impose that the uncertainty shock has a positive impact response on the VIX index and a negative impact response on the S&P 500 index. As opposed to the other two structural identifications adopted, the Sign-Restriction delivers a set of equally likely impulse responses rather than point identified estimates, see Baumeister and Hamilton (2015, 2020).

A potential concern of our analysis is whether and to what extent our IRFs, both here and in our statistical identification, simply reflect 'bad news', rather than uncertainty shocks. Including the S&P500 index in our benchmark model should mitigate this concern, given that financial markets are forward-looking and stock prices incorporate many sources of information. Our baseline VAR also includes other 'first-moment' variables: employment, expenditure, and the interest rate. Still, our structural shock to the VIX index could be contaminated by first-moment information not captured by these variables.

To investigate this issue, we also consider VARs that include the Sentiment Index, our best measure of consumer confidence available at daily frequency, see Shapiro et al. (2020). In particular, we estimate jointly an uncertainty and a sentiment shock with a PF identification scheme. In this case, the PF approach requires a sequential identification of the two shocks under consideration and we identify the uncertainty shock 'after' the sentiment shock. By imposing this identification order, we clean our uncertainty shock from first-order ('confidence' or 'bad news') contemporaneous contamination effects, see Caldara et al. (2016) for a detailed discussion. The results from this experiment are presented in Appendix C, Figure C.3 and show that our conclusions are, for all practical purposes, unchanged.

6 Conclusions

This paper provides novel causal evidence on the short-run effects of unexpected news and announcements about the pandemic, i.e. a Covid-induced shock. We analyse a set of daily economic and financial variables within a VAR on US data, over the sample January-July 2020. We find that a Covid-induced shock has large contractionary effects on key economic indicators such as employment, spending and business revenues, as well as standard financial indicators, such as the S&P 500 index, uncertainty and credit spreads. We also provide evidence of important distributional effects. Employment appears to be decreasing more in poor areas, while the opposite is true for private spending. Crucially, we find that exposure to Covid-induced shocks is highly heterogeneous at the sectoral level: industries that heavily rely on face-to-face interactions, such as entertainment and hospitality, see a reduction in their revenues more than three times larger than industries which can conduct businesses remotely, such as business services.

Furthermore, using various identification schemes, we show that our statistically identified Covid-induced shock can be interpreted as a structural uncertainty shock. Our interpretation holds both for aggregate financial and economic indicators as well as for distributional ones.

We believe there are several interesting avenues for future research. First of all, as more daily data become available, one could expand the analysis presented here, for example on international trade. Another interesting avenue of research is to understand if a Covid-induce shock has asymmetric effects with 'good' as opposed to 'bad' Covid news and announcements, or during the second wave of the pandemic. Finally it would be interesting to analyse more deeply the distributional effects of a Covid-induced shock, with particular focus on precautionary savings and portfolio rebalancing and their relation with the response of earnings and expenditure.

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A The Econometric Methodology

The Bayesian Algorithm. The baseline model is defined as:

$$Y_t = X_t \beta + \mu_t \tag{A.1}$$

where Y_t is $1 \times N$ matrix of endogenous variables, $\underbrace{X_t}_{1\times(NP+1)} = [X_{t-1}, .., X_{t-P}, 1]$ denotes the regressors in each equation and β is a $(NP+1) \times N$ matrix of coefficients. The error term is heteroscedastic:

$$\mu_t \tilde{} N(0, \Sigma_H) \text{ periods of CIU events}$$
$$\mu_t \tilde{} N(0, \Sigma_L) \text{ all other periods}$$

We use a natural conjugate prior for the VAR parameters implemented via dummy observations, see Bańbura et al. (2010):

$$Y_{D,1} = \begin{pmatrix} \frac{diag(\gamma_1\sigma_1...\gamma_N\sigma_N)}{\tau} \\ 0_{N\times(P-1)\times N} \\ .... \\ diag(\sigma_1...\sigma_N) \\ .... \\ 0_{1\times N} \end{pmatrix}, and\ X_{D,1} = \begin{pmatrix} \frac{J_P \otimes diag(\sigma_1...\sigma_N)}{\tau} & 0_{NP\times 1} \\ 0_{N\times NP+1} & \\ .... & \\ 0_{1\times NP} & I_1 \times c \end{pmatrix} \tag{A.2}$$

where γ_1 to γ_N denote the prior mean for the coefficients on the first lag, τ is the tightness of the prior on the VAR coefficients and c is the tightness of the prior on the constant. In our application, the prior means are chosen as the OLS estimates of the coefficients of an AR(1) regression estimated for each endogenous variable. We set $\tau = 0.1$. The scaling factors σ_i are set using the standard deviation of the error terms in our implementation indicating a flat prior on the constant. We also introduce a prior on the sum of the lagged dependent variables by adding the following dummy observations: where μ_i denotes the sample means of the endogenous variables calculated using AR(1) preliminary regressions. We set a loose prior of $\lambda = 10000\tau$

The baseline VAR model is estimated via Gibbs sampling. Conditional on Σ_H and Σ_N, the posterior distribution of $b = vec\left(\beta\right)$ is normal with mean M^* and variance V^* where

$$V^* = \left(\sum_{t=1}^{T}\left(R_t^{-1}\otimes X_t X_t'\right) + S_0^{-1}\right)^{-1}$$
$$M^* = V^*\left(vec\left(\sum_{t=1}^{T}\left(X_t Y_t' R_t^{-1}\right)\right) + S_0^{-1}\tilde{\beta}_0'\right)$$

where $R_t = \Sigma_H$ over periods characterized by the financial shock and $R_t = \Sigma_N$, otherwise. The prior for the VAR coefficients based on dummy observations is $N\left(\tilde{B}_0, S_0\right)$. Conditional on a draw for β, the conditional posterior for $\Sigma_i, i = 0, 1$ is inverse Wishart: $IW\left(\mu_i'\mu_i + s_0, T + t_0\right)$ where μ_i denotes the residuals associated with period of CIU shock when $i = 1$ and all other periods when $i = 0$. The prior for the VAR error covariance implied by the dummy observations is $IW\left(s_0, t_0\right)$.The baseline model is defined as:

$$Y_t = X_t\beta + \mu_t \tag{A.3}$$

where Y_t is $1 \times N$ matrix of endogenous variables, $\underbrace{X_t}_{1\times(NP+1)} = \left[X_{t-1}, .., X_{t-P}, 1\right]$ denotes the regressors in each equation and β is a $\left(NP+1\right)\times N$ matrix of coefficients. The error term is heteroscedastic:

$$\mu_t \tilde{} N\left(0, \Sigma_H\right) \text{ periods of CIU events}$$
$$\mu_t \tilde{} N\left(0, \Sigma_L\right) \text{ all other periods}$$

We use a natural conjugate prior for the VAR parameters implemented via dummy observations,see Bańbura et al. (2010):

$$Y_{D,1} = \begin{pmatrix} \frac{diag(\gamma_1\sigma_1...\gamma_N\sigma_N)}{\tau} \\ 0_{N\times(P-1)\times N} \\ .... \\ diag\left(\sigma_1...\sigma_N\right) \\ .... \\ 0_{1\times N} \end{pmatrix}, and\ X_{D,1} = \begin{pmatrix} \frac{J_P\otimes diag(\sigma_1...\sigma_N)}{\tau} & 0_{NP\times 1} \\ 0_{N\times NP+1} & \\ .... & \\ 0_{1\times NP} & I_1\times c \end{pmatrix} \tag{A.4}$$

where γ_1 to γ_N denote the prior mean for the coefficients on the first lag, τ is the tightness of the prior on the VAR coefficients and c is the tightness of the prior on the constant. In our application, the prior means are chosen as the OLS estimates of the coefficients of an

AR(1) regression estimated for each endogenous variable. We set $\tau = 0.1$. The scaling factors σ_i are set using the standard deviation of the error terms from these preliminary AR(1) regressions. Finally we set $c = 1/10000$ in our implementation indicating a flat prior on the constant. We also introduce a prior on the sum of the lagged dependent variables by adding the following dummy observations:

$$Y_{D,2} = \frac{diag\,(\gamma_1\mu_1...\gamma_N\mu_N)}{\lambda},\ X_{D,2} = \left(\begin{array}{cc} \frac{(1_{1\times P})\otimes diag(\gamma_1\mu_1...\gamma_N\mu_N)}{\lambda} & 0_{N\times 1} \end{array} \right) \tag{A.5}$$

where μ_i denotes the sample means of the endogenous variables calculated using AR(1) preliminary regressions. We set a loose prior of $\lambda = 10000\tau$

The baseline VAR model is estimated via Gibbs sampling. Conditional on Σ_H and Σ_N, the posterior distribution of $b = vec\,(\beta)$ is normal with mean M^* and variance V^* where

$$V^* = \left(\sum_{t=1}^{T} \left(R_t^{-1} \otimes X_t X_t' \right) + S_0^{-1} \right)^{-1} \tag{A.6}$$

$$M^* = V^* \left(vec \left(\sum_{t=1}^{T} \left(X_t Y_t' R_t^{-1} \right) \right) + S_0^{-1} \tilde{\beta}_0' \right) \tag{A.7}$$

where $R_t = \Sigma_H$ over periods characterized by the financial shock and $R_t = \Sigma_N$, otherwise. The prior for the VAR coefficients based on dummy observations is $N\left(\tilde{B}_0, S_0\right)$. Conditional on a draw for β, the conditional posterior for $\Sigma_i, i = 0, 1$ is inverse Wishart: $IW\left(\mu_i'\mu_i + s_0, T + t_0\right)$ where μ_i denotes the residuals associated with period of CIU shock when $i = 1$ and all other periods when $i = 0$. The prior for the VAR error covariance implied by the dummy observations is $IW\,(s_0, t_0)$.

B Tables and Figures, Covid-Induced Shock

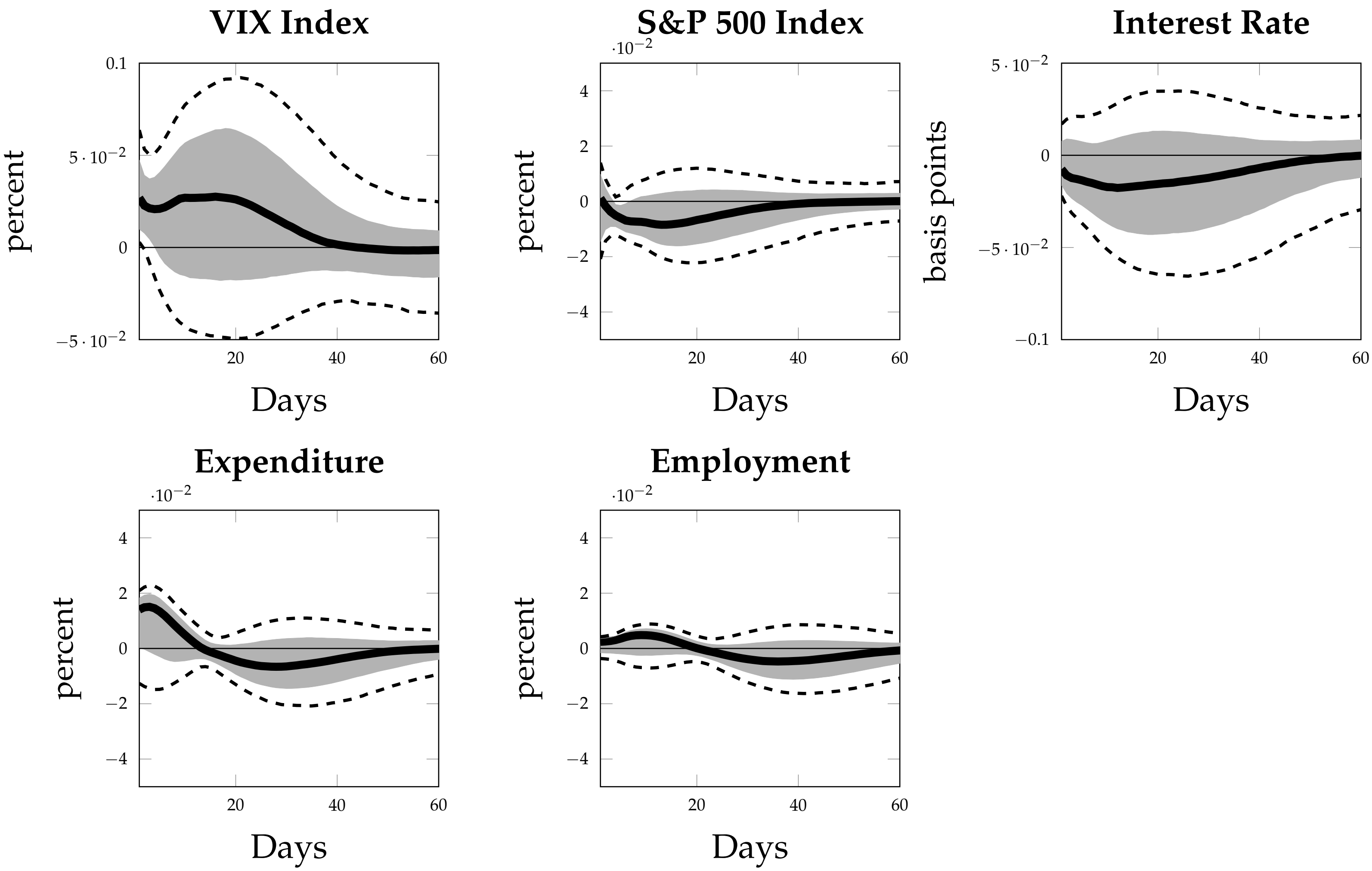

Figure B.1 – IRFs to a Covid-induced shock, random event dates. Solid black lines represent the median while shaded areas and broken lines represent the 68 and 90 percent credibility sets, respectively.

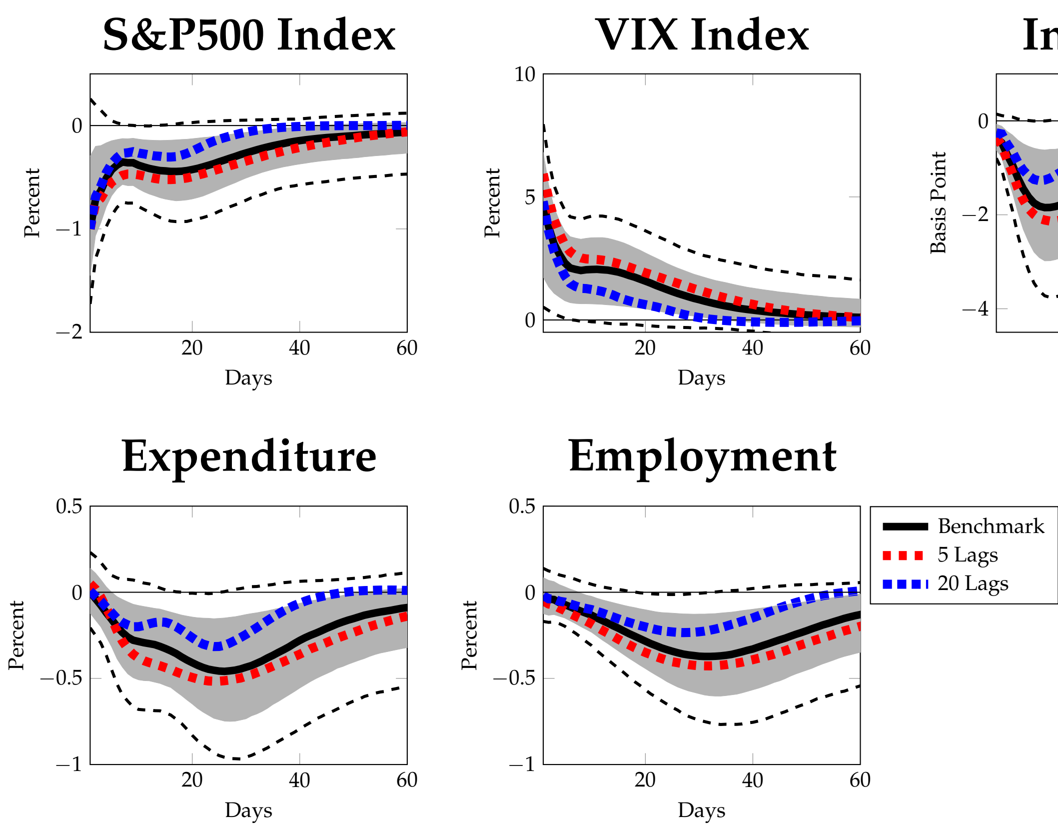

Figure B.2 – IRFs to a Covid-induced shock lowering S&P 500 by 1 percent. Different lag structure. Solid black line, median. Red dashed line, median 5 lags. Blue dashed line, median 21 lags. Shaded areas and dotted lines are the 68 and 90 credibility sets of the benchmark, respectively.

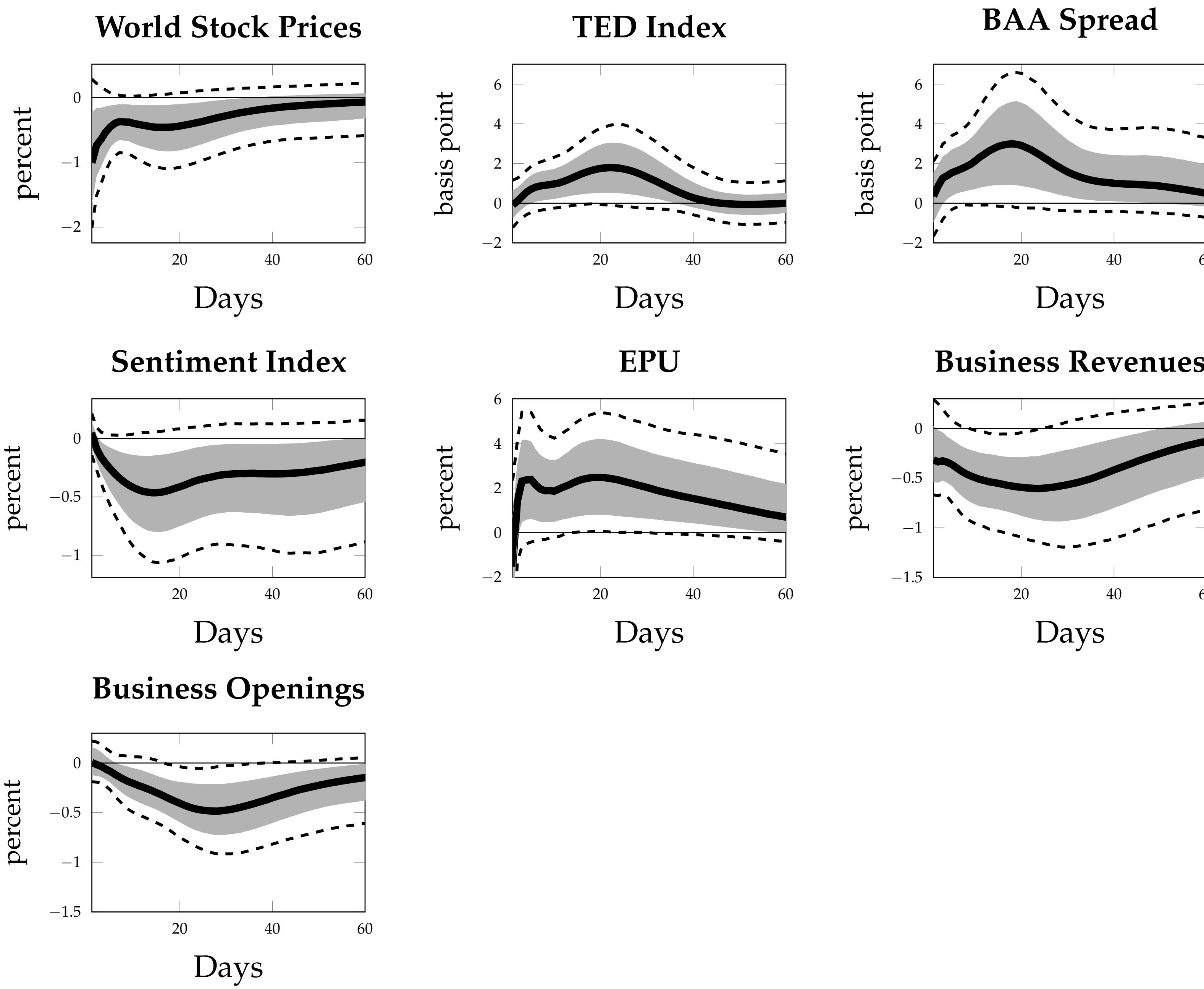

Figure B.3 – IRFs to a Covid-induced shock that lowers the S&P 500 Index by 1 pc. Black solid lines represent the median response. Shaded areas and dashed-lines represent the 68 and 90 percent credibility interval, respectively.

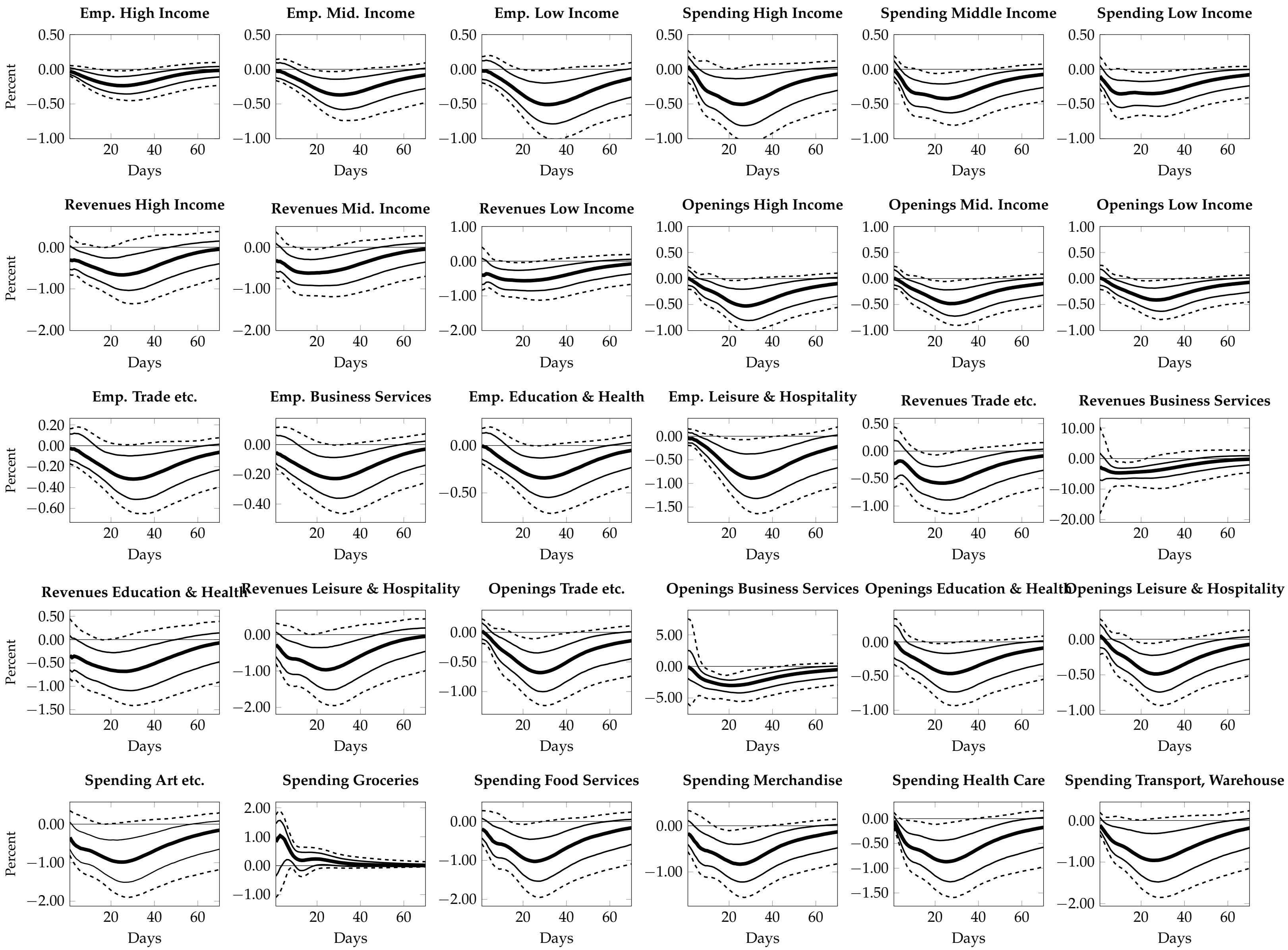

Figure B.4 – IRFs to a Covid-induced shock that increases reduces S&P500 by 1 percent. Solid and dashed lines represent the 68 and 90 percent credibility interval, respectively.

C Tables and Figures, Uncertainty Shock

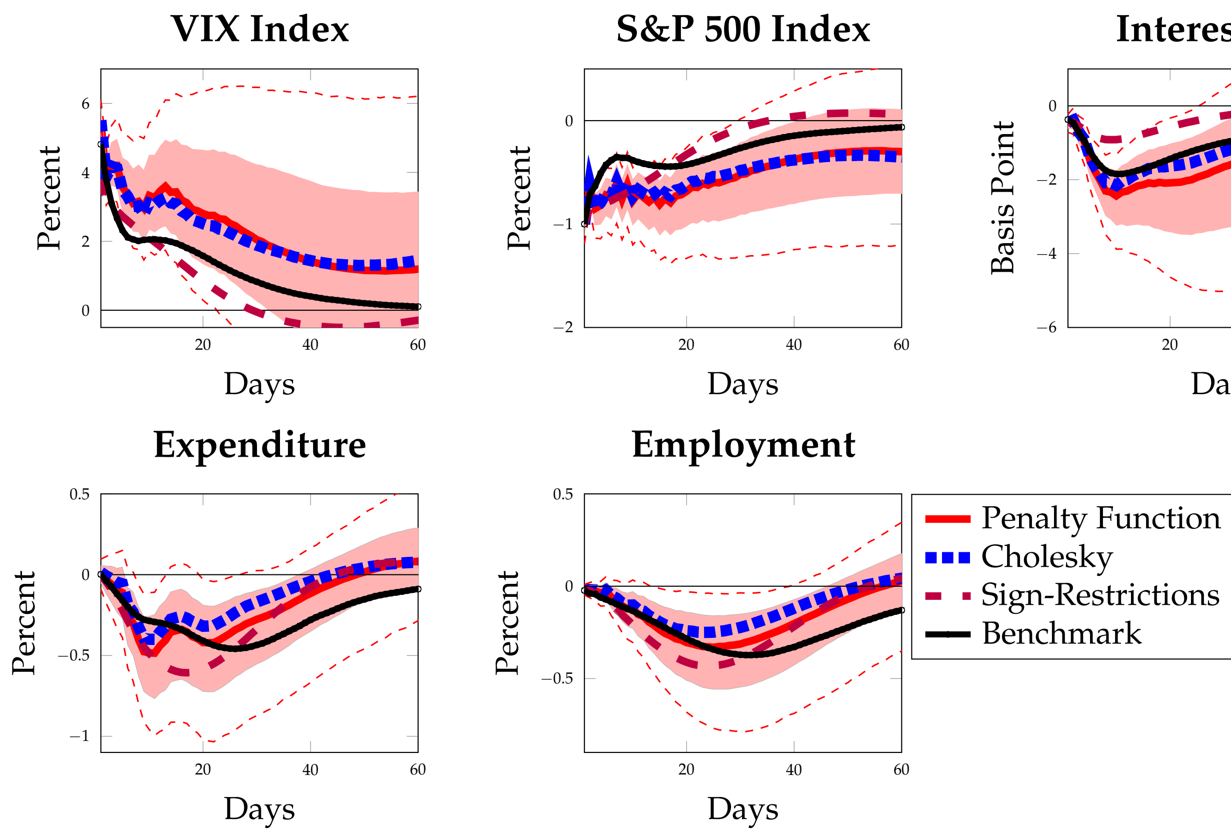

Figure C.1 – IRFs to a Covid-induced uncertainty (CIU) shock lowering S&P 500 by 1 percent, PF, Cholesky and Sign-Restrictions and benchmark identifications. Solid red lines identify the median for the PF identification, while shaded areas and broken lines represent the 68 and 90 percent credibility set from the same scheme, respectively.

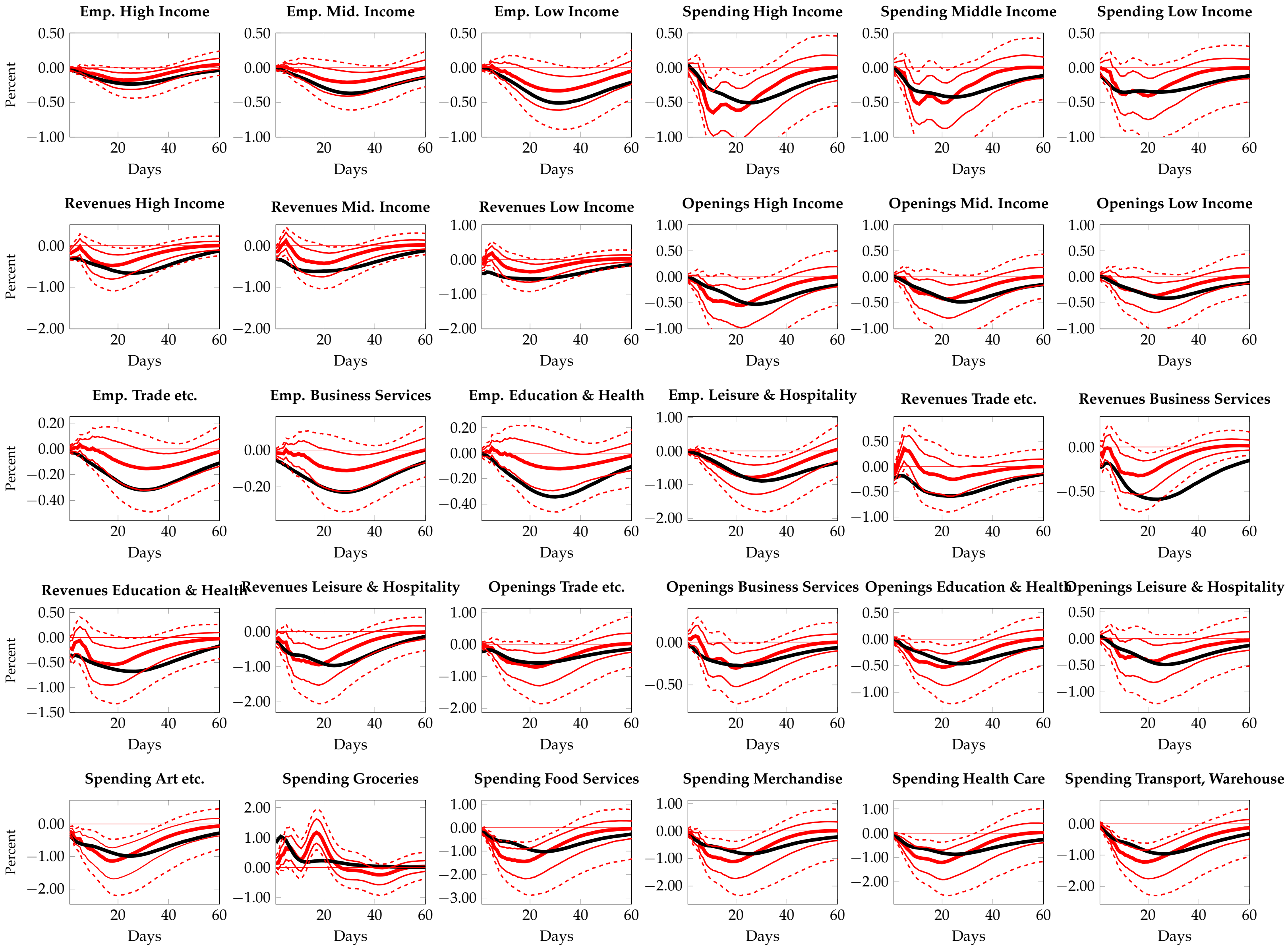

Figure C.2 – IRFs to a Uncertainty Shock that reduces S&P500 by 1 percent, Penalty Function identification. Red solid and dashed lines represent the 68 and 90 percent credibility interval, respectively. Black thick lines represent the posterior median response from the statistical models, see Figure B.4.

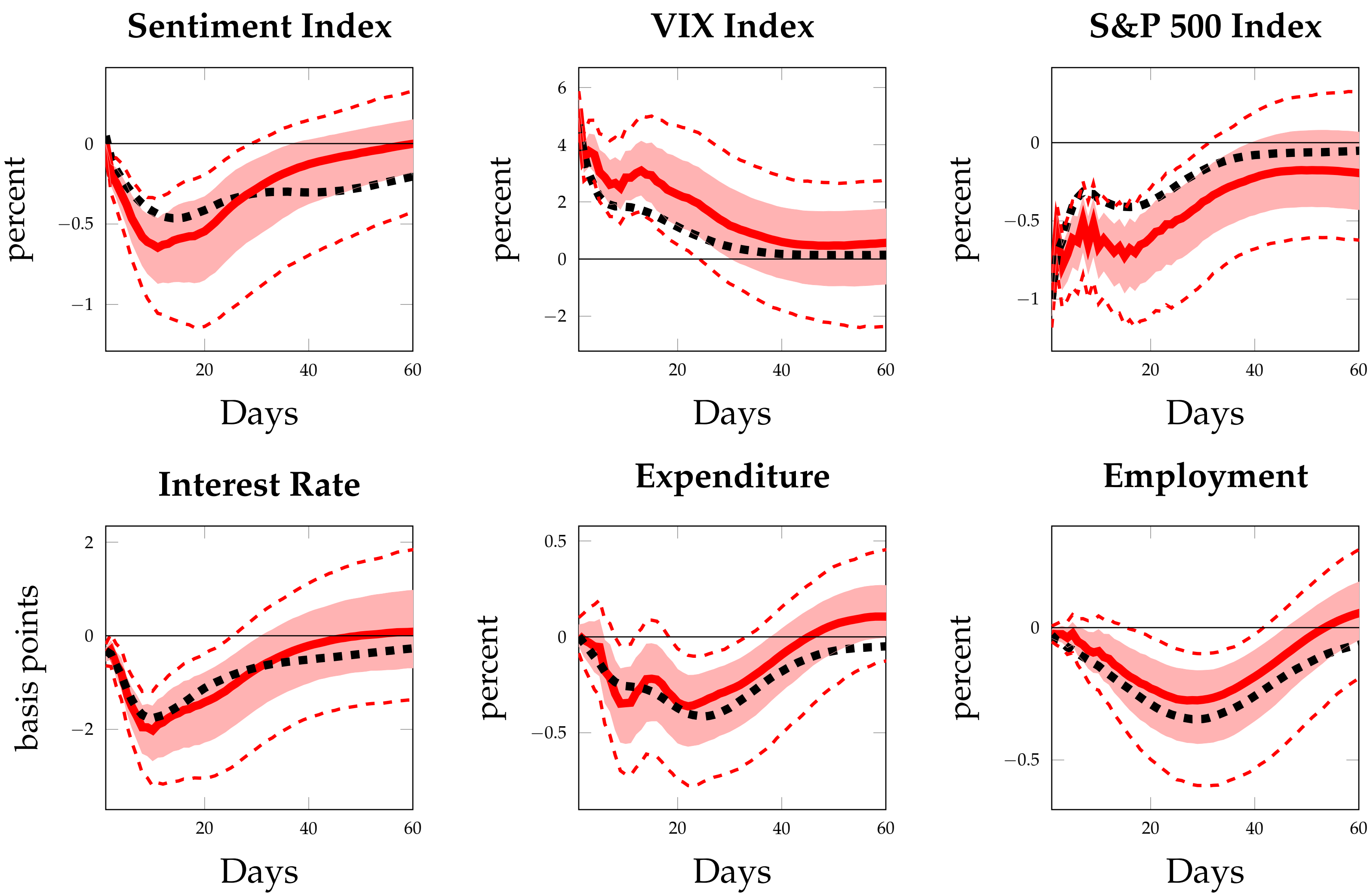

Figure C.3 – IRFs to a Covid-induced uncertainty (CIU) shock lowering S&P 500 by 1 percent, Uncertainty shock sequentially ordered after sentiment shock, Penalty Function Identification. Red solid lines identify the median while shaded areas and broken lines represent the 68 and 90 percent credibility sets, respectively. Thick, dashed black line, median of the benchmark statistical identification.