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The Nexus between Lockdown Shocks and Economic Uncertainty: Empirical Evidence from a VAR Model

The Nexus between lockdown Shocks and Economic Uncertainty: Empirical Evidence from a VAR model*

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Abstract

The contribution of this paper is twofold. First, we introduce a daily vector autoregression (VAR) model for the US economy that allows discerning between lockdown shocks and a real business cycle shocks. With this methodology at hand, we then evaluate the impact of lockdown measures on economic uncertainty in a second step. Overall, we only find a moderate positive impact on uncertainty levels that is, in particular, weaker than the impact of the real business cycle shock. Taking a more granular perspective, we observe that in particular uncertainty related to entitlement programs increases and monetary policy uncertainty decreases after a lockdown shock.

Keywords: COVID-19, lockdown, shock identification, market uncertainty

JEL classification: E60, E62, E65, G01

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1 Introduction

The nexus between (market) uncertainty and the real economy has been studied intensively in recent years and is at the forefront of political discussion. It gained additional momentum during the Covid-crisis as (i) the impact of the crisis on consumer behavior is unclear, (ii) new policy measures were introduced whose effects and costs are difficult to evaluate and (iii) the length and intensity of the crisis itself are unknown. With the increasing length of the crisis, market participants gained a better understanding of some of these key drivers of uncertainty. Consequently, aggregate uncertainty levels reached their peak during the first wave of infections, i.e. in March 2020, see Figure (1). This is also mirrored by the fact that the second and third waves affected asset prices considerably less than the first wave despite higher numbers of infections, hospitalizations and deaths.

From an empirical perspective, little is known about the contributors to the spike in uncertainty. In particular, the literature largely refrains from assessing the impact of lockdown measures on uncertainty, most probably, due to endogeneity concerns in the estimation process. In this vein, disentangling the effects of lockdown measures from other factors is troublesome as the economy is hit by a multitude of shocks over the business cycle. Since 2020, lockdown shocks are an additional source leading to fluctuations in real economic variables. The endogeneity arises from the fact that policymakers base their decision on many factors, including economic considerations. We close this gap in the literature and isolate the lockdown shock from other business cycle shocks. Specifically, we estimate daily and weekly VARs for the US economy via a mixture of sign and zero restrictions. The identification builds on the stylized fact that, contrary to broader stock market indices, the Amazon share price increases when lockdown measures are tightened. Consequently, we assume that a lockdown shock increases the share price of Amazon while it decreases the S&P 500 Industrials total return index. In contrast to that, the other business cycle shocks are described by a situation where the Amazon stock price and the S&P 500 move in tandem.

Our contribution is, thus, twofold. First, we are, to the best of our knowledge, the first to identify lockdown shocks within a daily VAR framework. Second, we assess the impact of lockdown measures on a wide range of uncertainty measures. Overall, we find that lockdown shocks have a smaller impact on uncertainty than other contractionary real business cycle shocks. We argue that several opposing effects associated with the enforcement of lockdowns are likely behind this finding. When we take a more granular perspective, we observe that, in particular, monetary policy, government spending and regulation uncertainty decrease after a lockdown shock.

Several studies analyze the impact of the COVID-crises on uncertainty and volatility. Albulescu (2021) finds that Covid cases, as well as fatality ratios, positively affect market volatility in the US. Bakas and Triantafyllou (2020) investigate the impact of economic uncertainty associated with the pandemic on the volatility of commodity prices and find a strong positive relationship. Caggiano, Castelnuovo, and Kima (2020) show that the COVID-related uncertainty results in a 14% cumulative loss in the world-wide industrial production levels over one year, under the assumption that from February 16 to March 16, the VIX exclusively moved due to the COVID outbreak. Zaremba et al. (2020) is the work closest related to ours, as they also analyze the relationship between policy responses to the COVID-crisis and stock market volatility. For a panel of 67 countries, they find that policy responses such as school closures or public event cancellations increase equity market volatility.

The paper is structured as follows. Section 2 introduces the data set and the methodology. Section 3 reports our empirical results and Section 4 concludes.

2 Identifying lockdown Shocks

As outlined above, our goal is to analyze the effect of lockdowns within a VAR framework. Before we outline the methodology behind the VAR in Section 2.2, we first introduce our data set in Section 2.1.

2.1 Data

Our findings stem from a series of VAR models with five variables each for the US economy covering the period from 03/17/2020 to 11/27/2020. The vector of endogenous variables, Y_t, consists of the S&P 500 Industrials total return index (SPI_t), the total return stock index for Amazon ($Amazon_t$), the Google Community Mobility Reports index for workplaces ($Workplaces_t$), an uncertainty index ($Uncertainty_t$) and the number of patients in hospitals that have been tested positive for Covid-19 ($Hospitalized_t$). Google $Workplaces_t$ describes by how much the aggregate mobility changes in comparison to a baseline scenario. More precisely, it indicates to what degree employees have been at their workplace, i.e. the percentage change from the baseline scenario.[1] We consider the log of all other raw time series and multiply them with 100 so that the impulse responses show deviations from the trend in percent. The data for the stock indices are taken from Thomson Reuters Datastream. The COVID Tracking Project provides us with data on active cases and hospitalisation.[2] Data availability on hospitalization is the limiting factor for our sample, as the data set exhibits no entry prior to 03/17/2020. We distinguish between a core set of variables that are necessary for the identification of a lockdwon shock and non-core variables indicating the responses of variables of interest to the lockdown shock. The list of core variables includes the stock indices, the mobility index and the number of hospitalized persons as these variables identify the lockdown shock. These variables remain unchanged in all estimations. Additionally, in every model, one non-core variable is included. The replacement of the non-core variable allows us estimating alternative models.

Figure (2) outlines the development of the core variables before any transformation has been made. As the number of hospitalized persons indicates, there are three waves of the pandemic in our sample. The first wave occurred in March and April, the second in June and July and the third in October and November. For the S&P Index, we observe a decline of 43% from 2/12 until 3/23, i.e. during the first wave of infections. Afterward, we see a strong rebound. Since mid-November, the index is above pre-crisis levels despite high numbers of infections and hospitalization associated with the second and third wave. Some economists thus argue that the stock market is not well anchored any more. While the question of stock market sustainability is beyond the scope of this study, such an argument is only valid if one argues that the efficient market hypothesis is not valid, which is a strong assumption. However, as we outline below, we receive qualitatively similar results when we rely on the household‘s expectations of the coronavirus impact on GDP as the real economic variable instead. The corresponding data stems from the Cleveland Fed‘s daily consumer survey.[3] In comparison to the S&P Industrials Index, the decrease of the share price of Amazon in March is small. Furthermore, the trough of the Amazon stock price occurs earlier and the rebound is more pronounced. In fact, the Amazon stock price more than doubles from March to September. The correlation between daily returns of the two

[1]See Aktay et al. (2020) for a detailed description of how the index is constructed.

[2]See https://covidtracking.com/data/national for more details.

[3]See https://www.clevelandfed.org/en/our-research/indicators-and-data/consumers-and-covid-19.aspx for details.

stock market indicators is 0.36. The mobility index also decreases substantially during the first wave. Among the core variables, it displays the weakest rebound. During the third wave, the index decreases further.

We are interested in the change of economic or market uncertainty in response to lockdown shocks. However, uncertainty is a concept rather than a measurable time series. In line with the literature on economic uncertainty, we focus on two methodologies that allow for the construction of proxies. More precisely, we focus on market-based volatility measures and textual analysis. For the former, we rely on the CBOE Volatility Index (VIX), which we receive from Datastream. Baker, Bloom and Davis (2016) construct a daily Economic Policy Uncertainty (EPU) index based on newspaper coverage frequency. They count the relative amount of articles that include a combination of pre-specified buzzwords. Specifically, the EPU marks the share of articles that contain the following triple: "economic" or "economy"; "uncertain" or "uncertainty"; and one or more of "congress", "deficit", "Federal Reserve", "legislation", "regulation" or "White House". Baker, Bloom and Davis (2016) also expand the list of buzzwords to measure a more specific category of uncertainty. For instance, articles that additionally contain the term "taxes", "tax", "taxation" or "taxed" would be included in the taxes uncertainty sub-index. In a similar vein, Baker et al. (2019) construct an Infectious Disease Equity Market Volatility Tracker (IDEMVT). Finally, Baker et al. (2020) construct uncertainty indices via data from Twitter. They differentiate between economic (TEU) and market uncertainty (TMU). More precisely, they collect all tweets containing buzzwords related to uncertainty as well as keywords related to the economy or related to equity markets.

We always aim for a model with daily data. However, from the uncertainty measures, only the VIX, the Twitter-based indices, the broad EPU and the DEMVT are along with the rest of the variables in Y_t available on a daily frequency.[4] The other sub-indices are available on a monthly frequency only. We overcome this issue as follows. First, we always estimate VARs with daily data when the underlying uncertainty series is available in that frequency. Second, we show that a VAR with weekly data yields similar results for those variables. Finally, we interpolate the uncertainty sub-indices available on a monthly frequency to weekly data and then estimate weekly VARs. For the uncertainty measures, we always assign the monthly entry to the last Friday in a month and then interpolate the gaps. For

[4]The Twitter indices are furthermore only available until 09/15/20.

the rest of the variables in Y_t, we always consider the entry on each Friday.[5]

2.2 Methodology

We quantify the effect of a lockdown within an structural VAR (SVAR) framework. Since the seminal work by Sims (1980), the SVAR became the "workhorse" econometric model when dealing with endogenous variables. Due to the endogenous nature of the variables we analyze, a VAR approach is a logical approach to unveil linkages. To be more illustrative, consider the decision making process behind a lockdown. Policymakers face a trade-off between the economic damage (proxied by SPI_t) and low numbers of infections to not overwhelm the health system (proxied by $Hospitalized_t$), see e.g. Alfano and Ercolano (2020). Hence, the strength of a lockdown decreases when hospitalisation is low which in return pushes up stock prices. In contrast to that, Elenev, Landvoigt and Van Nieuwerburgh (2020) and Basu et al. (2020) show that Amazon benefits from lockdowns. Accordingly, their stock prices should drop, when $Hospitalized_t$ decreases. Our model can be written as

$$Y_t = C + A_0 Y_t + A_1 Y_{t-1} + \ldots + A_p Y_{t-p} + \varepsilon_t, \qquad (1)$$

where Y_t is a 5x1 vector of endogenous variables and C captures deterministic effects. Furthermore, A_0 and A_1 to A_p are 5x5 matrices that capture effects of contemporaneous and lagged changes in Y_t. Finally, ε_t are the structural error terms and p describes the lag-length. In line with the Hannan-Quinn information criterion, we set p to two for the daily model. For the weekly model, we assume $p = 1$ so that the degrees of freedom are maximal.

However, the SVAR model is not yet identified. To overcome this issue, we utilize a combination of sign and zero restrictions. We rely on a Bayesian framework. More precisely, we follow Arias, Rubio-Ramirez and Waggoner (2018) who implement an algorithm that draws from a conjugate uniform-normal-inverse-Wishart posterior over the orthogonal reduced-form parameterization and transform the draws into the structural parameterization.

The identification via sign and zero restrictions deserves special attention. Our goal is to disentangle the lockdown shock from a business cycle shock, such as a monetary policy or an aggregate supply or demand shock. While both contractionary shocks reduce SPI_t

[5] If a Friday is a bank holiday, we refer to the previous Thursday instead.

by definition, their impact on the Amazon stock price differs, see Table 1. According to Elenev, Landvoigt and Van Nieuwerburgh (2020) and Basu et al. (2020) Amazon is benefiting from lockdowns. For this reason, we assume the positive sign for the lockdown shock. Moreover, we assign a decrease in $Workplaces_t$ as businesses were closed and more employees are working remotely. Finally, a lockdown leads to a lower amount of hospitalization in comparison to a scenario with no lockdown. To account for the fact that the hospitalization falls with some delay, we restrict the periods 10 to 12 working days after the shock. For all other variables, we assume that the restrictions hold for $t \in \{0; 1; 2\}$. When the weekly model is applied, we assume that $Hospitalized_t$ decreases in the following two weeks and all other restrictions hold in $t = 0$ only. In contrast to that, the business cycle shock also leads to reductions in the share price for Amazon. Furthermore, it does not change peoples' mobility with respect to their workplaces, i.e. we apply a zero-restriction that holds in the first period only. Finally, we do not impose any restriction on the hospitalization. As $Amazon_t$ is the only variable that is expected to increase after a lockdown and decrease after a business cycle shock, it is the key variable in the disentangling process of the two shocks.

Table 1: Shock Identification

Variables	$Hospotalized_t$	SPI_t	$Amazon_t$	$Workplaces_t$	$Uncertainty_t$
Lockdown Shock	$-^*$	-	+	-	unrestricted
Business Cycle Shock	unrestricted	-	-	0	unrestricted

Notes: In the daily (weekly) model, '+' describes an increase and '-' a decrease in the underlying variable on impact and for the subsequent two periods (on impact only). Moreover, '$-^*$' represents a decrease in the underlying variable in periods ten to twelve in the daily model and one and two in the weekly model. Finally, '0' refers to a zero restriction on impact.

3 Results

Figure (3) outlines the IRFs for the uncertainty measures from the daily VAR models. We focus on the uncertainty variables as the other variables' reactions are predetermined by the imposed restrictions. For a better comparison, we standardize both shocks so that they imply a 1% decrease in the SPI_t. Interestingly, we find that the VIX tends to decrease after a lockdown shock and increases after the business cycle shock. The explanation for the business cycle shock is straightforward, as bad news increase market uncertainty. In fact, GARCH and particularly EGARCH models reflect this stylized fact, see e.g. Brandt and Jones (2006). The response to the lockdown shock is more complex. The fact that tighter lockdown measures are enforced might be interpreted as a signal that the pandemic situation is worse than expected. Besides the bad news story, other signaling effects also play a role. If policymakers enforce a lockdown, they implicitly unveil their willingness to fight the disease, which could reduce uncertainty. Finally, the implementation of a lockdown reduces uncertainty about the lockdown itself. Prior to any announcement, households have certain believes about the future paths of lockdowns. With the announcement, these beliefs are updated. In this sense, the announcement of a lockdown contains a form of forward guidance. In a similar vein, the Twitter Economic and Market Uncertainty measures also unveil that the median response of the lockdown shock is substantially lower in comparison to the response of the business cycle shock in the medium term. Moreover, the 16th percentile of the two Twitter Uncertainty measures only increase after the business cycle shock has hit the economy.

For the Policy Uncertainty, we find that a lockdown leads to an increase in uncertainty. In comparison to the Policy Uncertainty's response to the business cycle shock, the drop in uncertainty is of comparable size but occurs with some delay. We observe similar patterns for the IDEMVT, although the impact of the business cycle shock is stronger after ten trading days. This is also mirrored by the fact that only the 16th percentile of the "other shock" is above zero from period twelve onward. Altogether, we find that a contractionary business cycle shock leads to higher uncertainty levels in four of the five analyzed cases highlighting that either signaling effects or updates of households' beliefes play a crucial role in the transmission of lockdown shocks.

Figure (4) shows the developments of the mentioned variables in the weekly model. We refrain from the estimation of the Twitter indices, as the number of observations is too small after all adjustments. As before, the VIX tends to increase after the business cycle shock only. After six weeks, we again observe that the contractionary business cycle shock implicates higher uncertainty levels than the lockdown shock for all three variables.

Finally, Figures (5) and (6) unveil the response of the sub-indices. While we present evidence on all sub-indices, we restrict our attention to the most relevant results. We find that, in particular, monetary policy, government spending and regulation uncertainty tend to decrease after a lockdown shock while they increase after the business cycle shock. Furthermore, as financial regulation tends to increase after both shocks, the drop in regulation in response to lockdowns stems from the regulation of other sectors. In line with the argumentation from above, the announcement of the lockdown reveals information on all kind of regulation so that uncertainty decrease. In a similar vein, the governments communicate compensation plans for the sectors largely affected by the lockdown with the announcements. However, the communication on the entitlement programs could be more precise, as uncertainty related to it increases disproportionally after a lockdown shock. Through forward guidance, the Fed also laid down its response to further lockdown measures. For instance, in an FOMC statement on 03/03/20, the Committee expresses that it "is closely monitoring developments and their implications for the economic outlook and will use its tools and act as appropriate to support the economy." The fact that monetary policy uncertainty decreases, shows that the Fed's communication strategy works. Interestingly, uncertainty about healthcare does not display a clear reaction after the lockdown shock.

All results are robust to changes in (i) the lag-length of the VAR, (ii) the length for the restrictions to hold, (iii) the variables included [6], (iv) "controversial" sign-restrictions such as hospitalisation or the zero restriction and (v) adding dummy variables that control for day of the week effects. All impulse-response functions are available upon request.

4 Conclusions

This paper has two main contributions to the literature that assesses macroeconomic consequences of lockdowns. First, we introduce a daily (weekly) VAR model that takes the endogeneity of the underlying variables into account and allows discerning between lockdown shocks and a real business cycle shock. Second, we analyze how lockdown shocks influence policy uncertainty. Overall, we find that lockdowns have only a moderate impact that is smaller than the impact of the business cycle shock identified in our model. Nevertheless, we observe that lockdown shocks lead to sizable increases in fiscal and tax policy uncertainty as well as in uncertainty that is related to entitlement programs. Other sectors, such as monetary policy uncertainty see no decline. It is by now standard that monetary policymakers guide market participants via communication. Hence, one possible

[6] In particular, other mobility data (e.g. home) and other indicators for pandemic situation such as the number of active cases lead to similar results.

interpretation is that the rising uncertainty levels are caused by an unclear communication strategy in the fiscal sector.

Several expansions are feasible but beyond the scope of this analysis. Obviously, the identification strategy could be exploited to analyze other research questions. For instance, other research might estimate the effect on the yield curve. Moreover, we do not analyze the mechanism behind the reaction of uncertainty levels. In particular, this paper does not include a structural model that helps explain the different movements in uncertainties.

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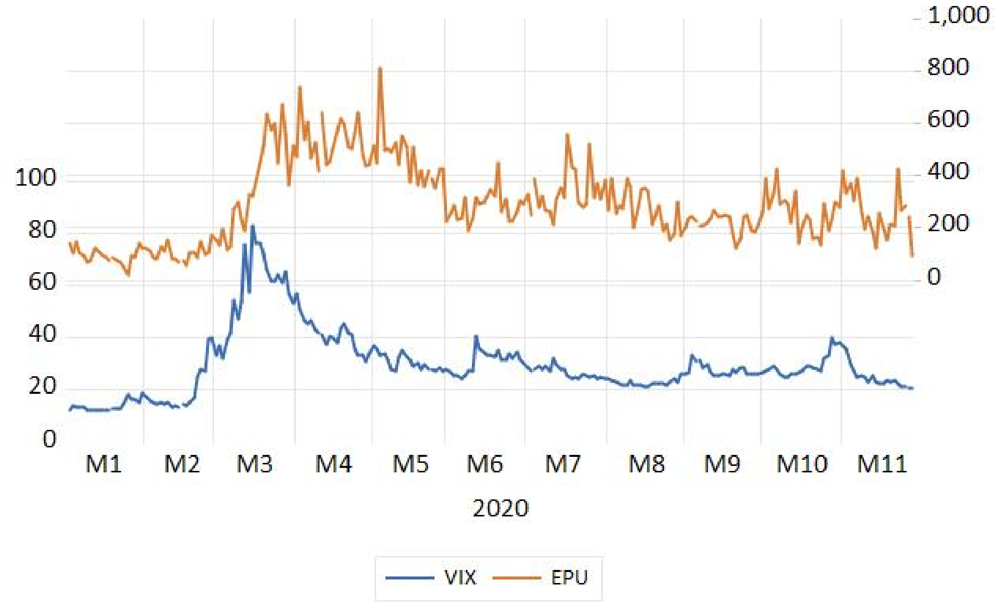
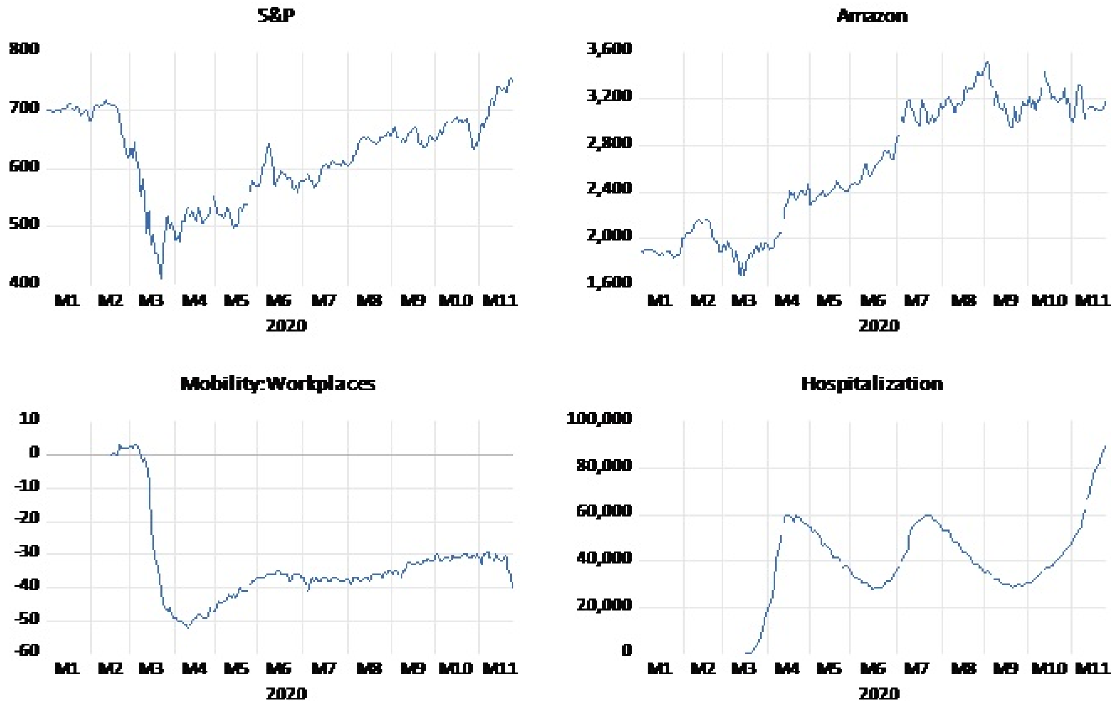
A Figures and Tables

Figure 1: Developments of Uncertainty and Volatility in 2020



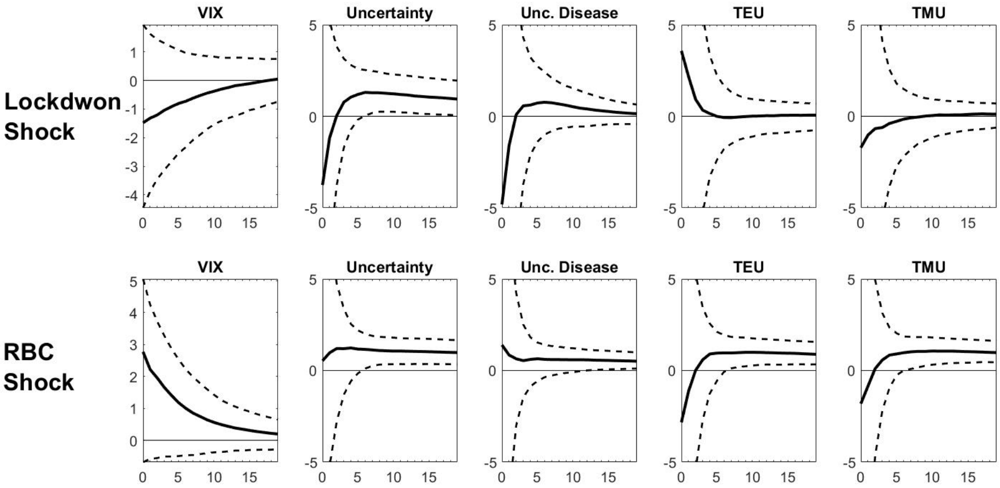
Notes: The left (right) axis corresponds to the VIX (the Economic Policy Uncertainty Index by Baker, Bloom and Davis (2016)).

Figure 2: Developments Core Variables in 2020



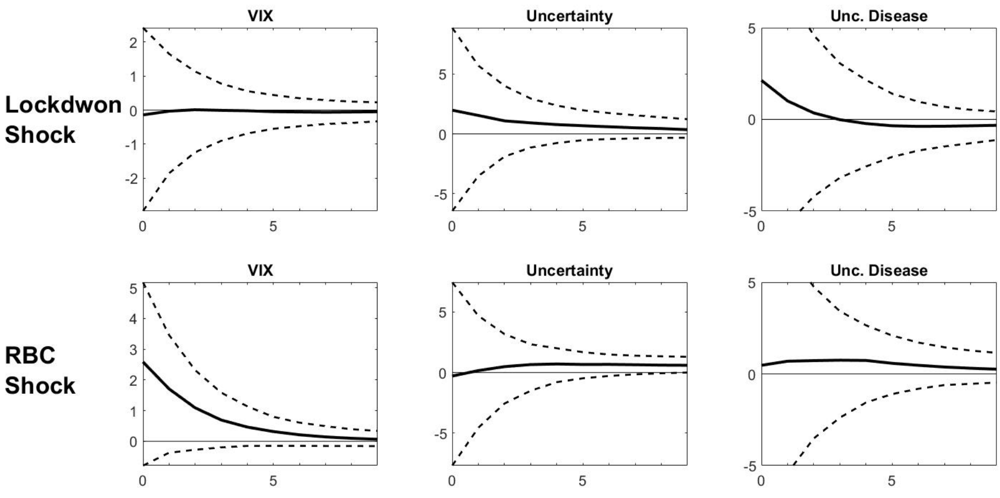
Notes: The upper row displays the stock market indices and the lower row shows the development of the mobility index and the hospitalisation.

Figure 3: Daily VAR models



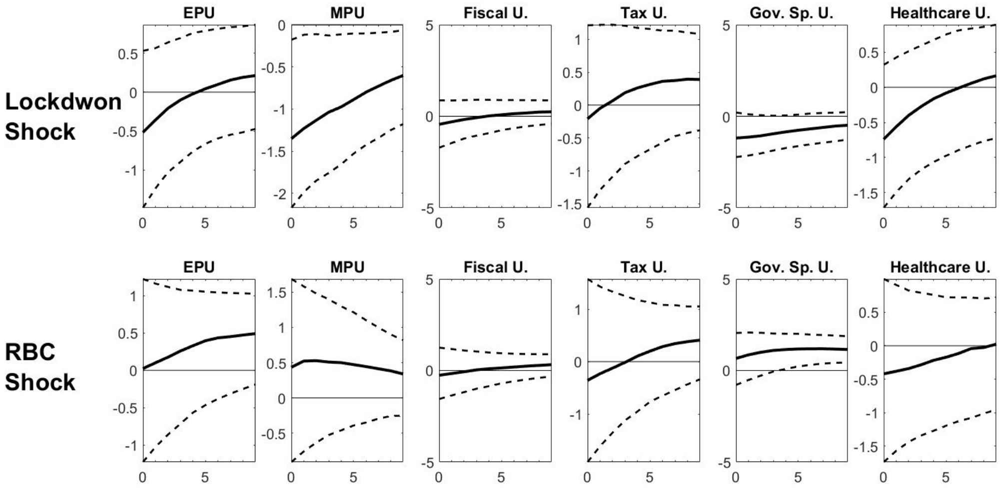
Notes: The solid line represents the median response, the 16th and 84th percentiles are displayed via the dotted lines. The upper (lower) panel describes the response to a lockdown shock (the contractionary business cycle shock).

Figure 4: Weekly VAR models I



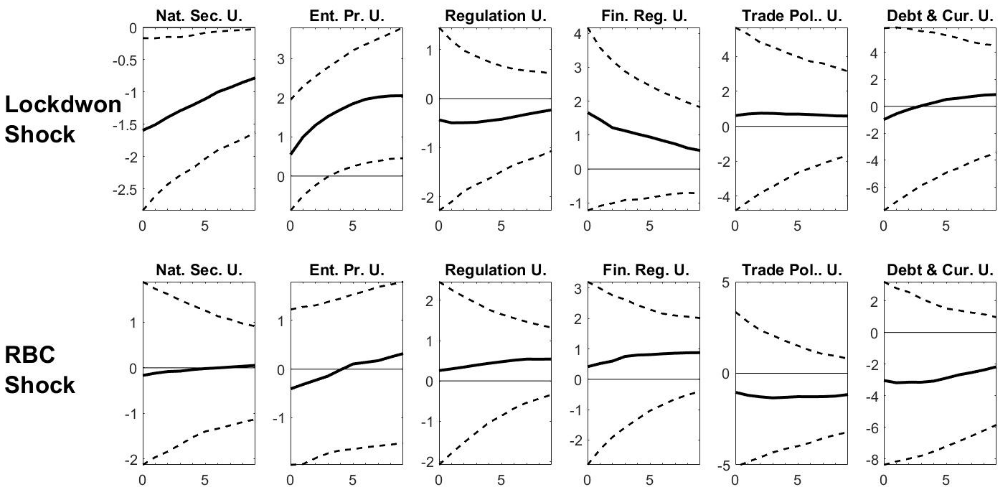
Notes: The solid line represents the median response, the 16th and 84th percentiles are displayed via the dotted lines. The upper (lower) panel describes the response to a lockdown shock (the contractionary business cycle shock).

Figure 5: Weekly VAR models II



Notes: The solid line represents the median response, the 16th and 84th percentiles are displayed via the dotted lines. The upper (lower) panel describes the response to a lockdown shock (the contractionary business cycle shock).

Figure 6: Weekly VAR models III



Notes: The solid line represents the median response, the 16th and 84th percentiles are displayed via the dotted lines. The upper (lower) panel describes the response to a lockdown shock (the contractionary business cycle shock).