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macroeconomic fluctuations

Michał Brzoza-Brzezina and Grzegorz Wesołowski

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Michał Brzoza-Brzezina[†] Grzegorz Wesółowski[‡]

Abstract

This paper argues that noisy information about lockdown can cause undesired economic fluctuations. We construct a New Keynesian model with imperfect information about how long the lockdown would last. On the one hand, a false information about the lockdown being persistent (which we call fear of lockdown) lowers consumption, investment, employment and output. We show that the fear of lockdown may account for more than half of the decline in economic activity caused by the lockdown itself. On the other hand, a true information about lockdown being introduced can also be misinterpreted and hence cause an impact on the economy being smaller than desired by the authorities. These undesired fluctuations can be reduced if communication about lockdown policy is precise, for which our policy conclusion calls.

JEL:E32, E61, E65

Keywords: Covid-19, lockdown, communication, imperfect information

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[†]SGH Warsaw School of Economics and Narodowy Bank Polski, email: mbrzez@sgh.waw.pl

[‡]Narodowy Bank Polski, email: grzegorz.wesolowski@nbp.pl

1 Introduction

Lockdown has been widely used as a policy response to the Covid-19 pandemic in the first half of 2020. It was both very effective in limiting new infections and very harmful for economic activity. A large literature (reviewed in Section 2) followed these events, documenting empirically and theoretically the impact of lockdown on the economy and on the epidemic.

In this paper we pursue the idea that it was not only physical lockdown that affected economies worldwide, but also beliefs about its future course. There is plenty of evidence (though admittedly mainly anecdotal) that agents did not know how persistent the lockdown would be. Would it last just for a few weeks, or maybe until a vaccine against Covid-19 is invented? In most countries even public authorities were quite vague about its duration. Even when the initial lockdown was gradually lifted, the fear of another one during the second wave, expected in Fall 2020, remained widespread. This uncertainty affected agents' expectations what has been reflected in macroeconomic projections of the OECD, IMF and World Bank ¹ (see Figure 1). Imperfect information and the related possibility of non-fundamental beliefs could have affected agents' economic decisions. This motive has, so far, not been given attention on the literature and we try to fill this gap.

We concentrate on the particular dimension of imperfect information about how long restrictions would last. To this end we construct a New Keynesian (NK) model with skill accumulation as in Chang et al., 2002 and passive learning as in Blanchard et al. (2013). The former mechanism extends the standard DSGE framework with a wedge between working hours supplied by households and effectively utilized by companies and hysteresis on the labor market. Thus, it conveniently accommodates the nature of lockdown during which firms cannot utilize a portion of labor and agents can face skill deterioration if the restrictions are persistent. Passive learning, in turn, refers to the signal extraction problem of the agents. They observe the current lockdown which consists of long-lasting and temporary components and a noisy signal about the former. Solving this problem with the Kalman filter agents

¹See e.g. <http://oecd.org/employment-outlook>
<https://blogs.imf.org/2020/06/24/reopening-from-the-great-lockdown-uneven-and-uncertain-recovery/>
<https://blogs.imf.org/2020/07/15/the-next-phase-of-the-crisis-further-action-needed-for-a-resilient-recovery/>
<https://www.worldbank.org/en/news/feature/2020/06/08/the-global-economic-outlook-during-the-covid-19-pandemic-a-changed-world>

Figure 1: Annual GDP drop: OECD forecast conditional on the epidemic severeness

Source: OECD

infer on the future lockdown. Importantly, their judgment may be affected by a noise (false information) shock making them wrongly assess the severity of lockdown. We call this shock the fear of lockdown and analyze in detail its impact on the economy.

The fear of lockdown may depress economic activity resulting in self-fulfilling prophecy as agents reduce their spending causing a fall in consumption, investment and output. As a consequence the demand for labor declines and workers' skills deteriorate. Interestingly, not only the lockdown is inflationary, but so are the beliefs thereof. This finding stands in contrast to articles that investigated noise about persistent productivity (Blanchard et al., 2013; Chahrour and Jurado, 2018; Hürtgen, 2014) and found it to be a demand-type disturbance. The fear of lockdown, while affecting both demand (agents' spending) and supply (expected costs), bears prevailing supply-side effects as it raises prices. This - on top of the supply character of the lockdown shock may help explaining a moderate drop in inflation in the United States during the Great Lockdown as compared to the Great Recession amidst similar in magnitude - if not stronger - deterioration of GDP, capacity utilization and sentiment in both episodes (Figure 2).

Finally, we investigate how the communication precision affects the reactions of the real

Figure 2: Great Lockdown vs Great Recession: comparison of selected variables

Source: Fred

economy. We find that precise information makes the impact of pure noise shocks (i.e. false signals) small. Interestingly, the communication precision also affects the impact of fundamental shocks. Under imperfect information true lockdown shocks can be misinterpreted as false and hence, have a different impact on the economy than intended.

Basing on our calibration we estimate that the impact of uncertain information about the lockdown could have amounted to more than a half of the impact of the lockdown itself. Given the stylized nature of the mechanism and of the calibration, this estimate should be taken with at least two grains of salt. Nevertheless, the possibility of a non-negligible impact of imprecise communication on the economy leads us to formulate policy conclusions. In particular, assuming that output reaction that differs from the fundamental impact of the lockdown is undesirable, policymakers should be as clear as possible about the persistence of lockdown measures. While, amidst the widespread uncertainty, this could have been hardly possible in Spring 2020, precise communication should be aimed at if further restrictions on economic activity prove necessary.

The rest of the paper is structured as follows. Section 2 discusses the related literature. Section 3 presents the model and its calibration and in Section 4 we explain how pure beliefs

about the lockdown can affect the economy. Section 4 concludes.

2 Related literature

Our paper is related to two major streams in the literature. The first originates in the experience of the Covid-19 pandemic. The second relates to the notion that beliefs (possibly non-fundamental) can be the source of business cycle fluctuations. Below we offer a brief review of these research areas.

As already mentioned, a large body of literature emerged since the virus affected the world economy in early 2020. Being still very recent this literature exists mainly in the form of working papers. Given how young the literature is and how fast it grows we do not intend to offer an exhaustive review here. We rather refer to a small number of selected papers to show the main research directions and findings important from our perspective. This includes in particular the estimated impact of the pandemic on the economy, on expectations and inference about lockdown policies.

Several studies attempt to investigate the impact of lockdown on the economy. On the empirical side Chudik et al. (2020) use a multi-country VAR model to identify the Covid shock from the data, measure and forecast its impact on the world economy. In particular the authors forecast a long-lasting recession, with a heterogeneous impact of the pandemic between countries. They predict world GDP to be three percent below its non-pandemic counterfactual in 2021. The scenario for the US is even more grim - a 6.5% loss is expected. We stick to reporting this single finding, while noting that several other studies, both from academia and policy institutions confirm that the impact of the pandemic on the world economy is unprecedented and would probably be long-lasting. However, it should be noted that all these studies also report high levels of uncertainty surrounding their forecasts.

From our perspective, the impact of lockdowns on expectations and uncertainty matters a lot as well. Coibion et al. (2020) analyzed survey data from US counties and document a significant impact of Covid and lockdowns on income and employment as well as expected economic activity. In particular the paper documents a sharp and persistent increase in expected unemployment. The unemployment rate in counties affected by lockdowns rises by an average of 13 percentage points in the 12-month horizon and only slowly declines to

a 2 percentage point increase in the 3-5 year horizon. Altig et al. (2020) consider several measures of uncertainty, including i.a. implied stock market volatility, newspaper-based economic policy uncertainty and subjective uncertainty about future business growth in the UK and US. They document a dramatic increase in uncertainty about the pandemic and its economic impact in early 2020 with several indicators reaching all-time heights.

Some papers attempted to design optimal lockdown policies. For instance (Eichenbaum et al., 2020) construct a model that merges a simple real macroeconomic model with an epidemiological SIR framework. In the model agents have social interactions related to their economic activity (work, consumption) and thus transmit the disease. Households, being aware of these channels lower consumption and work effort in order to minimize the risk of getting infected. Nevertheless, an externality exists as households do not take into account their own impact on the epidemic and the optimal policy involves a lockdown. Ferguson et al. (2020) used a detailed model developed to support influenza planing in the UK and simulate the impact of various non-pharmaceutical interventions (social distancing, closures of schools and universities etc.) on the fatality rate of Covid-19. The Authors estimate that various social distancing measures would have to be in place at least 2/3 of the time (until a medical treatment is found) in order to effectively save a large number of lives.

All in all, the existing literature about the pandemic's impact on the economy documents a huge and long-lasting economic impact on the economy and expectations as well as suggests a long period of repeated lockdowns.

On top of the macro-epidemics literature reviewed above, our paper is related to the articles that investigate the role of beliefs in driving business cycles. This literature originates among others in the works of Pigou (1927) and Keynes (1936), who postulated that waves of optimistic or pessimistic beliefs might influence current economic conditions. More recently researchers started to test these ideas empirically or to embed them into state of the art macroeconomic models.

In this respect, most related to our approach are the works of Blanchard et al. (2013); Hürtgen (2014) who assume that agents face a signal extraction problem concerning the nature of technological progress. In this framework, productivity consists of two parts: a

persistent and a temporary one. Agents observe only aggregate productivity and receive a noisy signal about its persistent component. Bayesian estimation of these models point to a strong impact of noise shock on consumption and GDP over the US business cycle. Our framework treats the information about lockdown in a similar vein as a noisy signal from which agents attempt to extract the true information. Failures to do so result in economic fluctuations that are at the heart of our paper.

To the best of our knowledge these two streams in the literature have not been connected so far to discuss the impact of beliefs about lockdown duration on the economy. The closest connection known to us is Kozlowski et al. (2020). The Authors assume that the Covid-19 crisis will result in a persistent change in the perceived probability of extreme, negative shocks. As a consequence agents become less willing to undertake risky business projects and the pandemic can affect the economy for many years. However, in contrast to our paper this study focuses on the effects of risk - not beliefs resulting from imperfect communication.

3 Model and calibration

The model we use merges three streams from the literature. At its core is a standard new Keynesian framework with households that derive utility from leisure and consumption and provide labor and capital services to monopolistically competitive firms. These use the two factors to produce differentiated goods and price them under a standard Calvo scheme, so that prices are sticky. Differentiated goods are then combined into a final good by perfectly competitive aggregators and are used for consumption or investment purposes (the latter being subject to an investment adjustment cost).

Upon this core structure we impose three modifications. The first one follows Chang et al., 2002 and introduces hysteresis in the labor market. Briefly, when agents provide labor services, they accumulate skills that improve their effective labor quality. Conversely, when they do not work their skills deteriorate. Second, we allow for a lockdown that sets a part of labor supply idle. Third, following i.a. Blanchard et al. (2013) we introduce an information friction - agents do not possess full information about the length of the lockdown. Instead, they only receive a noisy signal about it.

In order to keep the model tractable we do not explicitly model the epidemic.² This has two consequences. First, lockdown is assumed to be exogenous. What we, hence miss is the feedback from lockdown policies to the epidemic and back to the lockdown. This can clearly have an impact on the model dynamics. We do not however, see a good reason why the feedback should affect the impact of imperfect information on economic developments (at least in a qualitative sense). Second, in our framework lockdown deteriorates welfare and it is pointless to speak about optimal policy here (lockdown can be optimal if it one takes lives saved into account). When drawing policy conclusions we will assume that that policymakers have reasons, that go beyond our model, to introduce a lockdown. We will be more specific on this assumption in Section 4.6. Although these issues put a clear limitation on our findings, we hope that we nevertheless we can provide a meaningful intuition behind the role of communication imperfections during the pandemic.

In what follows we describe the model in details using the convention that small letters denote real values of variables denoted by respective capital letters and variables without a time index denote steady state levels.

3.1 Households

A representative maximizes lifetime utility:

$$\max_{\{c_t\}, \{h_t\}, \{i_t\}, \{k_t\}, \{B_t\}} E_0 \sum_{t=0}^{\infty} \beta^t \left[\frac{c_t^{1-\sigma}}{1-\sigma} - \frac{h_t^{1+\nu}}{1+\nu} \right] \quad (1)$$

subject to the budget constraint:

$$P_t c_t + P_t i_t + B_t + T_t = W_t^h h_t (1 + \tau_t) + R_t^k k_{t-1} + R_{t-1} B_{t-1} + Div_t \quad (2)$$

and the capital accumulation rule with investment adjustment costs:

$$k_t = (1 - \delta) k_{t-1} + \left(1 - S \left(\frac{i_t}{i_{t-1}} \right) \right) i_t \quad (3)$$

²The reason is mainly technical - epidemiological processes are highly nonlinear and impossible to approximate using local methods. Our experience with models that integrate the new Keynesian model and the epidemiological SIR framework is that they are hard to solve even under perfect foresight (while our problem features a stochastic environment). We conjecture that the solution to this problem goes much beyond the scope of our project and leave it for further research.

Above, P_t , W_t^h , R_t^k and R_t are, respectively the price of final goods, the wage received by the household, the capital rental rate and the interest rate on bonds. Further, c_t denotes consumption, B_t bond holdings, k_t capital, i_t investments, Div_t dividends paid by imperfectly competitive intermediate goods producers, T_t lump-sum taxes levied by the government, τ_t is a labor market subsidy rate chosen by the government and $S(\cdot)$ a quadratic investment adjustment cost function (with $(S(\cdot))' > 0$ and $(S(\cdot))'' > 0$). We assume a standard quadratic cost function $S\left(\frac{i_t}{i_{t-1}}\right) = \frac{\kappa}{2} \left(\frac{i_t}{i_{t-1}} - 1\right)^2$. Finally, β denotes the discount rate, δ the capital depreciation rate, σ the inverse of the intertemporal rate of substitution and ν is the inverse of the Frisch elasticity of labor supply.

3.2 Producers

Final goods y_t used for consumption and investment purposes are assembled by perfectly competitive producers who buy goods $y_t(i)$ at price $P_t(i)$ and maximize profits

$$P_t y_t - \int P_t(i) y_t(i) di \quad (4)$$

subject to the technological constraint

$$y_t = \left(\int y_t(i)^{\frac{1}{\mu^p}} di \right)^{\mu^p} \quad (5)$$

The solution results in the demand function for intermediate goods

$$y_t(i) = \left(\frac{P_{H,t}(i)}{P_{H,t}} \right)^{\frac{-\mu^p}{\mu^p-1}} y_t \quad (6)$$

Intermediate goods producers combine labor and capital to produce differentiated goods according to technology:

$$y_t(i) = k_{t-1}^\alpha(i) n_t^{1-\alpha}(i) \quad (7)$$

where $n_t(i)$ is the effective number of hours employed by producer i and is defined below. They minimize production costs:

$$\min_{k_{t-1}(i), n_t(i)} [r_t^k k_{t-1}(i) + w_t n_t(i)] \quad (8)$$

Next they solve a pricing problem, maximizing the discounted stream of profits subject to the demand function for their goods. We assume a standard Calvo pricing scheme, with probability θ of receiving a signal to change the price:

$$\max_{P_t^{new}(i), \{y_{t+j}(i)\}_{j=0}^{\infty}} E_t \sum_{j=0}^{\infty} (\beta\theta)^j \Lambda_{t+j} \left(\frac{P_t^{new}(i)}{P_{t+j}} - mc_{t+j} \right) y_{t+j}(i) \quad (9)$$

Here $P_t^{new}(i)$ is the price set by the optimizing firm, mc_t is the real, marginal cost of production and Λ_t is the marginal utility of consumption of the representative household.

3.3 Skill accumulation and lockdown

Like in Chang et al., 2002 workers own skills x_t which increase the effective hours used by producers. However, at the same time they can be forced due to the lockdown to set a part l_t of the workforce idle:

$$n_t(i) = x_t(1 - l_t)h_t(i) \quad (10)$$

Agents accumulate skills x_t when they work:

$$\frac{x_t}{x} = \left(\frac{x_{t-1}}{x} \right)^{\phi} \left(\frac{(1 - l_{t-1})h_{t-1}}{h} \right)^{\mu} \quad (11)$$

Since the labor market is competitive, the real wage received by households is:

$$w_t^H = x_t(1 - l_t)w_t \quad (12)$$

3.4 Imperfect information

Agents do not possess full information about the persistence of the lockdown. Instead, following i.a. Blanchard et al. (2013) we assume that they receive a noisy signal about its duration. To be precise we assume that lockdown l_t consists of two components - a temporary one l_t^T and a persistent (though not permanent) one l_t^P :

$$l_t = l_t^T + l_t^P \quad (13)$$

$$l_t^T = \varepsilon_t^T \quad (14)$$

$$l_t^P = \rho_Z l_{t-1}^P + \varepsilon_t^P \quad (15)$$

where ρ_Z is an autoregression coefficient while ε_t^P and ε_t^T denote persistent and temporary i.i.d. lockdown shocks respectively. Agents observe only l_t , not either of its elements. Moreover, they receive a noisy signal

$$s_t = l_t^P + \varepsilon_t^N \quad (16)$$

about its persistent part, where ε_t^N is an i.i.d. noise shock (a false information about the lockdown being persistent). To infer whether the lockdown is persistent or temporary agents solve a Kalman filtering problem (see Appendix A).

3.5 Policymakers

The central bank stabilizes output and inflation by means of a standard Taylor rule

$$\frac{R_t}{R} = \left(\frac{R_{t-1}}{R} \right)^{\gamma_R} \left[\left(\frac{\pi_t}{\pi} \right)^{\gamma_\pi} \left(\frac{y_t}{y} \right)^{\gamma_y} \right]^{1-\gamma_R} \quad (17)$$

The government runs a balanced budget. Every period it collects lump-sum taxes T_t and finances the labor market subsidy $\tau_t W_t^h h_t$. The subsidy rate τ_t is set so as to reimburse the fraction $\gamma \in < 0, 1 >$ of wage income foregone due to the lockdown implying that:

$$W_t^h h_t (1 + \tau_t) = W_t x_t h_t (1 - l_t) + \gamma W_t x_t h_t l_t \quad (18)$$

This yields:

$$\tau_t = \frac{\gamma l_t}{1 - l_t} \quad (19)$$

Note that if $\gamma = 0$ there is no subsidy, while if $\gamma = 1$ the government fully compensates households the impact of lockdown on wages.

3.6 Market clearing

The model is closed by standard market clearing conditions. In particular, the goods market clears according to:

$$c_t + i_t + S\left(\frac{i_t}{i_{t-1}}\right)i_t = y_t \quad (20)$$

3.7 Calibration

We calibrate the model to the US economy and present parameter values in Table 5. Since the new Keynesian core of the model is standard, we follow the existing literature in its calibration. In particular, we set the discount rate to $\beta = 0.995$ to match a 2% real interest rate on annual basis. In line with standard practice the depreciation rate δ is calibrated to 2.5% and the capital share $\alpha = 0.33$. Parameters of the Taylor rule follow Taylor (1993). The Calvo parameter is set to $\theta = 0.8$, somewhat higher than suggested by estimates (e.g. Smets and Wouters (2007)) for the US. However, to keep the model concise we consider only one nominal friction (wages are not sticky), as a consequence price stickiness needs to be set at a higher level for the model to match e.g. the empirical evidence on the transmission of monetary policy shocks.

Now we move to parameters related to the less standard parts of the model. As for the skill accumulation mechanism, we closely follow the estimation presented in Chang et al. (2002). Accordingly we set $\phi = 0.8$ and $\mu = 0.11$, being the means of the posterior distributions in this study.

It is less obvious how to calibrate the information friction. Four parameters need to be calibrated, persistent shock autoregression ρ and the standard deviations of ε_t^P , ε_t^T and ε_t^N .³

³Using the Kalman filter to solve the signal extraction problem we assume that shocks are normally distributed. This implies their realizations to be symmetric, which may seem to be at odds with the nature of lockdown being a negative shock. Nevertheless, in principle nothing forbids agents to expect positive (“antilockdown”) shocks in the model. A temporary reduction of a permanent lockdown (negative ε_t^T shock) could happen for instance (think of restrictions being temporarily lifted during Summer 2020). Or the persistent lockdown could be permanently reversed with a negative shock ε_t^P once a vaccine becomes widespread.

We set $\rho = 0.9$ to give the persistent lockdown a half-life of approximately one year. This is supposed to reflect the (relatively consistent) publicly available information that it should take between one and two years to develop and introduce a vaccine against Covid-19. The standard deviations of the lockdown shocks are chosen such that they cause a 5% drop in GDP on impact, roughly half of the cumulative decline of US GDP in the first half of 2020.

Finally, let us concentrate on the volatility of noise. In the literature from which we draw (Blanchard et al., 2013) this is estimated from US data. However, information there is noisy with respect to technology, something that one can claim was always present in the data. Our case is different, information about the lockdown is fairly recent and unique, hence estimation on historical US data series would completely miss the point. Instead, we propose an alternative procedure.

First, we note that the noise by definition causes non-fundamental expectations about the future lockdown. Using Google searches in a number of countries for flights in April and in the Summer as instruments for mobility in period t and $t + 1$ we calculate the degree of lockdown in both periods. To this end we compare the number of flight searches in 2020 with those in normal times (i.e. 2016-2019). The results seem to be consistent with other measures of mobility, such as those presented by Worldometers.info and data on travel restrictions presented by United Nations World Tourism Organization. In contrast to the latter two sources, our approach allows to calculate the lockdown expected in Summer 2020 by comparing searches about flights in Summer done in April 2020 with those done in April of previous years. Having the instrument for lockdown and expectations about it, we compute the standard deviation of the noise shock in a simplified signal-extraction problem (see Appendix B for more details and formal description). This approach yields the standard deviation of the noise shock of approximately 13%. Given the stylized calibration process we later conduct an extensive robustness check with respect to this parameter.

One could even think of shocks that set $l_t < 0$, if policymakers introduce (after the epidemic) labor market measures supposed to make-up for lost product (e.g. by temporarily lifting the ban on trading on Sundays in some countries).

4 The fear of lockdown and its effects

In this Section we investigate the impact of lockdown and, in particular, of the information (signal) that agents receive about it. Our primary goal is to understand how imperfect communication about the lockdown affects the economy. To this end we first show how the two types of lockdown work. Then we move to the impact of noisy signals. Finally, we discuss how the impact of noise depends on various features of the economy and, in particular, on the communication strategy.

4.1 Temporary and persistent lockdown

We start with simulating fundamental lockdown shocks that lower GDP on impact by around 5%. As already mentioned, our model features two types of such shocks, a temporary and a persistent one. Figure 3 shows the reaction of GDP, consumption, investments, effective labor hours used by firms, skills and inflation to both shocks. Not surprisingly, in a qualitative sense the two shocks work similarly. The reduction of effective labor hours drags GDP down. As income falls, so do consumption and investments. As households do not work, they loose skills. As a result, the skill accumulation mechanism aggravates the initial response widening the wedge between supplied and effective labor even further. Not surprisingly this factor is much more important in case of the persistent lockdown. Importantly, as the economy faces a supply shock, inflation increases. The main difference between the temporary and persistent lockdown is quantitative. The latter has much more serious consequences, which result not only from its immediate impact on effective labor supply but also from agents' reaction to the expected prolonged slowdown.

Figure 3: Impulse responses to fundamental lockdown shocks

Note: values are expressed in percentage deviations from the steady state, with the exception for inflation expressed in percentage points. The time unit is one quarter.

4.2 The fear of lockdown

Let us now move to our main point of interest - what happens when agents receive a signal that a persistent lockdown started? In what follows we will assume that the signal was fake, no lockdown occurs in practice. Hence, the impulse responses shown will be reactions to pure noise, not contaminated by any physical lockdown, whether temporary or persistent. Certainly, in the real world agents would not react to noise amidst no observed and expected lockdown, therefore the simulation of the pure noise does not aim at fully resembling the observed reality, but rather at explaining the transmission mechanism of the fear of lockdown that may be a part of it.

Having received the signal agents expect an economic contraction. In response, households lower consumption and investments (Figure 4). As a consequence output declines and firms lower labor demand. The drop in labor hours translates into skill deterioration that makes the downturn last longer. Thus, the responses of macroeconomic aggregates to the fear of lockdown resemble their counterparts in the case of fundamental shocks. Interestingly, this also holds for inflation. Hence, in contrast to technology noise shocks studied in the earlier literature (e.g. (Blanchard et al., 2013; Hürtgen, 2014)), the lockdown noise shock

is inflationary. Importantly, the response to the fear of lockdown is economically significant. One standard deviation of noise shock lowers GDP on impact by more than half of the response to fundamental shocks. Certainly, one can rightfully suspect that this result hinges on the model calibration. We address this issue in subsequent sections.

Figure 4: Impulse responses to the noise about lockdown

Note: values are expressed in percentage deviations from the steady state, with the exception for inflation presented in percentage points. The time unit is one quarter.

4.3 Fear and the structure of the economy

Having established that pure beliefs about the lockdown can affect economic activity, let us check how this finding depends on the main features of the modeled economy. The calibration of macroeconomic parameters is fairly standard, so the main role of this part is to better understand and explain how the shock is transmitted. However, this exercise offers simultaneously a robustness check. In this section we analyze what (and to what extent) determines the impact of fear by manipulating standard parameters in the macroeconomic setup (Figure 5).

Figure 5: Impulse responses to the noise about lockdown depending on chosen parameters

Note: GDP expressed in percentage deviations from the steady state, inflation in percentage points. The time unit is one quarter.

We begin with a parameter that has been shown to play an important role in the literature on noisy technology - the response to inflation in the Taylor rule. Chahrour and Jurado (2018) show that low values of this parameter strengthen the impact of noise about productivity on output. In our model this parameter is important as well (see first row of Figure 5). However, in contrast, in the case of lockdown noise it is a strong monetary policy response that strengthens the reaction. This happens due to the inflationary impact of noise shocks. The central bank reacts to higher inflation by raising interest rates and hence lowers output. Consequently, a weaker response to inflation ($\gamma_\pi = 1.25$) weakens the reaction of output.

Hysteresis effects seem to be of little importance for our results (second row in Figure 5). In principle, this parameter determines how strongly changes in labor supply affect workers skills. If we switch off the parameter that governs it, such impact is absent. Nevertheless, GDP and inflation reactions to the fear of lockdown change only slightly as compared to the baseline. Similarly, we do not observe much of the impact after doubling the parameter value to reflect that the Covid-19 shock might have led to much stronger deterioration of skills than on average in the past.

Next, we consider the parameter that determines how the government subsidy to house-

holds responds to the lockdown. In the baseline such subsidy is absent. Here, we allow for either full or 50% reimbursement of the wage income loss ($\gamma = 1$ or $\gamma = 0.5$). As the third row in Figure 5 indicates, the subsidy attenuates the impact of the noise shock as it narrows the wedge between the wage effectively paid by firms and received by households. However, even eliminating this wedge completely does not make the impact of the fear of lockdown disappear. This suggests that the more important wedge is the one between households labor supply and labor effectively utilized by firms. To put it differently, during lockdown (and due to the fear of thereof) it is more important that workers cannot work than that they do not receive the full (hourly) salary.

Finally, we look at the role of price stickiness. Besides our baseline value we consider more sticky ($\theta = 0.95$) and less sticky prices ($\theta = 0.5$). Both increasing and decreasing price stickiness lowers the impact of noise on output and inflation. Thus, interestingly and in contrast to the previously discussed parameters the reaction seems to be non-monotonic. We look further into this issue while discussing the supply character of the noise shock in the next section.

4.4 Is fear a demand or a supply shock?

As the non-monotonicity of relation between price stickiness and response to the noise shock calls for more in-depth analysis, the left column of Figure 6 presents the on-impact reaction of output and inflation to the fear shock as a function of θ . The response of GDP is always negative and reaches a minimum at $\theta = 0.7$. The impact on inflation is not only non-monotonic but also changes the sign. For low values of θ (elastic prices) inflation declines, while under higher price stickiness inflation increases. These features seem puzzling, especially that fundamental shocks behave more predictably. In the remaining columns we plot, for comparison, reactions to a persistent lockdown and a time preference shock.⁴ Clearly, both functions are monotonic and both shocks have a well-defined supply (lockdown) or demand (preference) nature for all values of θ .

In order to understand the changing nature of the fear shock it is useful to consider its demand and supply effects. As for the former, it affects households' spending as they feel

⁴For this simulation we assume β to be stochastic and driven by an $AR(1)$ process with autoregressive parameter 0.8.

poorer and reduce consumption. If prices are allowed to adjust freely this leads, as expected, to lower inflation. However, when prices are sticky, the supply character dominates. After receiving a noisy signal, intermediate goods producers initially expect a persistent lockdown. Thus, they foresee costs to increase and hence, those who are allowed to adjust prices, raise them. This explains why under sticky prices the reaction of inflation is reversed and supply-side effects dominate. This feature potentially helps to explain missing deflation during the Great Lockdown as discussed in the Introduction (Figure 2).

Why then are the reactions non-monotonic in θ ? We see a role for monetary policy in the explanation. When prices are very sticky and θ approaches unity, the impact of the shock on inflation becomes low. Since inflation hardly changes, the monetary policy trade-off between inflation and output stabilization vanishes and the central bank can set nominal interest rates to counteract the output drop. As a consequence the reaction of output becomes small as well.

Figure 6: Maximum responses of GDP to selected shocks depending on price stickiness

Note: GDP expressed in percentage deviations from the steady state, inflation in percentage points.

4.5 Fear and information precision

In contrast to macroeconomic parameters, the parametrization of lockdown and communication thereof is specific for our study. In this section we look how it affects the main findings.

This exercise should be partly seen as explanatory and partly as a robustness check. Figure 7 shows how the impact of the noise shock on GDP depends on the noise volatility. The shape of the resulting curve resembles the one obtained in the literature investigating the impact of the noise about productivity (see e.g. Chahrour and Jurado (2018)). If the noise volatility is very small, it has little impact on macroeconomic variables by construction. However, if it is large enough, the signal about persistent lockdown becomes so noisy that agents attach little probability that it may convey information about fundamental lockdown. As a result, the impact of the noise shock decreases above a certain parameter value - in our case it is around 0.2, somewhat exceeding our calibration (0.135). In terms of robustness check it should be noted that, except for the case of a very precise signal, the noise has a significant impact on GDP which may be even stronger than under our baseline calibration.

Figure 7: GDP impulse responses to the noise about lockdown conditional on σ^N

Next, we investigate how the GDP response to the noise shock depends on the volatility of fundamental lockdown shocks. Figure 8 presents the maximum GDP response to the noise shock as a function of volatilities of two shocks: persistent and temporary lockdown keeping constant the baseline noise volatility. Fundamental volatilities matter as they impact the noise to signal ratio in the filtering problem. Indeed, when either persistent or temporary volatility is zero, the fear of lockdown does not influence agents' decisions. In this case

they can easily infer about fundamental shocks, thus they ignore noise. By the same token, the fear of lockdown is of little importance when the variance of one fundamental shock is unproportionally small compared to the other. Only when both variances are substantial, do agents find it difficult to distinguish between the two fundamental shocks. In this case noisy signals strongly shape their expectations about the future downturn caused by the lockdown.

Figure 8: Maximum GDP impulse responses to the noise about lockdown conditional on σ^T and σ^P

So far we have seen how the impact of the pure belief shock depends on the signal precision driven by fundamental and noise volatilities. Interestingly, responses to lockdown shocks depend on signal precision as well. To illustrate this, Figure 9 presents the reaction of GDP on impact to the persistent lockdown shock depending on its volatility and the standard deviation of the noise shock. Not surprisingly, the stronger the persistent lockdown, the more does GDP fall. What seems more interesting, is that when agents obtain more blurred signals, their response to the fundamental shock weakens. The logic behind the determinants of the noise shock impact applies here as well. As the signal precision deteriorates, agents wrongly interpret the (true) lockdown announcement to a larger extent as noise.

Figure 9: GDP responses to the noise about lockdown on impact conditional on σ^N and σ^P

All in all, the fear shock is very specific and different from ordinary shocks that inhabit DSGE models. First of all, its supply or demand features can dominate, depending on the pricing process. Second, the impact of the shock is non-monotonic in at least two important parameters: price stickiness and noise precision. Third, the mere presence of noise affects responses to fundamental (lockdown) disturbances.

4.6 Policy implications

We believe that our findings call for formulating policy conclusions. This is especially important in the context of the on-going Covid-19 pandemic and the pressing question how public authorities should design and communicate the lockdown policy. Before addressing this question, we would like to repeat that, since we do not explicitly account for the pandemic in our setup, lockdown obviously deteriorates welfare and it is pointless to optimize policy with respect to it. Only if lockdown explicitly saved lives in the model, it could be an optimal policy.

Hence, in formulating policy conclusions we will assume that policymakers have reasons, that go beyond our model, to introduce a lockdown. In particular we assume that they intend to achieve a given economic slowdown (and a related fall in social interactions) that

perfectly reflects the fundamental impact of the lockdown. Any further (positive or negative) effects related in particular to miscommunication are assumed undesired.

What are the consequences for communication policy? Under the assumption formulated above, it is in the interest of public authorities to make communication as clear as possible. Noisy communication has two unwelcome effects: (i) a false signal about lockdown can be interpreted as a true one and cause an unwelcome contraction and (ii) a true signal can be wrongly interpreted as being false, and hence weaken the effects of lockdown that authorities wish to introduce. Very noisy communication does not look like an appealing alternative. While (as shown in Figure 7) high noise can also reduce the non-fundamental reactions (i.e. reduce concern (i)), it does not solve the second problem. With information being more noisy the impact of true lockdowns becomes monotonically weaker.

Having said this, one should remember that noisy signals about the pandemic and the lockdown do not only stem from the authorities. There is plenty of information in the public domain, some being true, some false. The public sector has the means (e.g. statements of high-level officials) and the knowledge (best epidemiologists can be at its service) that allow to communicate precisely and efficiently with the public and possibly to override the cacophony. Our study calls for action in this area.

5 Conclusions

Lockdowns contributed heavily to the sharp breakdown of economic activity in early 2020. In this paper we argue that what affects the economy is not only the lockdown as such, but also imperfect information about its duration. Although lockdowns ultimately proved relatively short-lived in the first half of 2020, many agents facing information frictions have expected them to be long-lasting. Moreover, as life has shown, lockdowns in some form returned in many countries in Fall 2020 when the second wave of the pandemic hit.

We use a relatively standard business cycle model, extended for the presence of an information friction to analyze this very problem. The friction is related to information about the duration of the lockdown being imprecise (noisy). Agents face a signal extraction problem and commit mistakes not being able to perfectly separate signal from noise. In particular, they can treat a false signal about the lockdown as true information and react accordingly

(i.e. expect lower wealth and reduce consumption). As a consequence the economy contracts. Noisy information can also act in another unwelcome direction - it can decrease the (intended) impact of a true lockdown (as agents may treat the signal as noise).

Our mechanism is somewhat stylized and the calibration of the information process prone to uncertainty. So, our quantitative findings should be interpreted with caution. Nevertheless, for a wide range of parameter values describing the precision of the signal about lockdown duration, the impact of a false signal about a lockdown is substantial and can lower GDP by more than half of the impact of the fundamental lockdown shock. Only under very precise communication does such noise play a negligible role.

The main policy conclusion from our paper is that public communication about lockdown duration should be made as precise as possible. If the lockdown is to last for long, this should be communicated openly. Otherwise the authorities risk a limited impact on activity as agents may (falsely) interpret the signal as temporary. But if the government intends to apply short-term measures only, it should not be ambiguous either, as agents (if they misinterpret the signal) could react as if the measures were to stay for long. While it is understandable that during the first lockdown phase in Spring 2020 public authorities in many countries were wandering in the dark, over time and with more experience their reaction functions should crystallize. Authorities should use information they possess and communicate it precisely.

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Tables and figures

Parameter	Value	Description
β	0.995	Discount factor
ν^{-1}	0.5	Frisch elasticity of labor supply
δ	0.025	Capital depreciation rate
α	0.33	Capital share in output
κ	5	Investment adjustment cost curvature
μ^p	1.2	Product markup
θ	0.8	Calvo probability (prices)
γ_R	0.8	Interest rate smoothing
γ_π	1.5	Interest rate reaction to inflation
γ_y	0.125	Interest rate reaction to GDP
μ	0.11	Empl. hysteresis estimated by Chang et al., 2002
ϕ	0.8	Skill autoregression as in Chang et al., 2002
ρ	0.9	Autoregression of lockdown
σ^T	0.31	Standard deviation of temporary lockdown
σ^P	0.15	Standard deviation of persistent lockdown
σ^N	0.135	Standard deviation of noise
γ	0.5	Reimbursement share of lost wage income

Appendix A. The state space representation and the filtering problem

Consumers face a signal extraction problem which they solve by running the Kalman filter. Below this problem and its solution are presented. Let $\mathbf{X}_t = \begin{bmatrix} l_t^T & l_t^P \end{bmatrix}'$ denote the state vector, $\mathbf{S}_t = \begin{bmatrix} l_t & s_t \end{bmatrix}'$ the vector of observables and $\boldsymbol{\varepsilon}_t = \begin{bmatrix} \varepsilon_t^T & \varepsilon_t^P & \varepsilon_t^N \end{bmatrix}'$ the vector of shocks. The system of equations (13)-(16) can be presented in matrix notation as follows:

$$\mathbf{X}_t = \mathbf{A}\mathbf{X}_{t-1} + \mathbf{B}\boldsymbol{\varepsilon}_t \quad (21)$$

$$\mathbf{S}_t = \mathbf{C}\mathbf{X}_t + \mathbf{D}\boldsymbol{\varepsilon}_t \quad (22)$$

where:

$$\mathbf{A} = \begin{bmatrix} 0 & 0 \\ 0 & \rho \end{bmatrix}, \quad \mathbf{B} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \end{bmatrix},$$

$$\mathbf{C} = \begin{bmatrix} 1 & 1 \\ 0 & 1 \end{bmatrix}, \quad \mathbf{D} = \begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & 1 \end{bmatrix}.$$

The variance-covariance matrices $\mathbf{S}_1 = E_t [\mathbf{B}\boldsymbol{\varepsilon}_t\boldsymbol{\varepsilon}_t'\mathbf{B}']$ and $\mathbf{S}_2 = E_t [\mathbf{D}\boldsymbol{\varepsilon}_t\boldsymbol{\varepsilon}_t'\mathbf{D}']$ are given by:

$$\mathbf{S}_1 = \begin{bmatrix} \sigma_T^2 & 0 \\ 0 & \sigma_P^2 \end{bmatrix},$$

$$\mathbf{S}_2 = \begin{bmatrix} 0 & 0 \\ 0 & \sigma_N^2 \end{bmatrix}.$$

Agents form expectations based on the Kalman filter. Hence, the evolution of the expected state vector follows:

$$\mathbf{X}_{t|t} = \mathbf{A}\mathbf{X}_{t-1|t-1} + \mathbf{K} (\mathbf{S}_t - \mathbf{S}_{t|t-1}) \quad (23)$$

where

$$\mathbf{K} = \mathbf{P}\mathbf{C}' \left(\mathbf{C}\mathbf{P}\mathbf{C}' + \mathbf{S}_2 \right)^{-1} \quad (24)$$

is the Kalman gain matrix and

$$\mathbf{P} = \mathbf{A}[\mathbf{P} - \mathbf{P}\mathbf{C}' \left(\mathbf{C}\mathbf{P}\mathbf{C}' + \mathbf{S}_2 \right)^{-1} \mathbf{C}\mathbf{P}]\mathbf{A}' + \mathbf{S}_1 \quad (25)$$

captures uncertainty of the state vector (see Hamilton 1994, p. 380 for details).

Use (21) and (22) to derive $\mathbf{S}_{t|t-1} = \mathbf{C}\mathbf{X}_{t|t-1} = \mathbf{C}\mathbf{A}\mathbf{X}_{t-1|t-1}$ and substitute into (23):

$$\begin{aligned} \mathbf{X}_{t|t} &= \mathbf{A}\mathbf{X}_{t-1|t-1} + \mathbf{K} (\mathbf{S}_t - \mathbf{C}\mathbf{A}\mathbf{X}_{t-1|t-1}) \\ &= (\mathbf{A} - \mathbf{K}\mathbf{C}\mathbf{A})\mathbf{X}_{t-1|t-1} + \mathbf{K}\mathbf{S}_t \end{aligned} \quad (26)$$

Then substitute for

$$\mathbf{S}_t = \mathbf{C}\mathbf{X}_t + \mathbf{D}\varepsilon_t = \mathbf{C}(\mathbf{A}\mathbf{X}_{t-1} + \mathbf{B}\varepsilon_t) + \mathbf{D}\varepsilon_t = \mathbf{C}\mathbf{A}\mathbf{X}_{t-1} + (\mathbf{C}\mathbf{B} + \mathbf{D})\varepsilon_t \quad (27)$$

to get:

$$\mathbf{X}_{t|t} = (\mathbf{A} - \mathbf{K}\mathbf{C}\mathbf{A})\mathbf{X}_{t-1|t-1} + \mathbf{K}(\mathbf{C}\mathbf{A}\mathbf{X}_{t-1} + (\mathbf{C}\mathbf{B} + \mathbf{D})\varepsilon_t) \quad (28)$$

Agents use this equation to form expectations of the state vector.

Since in the linearized model certainty equivalence holds, agents treat these expectations like true state variables. The model solution under imperfect information is based on the same laws of motion (policy functions) as the perfect information model, whereas the unobserved state variables are replaced by their estimates from the Kalman filter (see Hamilton 1994; Hürtgen 2014 for details).

Finally, the imperfect information model is observationally equivalent to its perfect information counterpart with correlated shocks. This result is used to obtain impulse responses

presented in the paper (see Lemma 2 in Blanchard et al., 2013).

Appendix B. Calibration of noise volatility

This Appendix presents the simplified filtering problem of the agents as well as its application to the data on Google searches for flights that allow us to calibrate the noise shock volatility in Section 3.7.

B.1. Description of the simplified passive learning

Similarly to the full Kalman filtering problem described in Appendix A, we assume that agents observe two variables:

1. the lockdown that is a sum of persistent and temporary (measurement error) component:

$$LD_t = LD_t^P + LD_t^T$$

2. the noisy signal about the persistent component:

$$S_t = LD_t^P + \varepsilon_t^N \tag{29}$$

In order to infer on noise volatility, i.e. σ^N , from the available data we focus on two periods of time: April 2020 and Summer 2020 that we associate with - respectively - period t and $t+1$. We assume that expectations about lockdown in the period $t+1$ do not account for the temporary lockdown in this period and the persistent component is not autoregressive but instead features a unit root, i.e.:

$$E_t(LD_{t+1}) = E_t(LD_t^P) \tag{30}$$

Assuming normal distribution of LD_t^P , LD_t^T and ε_t^N it follows that:

$$E_t(LD_{t+1}) = S_t \frac{(\sigma^P)^2}{(\sigma^P)^2 + (\sigma^N)^2}$$

i.e. expectations of the future lockdown depend on the signal and its precision.

B.2. Using data on flight searches

We use Google Trends tool to download numbers of searches for phrases “flights April” and “flights Summer” for a number of countries (if English is not an official language of a country we translate the phrases into the respective official language) for years 2016-2020. As Figure 10 illustrates for the US case, there has been a consistent pattern of such searches in years 2016-2019, i.e. in “normal” times. The year 2020 saw a substantial drop in people’s interest in traveling. We associate its scale with the size of the lockdown assuming that if people are forced not to work, they are also unable to travel both in business and as tourists. We compare our lockdown proxy with another available measure of mobility presented by Worldometers.info in Figure 11 and find that these two are broadly in line.

Figure 10: Google Trends searches for phrases “flights April” (left panel) and “flights Summer” (right panel) in the US.

Source: Own calculations based on Google Trends data.

Note: shaded areas denote late March and April (week number 11-17) and Summer (week number 27-35).

The advantage of using the proposed measure, however, is that we can proxy for the lockdown in the Summer (i.e. in period $t + 1$), as expected in April, (i.e. in period t). It is given by searches “flights Summer” observed in April. As Figure 10 shows, this phrase was also searched much less in 2020 as compared to previous years. Having calculated proxies for LD_t , LD_{t+1} and $E_t(LD_{t+1})$ for a number of countries, we verify their quality by comparing them with Worldometers.info measure as well as data on travel restrictions presented by United Nations World Tourism Organization. We drop countries for which data is unreliable leaving finally seven of them: US, UK, Canada, Australia, Germany, France and Poland. As a final step, we calculate LD_t^P , LD_t^T , ε_t^N and σ^N using equations presented in Appendix B.1. To this end we first use eq. 30 to infer on the persistent productivity component based on

expected lockdown in period $t + 1$. Next, we calculate the value of σ^P from cross-country dispersion of LD_t^P and guess the value of σ^N to calculate the signal S_t . Finally, we compute ε_t^N from eq. 29 and its standard deviation using cross-country realizations of this shock. We verify whether the obtained value of σ^N is equal to the guessed one and if not - we modify the guess until they converge.

Figure 11: Comparison of mobility measure implied from Google Trends and Worldometers.info in April (left panel) and in the Summer (right panel).

Source: Own calculations based on Google Trends and Worldometers.info data.