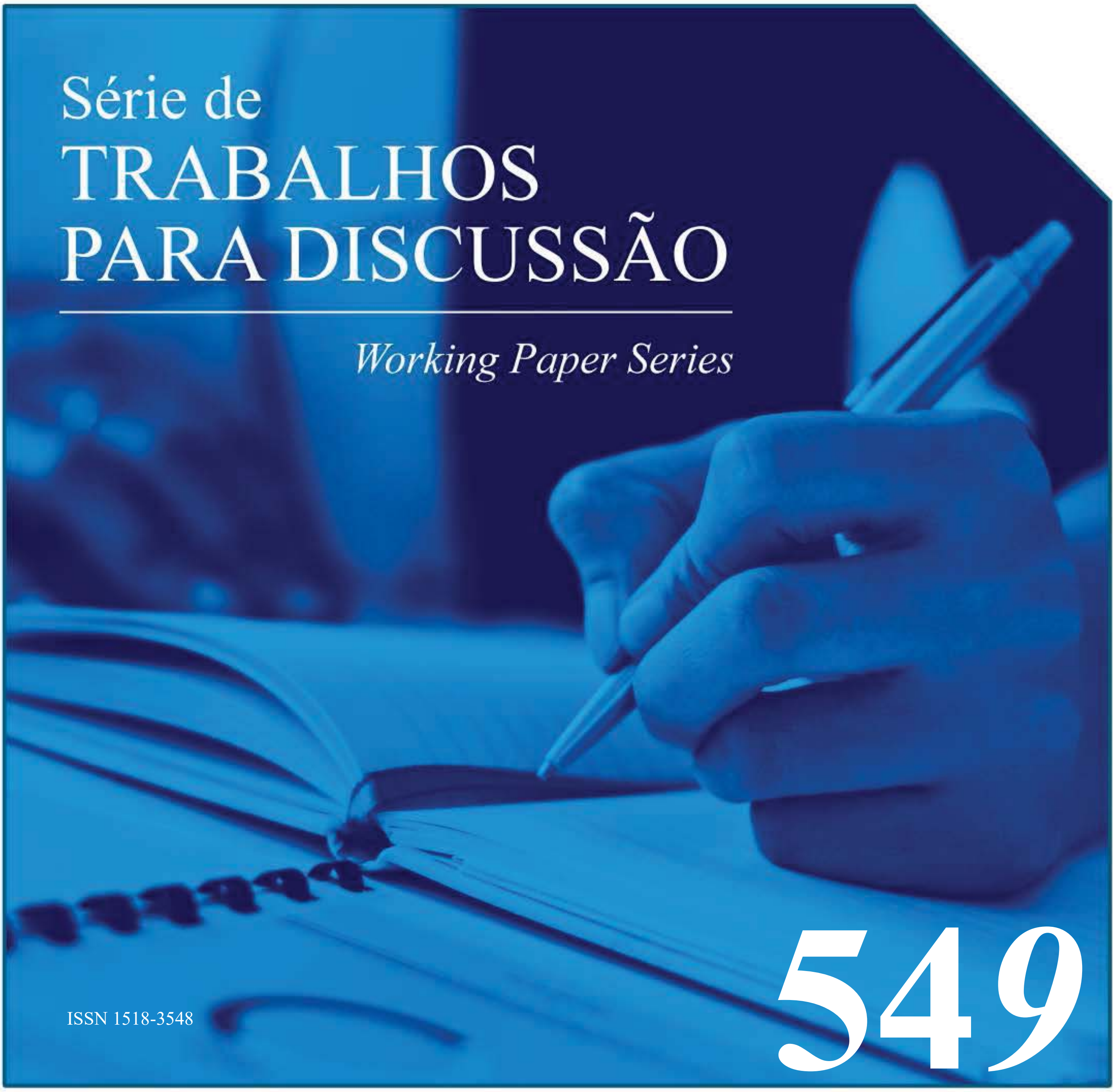

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Blurred Crystal Ball: investigating the forecasting challenges after a great exogenous shock

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Non-technical Summary

An event like Covid-19 pandemic brings about a deadly human toll and mayhem to the economy. The design of the necessary and sufficient responses requires informed decision, grounded on data and forecasts. However, the magnitude of the shock to the economy imprints itself in extreme variations of most economic variable measures. The analysis of time series running mostly with normal time values but ending with extreme values poses a great challenge to the reliable econometric techniques that policy makers and forecasters regularly use. The challenge is even greater if crisis is unfolding, since one has to cope with information at the edge to anticipate what shall come next, and what may structurally change in the economy.

Many distinguishing researchers came forward with their own assessments of the lasting macroeconomic impacts of the Covid-19 pandemic. Modestly, this paper attempts a different instance: investigating how a practitioner can cope with some pressing forecasting challenges while avoiding naïve pitfalls. We invite the reader to relinquish the clarity of ex-post reflections and to frame her/himself within the outlook of early September of 2020 instead, with the ex-ante uncertainty about many pandemic recovery questions: if, when, how much and how fast would the economy recover.

This paper proposes didactic exercises without claiming any quantification. It experiments with usual US economy data sources and macroeconomic models to exemplify these challenges and their possible overcoming. It tries and tests standard econometric, machine learning and model simulation techniques on time series whose final edge displays amplitude never observed in the sample, which starts in 1959.

Finally, it summarizes from these exercises some empirical, pragmatical conclusions, in favor of open-mindedness, simplicity but diversity in the empirical toolset.

Sumário Não Técnico

Um evento como a pandemia da Covid-19 resulta em mortes para a população e caos para a economia. O desenho de respostas necessárias e suficientes requer decisões informadas, baseadas em dados e previsões. No entanto, a magnitude do choque para a economia manifesta-se em variações extremas na maioria das variáveis econômicas. A análise de séries temporais compostas essencialmente por valores relativos a conjunturas normais, mas terminando em valores extremos, representa um grande desafio para as confiáveis técnicas econométricas que os economistas e formuladores de políticas usam regularmente. O desafio é ainda maior enquanto a crise ainda prossegue, pois devem lidar com a informação sem precedente para antecipar o que virá a seguir e o que pode mudar estruturalmente na economia.

Muitos pesquisadores reconhecidos apresentaram suas próprias avaliações sobre os impactos macroeconômicos duradouros da pandemia da Covid-19. Modestamente, este artigo tenta uma abordagem diferente: investigar como um profissional pode lidar com alguns desafios urgentes de previsão, evitando armadilhas ingênuas. Convidamos o leitor a deixar a clareza das reflexões ex-post e, em vez disso, colocar-se na conjuntura do início de setembro de 2020, com a incerteza ex-ante sobre muitas questões de recuperação da pandemia: se, quando, quanto e com que rapidez seria a recuperação da economia.

Este artigo propõe exercícios didáticos sem reivindicar qualquer quantificação. Os experimentos utilizam fontes de dados e modelos macroeconômicos usuais para a economia dos EUA visando exemplificar esses desafios e suas possíveis superações. O trabalho tenta e testa técnicas econométricas padrão, aprendizado de máquina e simulação de modelo sobre séries temporais cuja borda final exibe amplitude nunca observada na amostra, que se inicia em 1959.

Finalmente, a partir desse exercício, o artigo traz algumas conclusões empíricas e pragmáticas, em favor da mente aberta, simplicidade, mas diversidade no conjunto de ferramentas empíricas.

Blurred Crystal Ball: investigating the forecasting challenges after a great exogeneous shock*

Marcelo A. T. Aragão**

Abstract

An event like Covid-19 pandemic brings about a deadly human toll and mayhem to the economy. With such a great exogeneous shock, policy makers and forecasters alike face a set of challenges to keep on contributing to the economic response. Many distinguishing researchers came forward with their own assessments of the lasting macroeconomic impacts of the Covid-19 pandemic. Modestly, this paper attempts a different instance: investigating how a practitioner can cope with some pressing forecasting challenges while avoiding naïve pitfalls. Without claiming any quantification, it experiments with usual US economy data sources and macroeconomic models to exemplify these challenges and their possible overcoming. Finally, it summarizes some empirical, pragmatical conclusions.

Keywords: exogeneous shock, Covid-19, economic uncertainty, stochastic volatility, economic forecasting, vector autoregressions, long short- term memory networks, impulse response simulations.

JEL Classification: D80, E17, E31, E32, E37, E66, J21

* *We acknowledge the effort and the kindness of those who make data sources, economic models freely available and analytics tools, without which we could not have the exercises presented here. Moreover, we much appreciate the insightful comments from Aquiles Farias and Euler Mello, on early drafts.*

** *International Affairs Department, Central Bank of Brasil.*

1. Background: an unprecedented exogeneous shock with an unprecedented magnitude and synchronicity

The outbreak of Covid-19 has significantly disrupted the economies. Compared to other previous costly and deadly disasters in recent US history, Covid-19 stroke with force and with distinguishing features:

- it is a pandemic, i.e., it is word wide, striking both emerging and advanced economies;
- besides its spread, it is also too acute, striking all near synchronously, in macroeconomic time, within only two quarters of 2020;
- it impacted both supply and demand side, sometimes involuntarily, through lockdowns, closures, and mobility restrictions;
- it propagated into financial and real sides through an array of transmission channels;
- it has risen uncertainty, as well as changed behaviors, expectations, and preferences;
- so far, no one can tell whether it will cause structural break or be a blip of outliers;
- its spillovers require coordinated mitigation of equivalent speed, depth, and breadth;
- it hit the economy when monetary and fiscal toolsets used to ease the great financial crisis (GFC) impact have not fully unwound.

Taken together, these distinguishing features[1] escalate the challenges to modelling, to the estimation of economic models and to their application to forecasting, let alone to economic analysis and to policy making. Practitioners of machine learning face similar challenges, but their standard drop-outliers approach may be unsuitable here if the shock retains some persistence that impacts subsequent quarters. Such persistence is the object of interest, exactly what is relevant to anticipate, so it cannot be disregard as one-time noise.

[1] *When this article was written Covid-19 is a healthy and economic crisis still unfolding. Its persistent consequences will be matter of study and debate for year to come.*

Narrowing the scope to US economy, the two graphs in Figure 1 depict the unprecedented magnitude of Covid-19 pandemic impact in relevant macroeconomic variables: real gross domestic product and unemployment rate.

Figure 1: Real GDP and unemployment rate (%chg.)

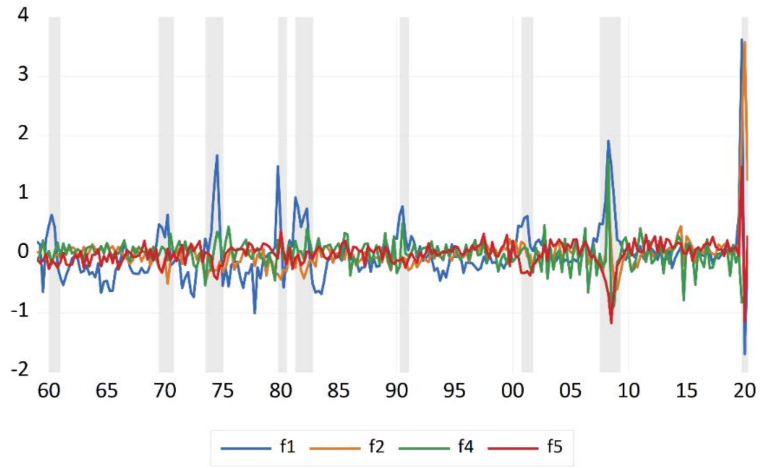
In fact, a static factor model (SFM) over a set of 248 economic variables, in quarterly periodicity, described in Fred-MD by McCracken & Ng (2016), outputs several common factors. The top four in variance are depicted in Figure 2. Therefore, the Covid-19 shock is reflected in all economic variables, with an amplitude never observed in the sample, which starts in 1959[2].

The WEO IMF (June 2020) reckons "there is pervasive uncertainty around this forecast. The forecast depends on the depth of the contraction in the second quarter of 2020 (for which complete data are not yet available) as well as the magnitude and persistence of the adverse shock." This statement highlights the doubts about depth (level)

[2] *The shocks are sizable even considering longer horizons, see: https://bfi.uchicago.edu/insight/chart/u-s-real-gdp-per-capita-1900-2017-current-economy-vs-historical-trendline/*

and breadth (persistence) of the on-going shock and about possible aftershocks from infection resurgences.

Figure 2: Four of the eight Common Factors in the Static Factor Model for Fred-MD



If the reader relinquishes the clarity of ex-post reflections and instead frames her/himself within the outlook of early September of 2020, with the ex-ante uncertainty about many pandemic recovery questions – if, when, how much and how fast – the exercises we report here and the course of forecasting approaches we attempt shall be better understood and realized.

This paper is structured as follows. Section 2 reviews a recent and fast-growing body of literature on studying the economic impact of Covid-19 shock. Section 3 outlines data samples used in the set of empirical exercises that will be described, in sequence, from Sections 4 to 11. Each section focuses on a specific challenge to develop useful forecasts for policy making. Finally, Section 12 generalizes conclusions and broad guidelines.

2. Related works

Although we are still living the Covid-19 emergency and its economic fall-out, there are several attempts to quantify its macroeconomic impact or estimate its likely propagation into the future. Most are not yet peer reviewed. Most build upon the preceding literature on natural disasters by Hallegatte & Przyluski (2010) and Cavallo et al. (2013).

Coibion et al. (2020) explore a large-scale survey microdata of households to characterize how labor markets are being affected by the Covid-19 pandemic. In our paper, we rely on model-based, empirical exercises.

Atkeson (2020) simulates scenarios from an estimated (Susceptible, Infectious, or Recovered) SIR model. The work from Fernández-Villaverde & Jones (2020) attempts to estimate a standard epidemiological model of Covid-19 using data from U.S. states, and various countries. While Eichenbaum et al. (2020) go further, in a seminal attempt, by extending the canonical epidemiology model to study the interaction between economic decisions about consumption and working and the dynamics of the pandemic. In this paper, we take epidemiologic projections as given by health professionals. Moreover, we assume that Covid-19 observed data and projections are completely exogeneous in the short run, thus we do not investigate how retail consumption or working hours might contribute to the dynamics of infection, for example.

Ludvigson et al. (2020) study the dynamic responses to costly and deadly disasters in recent US history. Then they try to quantify the macroeconomic impact of such disasters, and to translate these estimates into an analysis of the likely impact of Covid-19 in terms of industrial production and employment. Baker et al. (2020a) feed Covid-induced first-moment and uncertainty shocks into an estimated VAR-IV model that is proposed by Baker et al. (2020b), and which links disaster effects to economic activity measured as quarterly GDP growth. They resort to cross-country as well as to heterogeneous firm-level data to establish causal relationship from uncertainty to activity. Their illustrative exercise implies a year-on-year contraction in U.S. real GDP of nearly 11 percent as of 2020 Q4. Differently, we exploit standard econometric and macroeconomic models of the type policy makers are used to. The former type takes time series as inputs, the later takes sequences of shocks to condition economic scenarios, borrowing the same feeding approach. Both papers model uncertainty. The former assumes uncertainty as an endogenous factor that amplifies the shock impact in the next periods. The later tries to identify the causal effect of uncertainty to activity.

Some other works submit Vector Autoregression (VAR) projections for a few relevant economic variables, e.g., Djurovic et al. (2020), Lenza & Primiceri (2020), Ludvigson et al. (2020) and McKibbin & Fernando (2020), mostly industrial production, consumption, and employment. While Lenza & Primiceri (2020) also introduce a methodologic innovation on how to deal with such unprecedented variation to properly estimate density, hence uncertainty, in VARs. Those inspire this paper. However, two differences set us apart. Firstly, we do not claim or intend to contribute with impact assessments or specific forecasts. Secondly, we do not introduce a new technique, rather we resort to the application of few ones, those that are well documented and well known to practitioners. Otherwise, we do not restrict analysis to few variables, rather, we value medium-sized models, wherewith we can examine as many economic variables as necessary for realistic decision making. Moreover, we aim to contribute to assess instead the clear and present challenges that practitioners face, thereupon raise relevant questions rather than on offer definitive answers.

Finally, Fernández-Villaverde & Jones (2020) discuss the tradeoffs between economic performance and health safety and sort out the most affected jurisdictions by cross-correlating outcomes. The analysis focuses on observed data and not on predictions. A more comprehensive discussion on the Covid-19 literature is compiled in Brodeur et al. (2020).

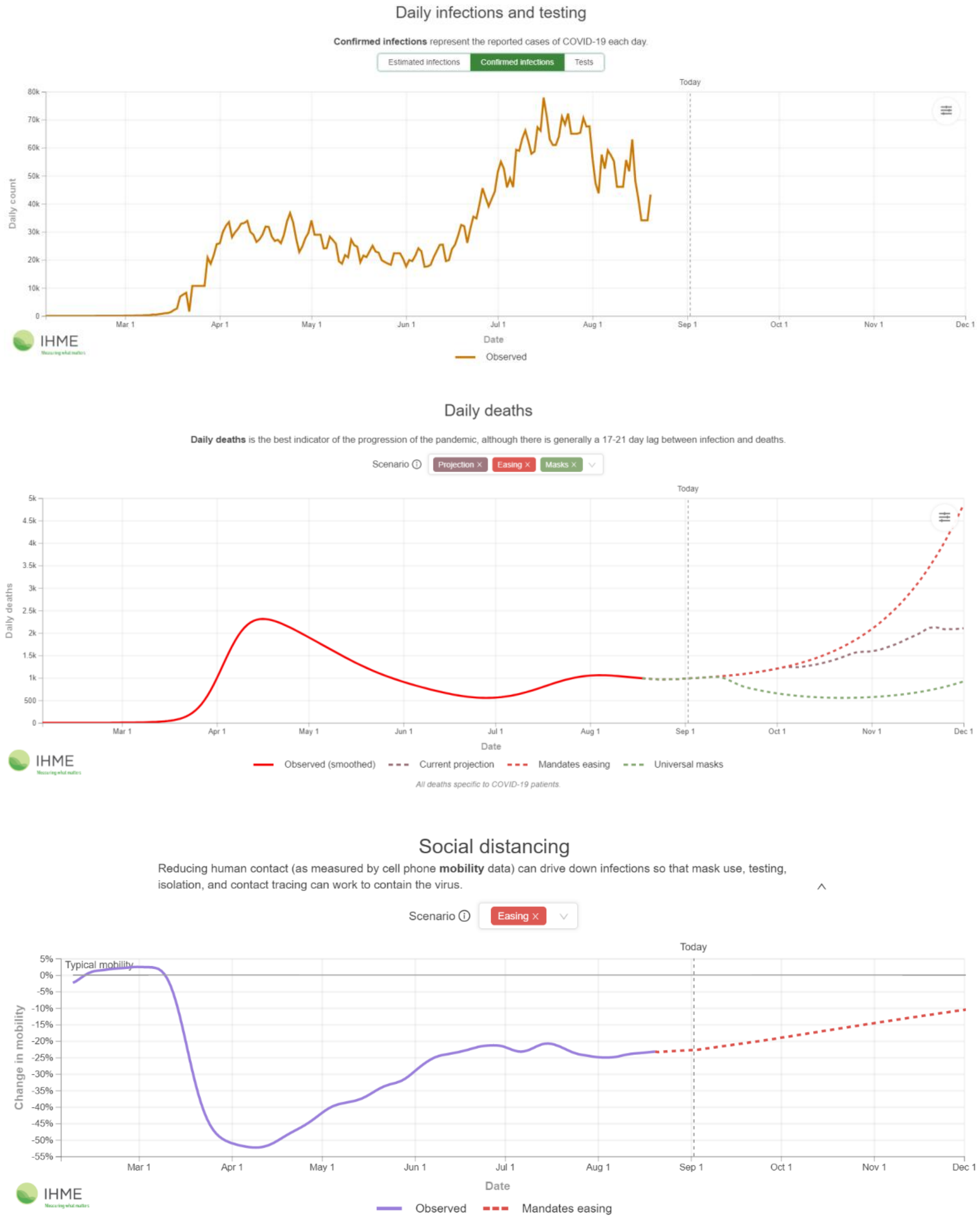
3. Realized data and projections

As hinted, all Covid-19 projections[3] in conditional scenarios were obtained from the Institute for Health Metrics and Evaluation (IHME) – an independent global health research center at the University of Washington. The series for infections, deaths, and mobility are illustrated in Figure 3.

IHME baseline projection assumes "social distancing mandates are re-imposed for 6 weeks whenever daily deaths reach 8 per million (0.8 per 100k). They also include two additional scenarios: Mandates easing, which reflects continued easing of social distancing mandates, and mandates are not re-imposed; and Universal masks, which reflects 95% mask usage in public in every location". We shall use the terms **easing** and **masks** to denote alternative projection scenarios further on.

[3] *See for details: https://covid19.healthdata.org/united-states-of-america (updated on Sept, 18th, 2020)*

Figure 3: IHME Graphs for infections, deaths, and mobility as proxy to social distancing



We use US economic data compiled as Fred-MD, with 128 monthly time series, in 10 thematic groups; and as Fred-QD[4], with 248 quarterly time series, in 14 groups. Both start from 1959 Q1 to the latest available set[5]. The accompanying papers McCracken

[4] *See details at https://research.stlouisfed.org/econ/mccracken/fred-databases/*
[5] *Both downloaded on Sept 1st; hence data is incomplete for 2020 Q3.*

& Ng (2016) and McCracken & Ng (2020) include in their appendices details about descriptions and suggested stationarity transformations for these time series. We also use FRB/US time series dataset with observed data and projections that accompany the FRB/US semi structural model by Brayton et al. (2016) from FED Reserve Board[6].

4. Challenge 1: Choosing the relevant dynamic drivers

The Fred-QD and Fred-MD are deemed a representative and a comprehensive dataset that characterize the US economic outlook. We adopt this assumption. Thus, we applied the corresponding transformations prescribed by McCracken & Ng (2020) to all. Then, each is taken as dependent variable and regressed[7] against an independent Covid-19 variable from IHME, according to the specification below:

$$y_t^c = \beta_1 + \beta_2 y_{t-1}^c + \beta_3 covid\_var_t + \varepsilon_t^c \ (eq. 1)$$

where y_t^c is a transformed economic variable of thematic group c, at quarter t, $covid\_var_t$ is one of three time series: Covid-19 confirmed infection **cases**; Covid-19 confirmed **deaths**; and personal **mobility**, as a proxy of social distancing. These three are aggregated into quarterly periodicity and used in log level scale.

Endogeneity bias is mitigated with GMM estimations of $(eq. 1)$, instrumented with usual lagged variables and with the lagged eight loading factors of Fred-QD denoting the exogenous information set about US economy before Covid-19.

Table 1 reproduces the median, per group *c*, of adjusted R^2 increase by adding the third term into $(eq. 1)$, and of the p-value for the β_3, for the regression of each variable y_t^c against each Covid-19 variable, expressed as $(eq. 1)$ [8].

[6] See details at https://www.federalreserve.gov/econres/us-models-package.htm

[7] Estimated with robust HAC variance-covariance estimator proposed by [Newey & West 1987] and automatic bandwidth selection to overcome serial correlation and heteroskedasticity in the error terms.

[8] For robustness, a similar exercise was repeated for Fred-MD monthly data yielding qualitatively comparable results.

Table 1: Summary of GMM estimations (eq. 1) against Covid-19 variables

		Covid-19 Infections		Covid-19 Deaths		Mobility [Diff]	
	#vars	med(R2 adj)	med(p-Value(β3))	med(R2 adj)	med(p-Value(β3))	med(R2 adj)	med(p-Value(β3))
1 NIPA	23	0.382	0.000	0.356	0.000	0.361	0.000
2 Industrial Production	16	0.631	0.000	0.583	0.000	0.593	0.000
3 Employment	50	0.741	0.000	0.674	0.000	0.686	0.000
4 Housing	11	-	0.000	-	0.000	-	0.000
5 Inventories, Orders and Sales	9	0.270	0.000	0.260	0.000	0.259	0.000
6 Prices	48	-	0.000	-	0.000	-	0.000
7 Earning and Productivity	14	-	0.000	-	0.000	-	0.000
8 Interest rates	20	-	0.000	-	0.000	-	0.000
9 Money and Credit	17	0.193	0.000	0.181	0.000	0.184	0.000
10 Household balance sheet	9	0.008	0.028	0.008	0.028	0.008	0.028
11 Exchange rates	6	-	0.019	-	0.035	-	0.030
12 Soft Data	2	0.426	0.000	0.419	0.000	0.419	0.000
13 Stock Market	10	-	0.025	-	0.008	-	0.016
14 Firms balance sheet	13	-	0.037	-	0.037	-	0.037
	248		0.00		0.00		0.00

This exercise shows that changes in economic variables can be partially explained by Covid-19 variables, using lagged economic variable as a control for past relevant information. These results are fragile, if strong conclusions are to be drawn, since the specification is simple and Covid-19 variables are not null only for two quarters[9]. Nevertheless, these results match anecdote, news, and expert economists' opinion about over which segments the economic impact, although widespread, is felt more immediately and directly: industrial production; employment; activity – NIPA; expectational soft data; inventories, orders and sales; and money aggregates and credit. These results also encompass the choice of variables studied in the related works in Section 3. On the other hand, stock market and balance sheets seem less correlated with Covid-19 variables. In most groups, there are supply and demand side variables. Reports about prices were mixed considering the sectoral heterogeneity and higher volatility rather than variation in the mean, in the first two quarters of 2020 with the pandemic. Likewise, level changes have become less significant and more dependent on other drivers Forbes (2019). Few variables with great variations fail to fit an acceptable β_3 estimation or to satisfy a model misspecification test, notably government expenditure and investment (GCEC1).

This exercise may also help choosing which variables to include in a Vector Autoregression analysis, of the nature described in the related work, instead of relying only on the obvious choices. We are aware that automatic Bayesian variable selection could also be used to select variables for VARs, as argued by Korobilis (2013) for avoiding over-parameterization. However, Korobilis (2013) concedes that there may be

[9] *For sake of robustness, repeated regression estimations, for a sample from 1986 Q1 and from 2009 Q3, and the median p-Value for Covid-19 variable coefficient remains significant to level inferior to 1%.*

scalability challenges to handle hundreds of dependent variables, as Fred-QD has. Moreover, one can argue about the discretionary definition of shrinkage priors. We are aware well-known shrinkage estimators could also be helpful. However, the small number of points would make discretionary definition of hyperparameters also arguable. Contrarily, we prefer to deem Covid-19 variables as independent and hundreds of economic variables as dependent, therefore we prefer simple, individual regressions as in $(eq.1)$. Nonetheless, note that none of the works reviewed in Section 3 employs any method to choose economic drivers.

We believe that a policy maker may also benefit exploring these shocks within the framework of a model with more structure whereon the policy maker can identify and prioritize different transmission channels, hence for the design of target policy decisions or responses. Hence, we choose the FRB/US model Brayton et al. (2016). The model has 285 equations. The model calibration seeks to be both realistic and representative of the US economy.

We assume that $\beta_3\mathrm{Covid\_var_t}$ can be interpreted as a sequence of two subsequent shocks to the variation of y_t^c that are explained orthogonally by the pandemic crisis when *t* is either 2020 Q1 or Q2. Such shocks can be simulated within the FRB/US model. Then, the move from Fred-QD to FRB/US requires finding a set of economic variables, or concepts that match in both, moreover, they should fulfil three criteria:

i. the contribution of Covid-19 variable is significant in statistical terms of *eq. 1* and sizable in its own scale. The gain in terms of adjusted R^2 and the satisfaction of J-statistic test for model misspecification were also considered;

ii. the response to shock of this variable in FRB/US model should not be negligible;

iii. this variable allows for a credible economic narrative of the pandemic in 2020.

Table 2: Economic variables from which Covid-19 shocks were extracted

Shocks	per.	Description
GDPC1	q	Real Gross Domestic Product
PCECC96	m	Real Personal Consumption Expenditures (rPCE)
PCDGx	q	rPCE: Durable Goods
PCNDx	q	rPCE: non Durable Goods
FPIx	q	Real Private Fixed Investment
INDPROD	m	Industrial Production
PAYEMS	m	Total non farm employees
USPRIV	m	Total private industries employees
RSAFSx	m	Real Retail and Food Services Sales
BUSINVx	q	Total Business Inventories
CONSUMERx	q	real consumer loans
USEPUINDXM	q	US EPU index
OILPRICEx	m	Real Crude Oil Price

5. Challenge 2: Extracting exogenous signals out of economic variables

We computed the shocks for each quarter according to $(eq. 1)$. Then, the next challenge is to validate, or at least corroborate, if this set of shocks in Table 1 can be reliably extracted through GMM estimations[10]. Instead of testing with a space of estimators or estimations techniques, we confronted the extracted shocks against agnostic, statistical techniques: an OLS regression with lagged y_t^c and two dummies for 2020 Q1 and Q2, and a univariate unobserved-components stochastic volatility outlier-adjusted (UCSVO) model by Stock & Watson (2016).

For each of the 13 variables in Table 2, we estimate the linear regression **dmy** model[11] and the **UCSVO** model[12]. Remind that both models are univariate with no explicit epidemiologic information, therefore unlearned about Covid-19. For the dmy model, we compute the contribution of each dummy. For the **UCSVO** model, we computed the difference between the transformed variable y_t^c and its stochastic trend τ_{y^c}, which results in its idiosyncratic volatility plus any identified outlier[13]. Such validation attempts to ease measurement concerns about untested cases, underreported deaths,

[10] *Sometimes the impact in 2020 Q1 is mostly March, thus, for sake of precision, for the series in Table 2 that are also available in monthly periodicity, eq 1 is also estimated with these monthly series. The contributions are aggregated. This additional rigor is relevant for employment series.*

[11] *The estimation of* $y_t^c = \beta_1 + \beta_2 y_{t-1}^c + \beta_3 dmy2020Q1 + \beta_4 dmy2020Q2 + \varepsilon_t^c$

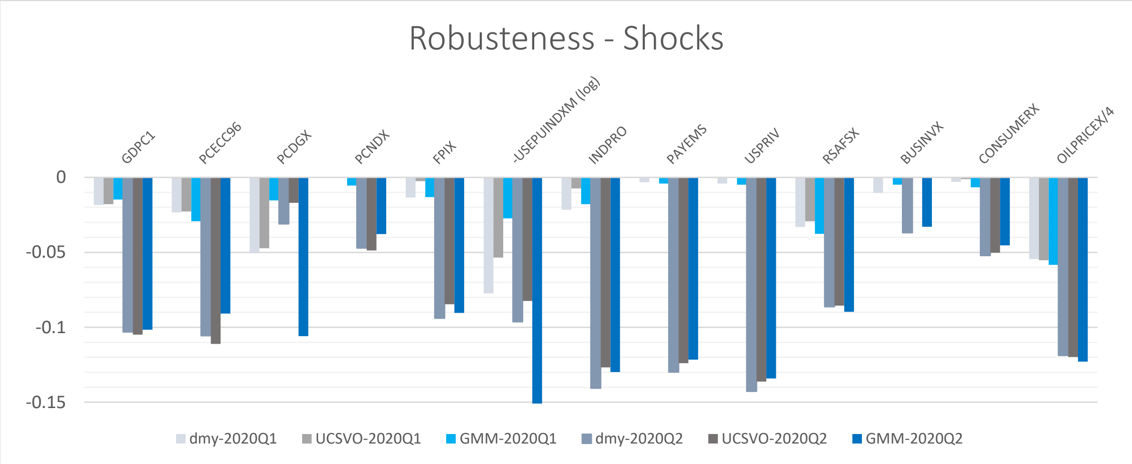
[12] *The UCSVO estimation uses the great moderation part of the sample (1986-2020), to avoid the previous high inflation period influencing unduly the stochastic trend. Results do not differ much for the full sample.*

[13] *In fact, we estimated one UCSVO model for each 248 variables in Fred-QD, using Gibbs Sampling to estimate its latent factors, and most of them have identified a sizable outlier for 2020 Q2.*

incomplete or imprecise proxy mobility data. Especially for 2020 Q2, stochastic trend deviation is much comparable to Covid-19 contribution through GMM estimation[14].

These results from **dmy** and **UCSVO** models are plotted against those shocks obtained via **GMM** model $(eq. 1)$ in Figure 4.

Figure 4: Comparing shocks extracted via GMM and UCSVO estimation



These results warrant the Covid-19 is the dominant explanatory variable for the dynamics of some relevant economic variables, remarkably of activity and employment. Note that the dummies hint only small extra variation over Covid-19 unexplained variation. Thus, the pandemic can be argued to be the paramount economic factor in 2020 H2, as pundits expected.

These two approaches to extract exogenous signals can be better evaluated from their consequences. Therefore, the FRB/US model[15] was fed with eight joint shocks (those highlighted in green in Table 2)[16] and simulated from 2020 Q1 onwards[17]. The

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[14] *The USCVO model is proposed by Stock and Watson (2016) with an explicit model-based treatment of outliers. The outlier detection is modeled as a mixture of normal via the i.i.d. multinomial variable, with calibrated expected frequency in the sample, so as to avoid mistaking a single large outlier for a more systematic increase in the volatility of the transitory component. If the exogeneous shock subdues, then its variation becomes mostly outlier, ex-post. If it turns to be persistent, the more likely is the subsequent estimations to identify the variance of observed shock, initially as outlier, then gradually shift to interpret the shock from outlier to an increase in the volatility of the transitory component. Here, we notice that shocks for 2020 Q1 have larger outlier component when we estimate with the sample up to 2020 Q1, relatively to when we estimate with the sample up to 2020 Q2, whilst the idiosyncratic volatility raises to absorb a small part of 2020 Q1 variance.*

[15] *The FRB/US models the binding constraints of zero interest rates. That's essential to credible exercises, and hardly captured in pure VAR exercises.*

[16] *The remaining variables in Table 2, those in bold black type face are redundant and subsume the direct effect on their components, while those in orange type face will be useful on the next exercises.*

[17] *We are deliberately overriding the observed data for 2020 to we write a Covid-19 economic tale in order to assess how the exercise confronts to reality.*

results are contrasted in Figure 5. The obtained dynamic is similar, with little more modest effects if USCVO shocks are assumed.

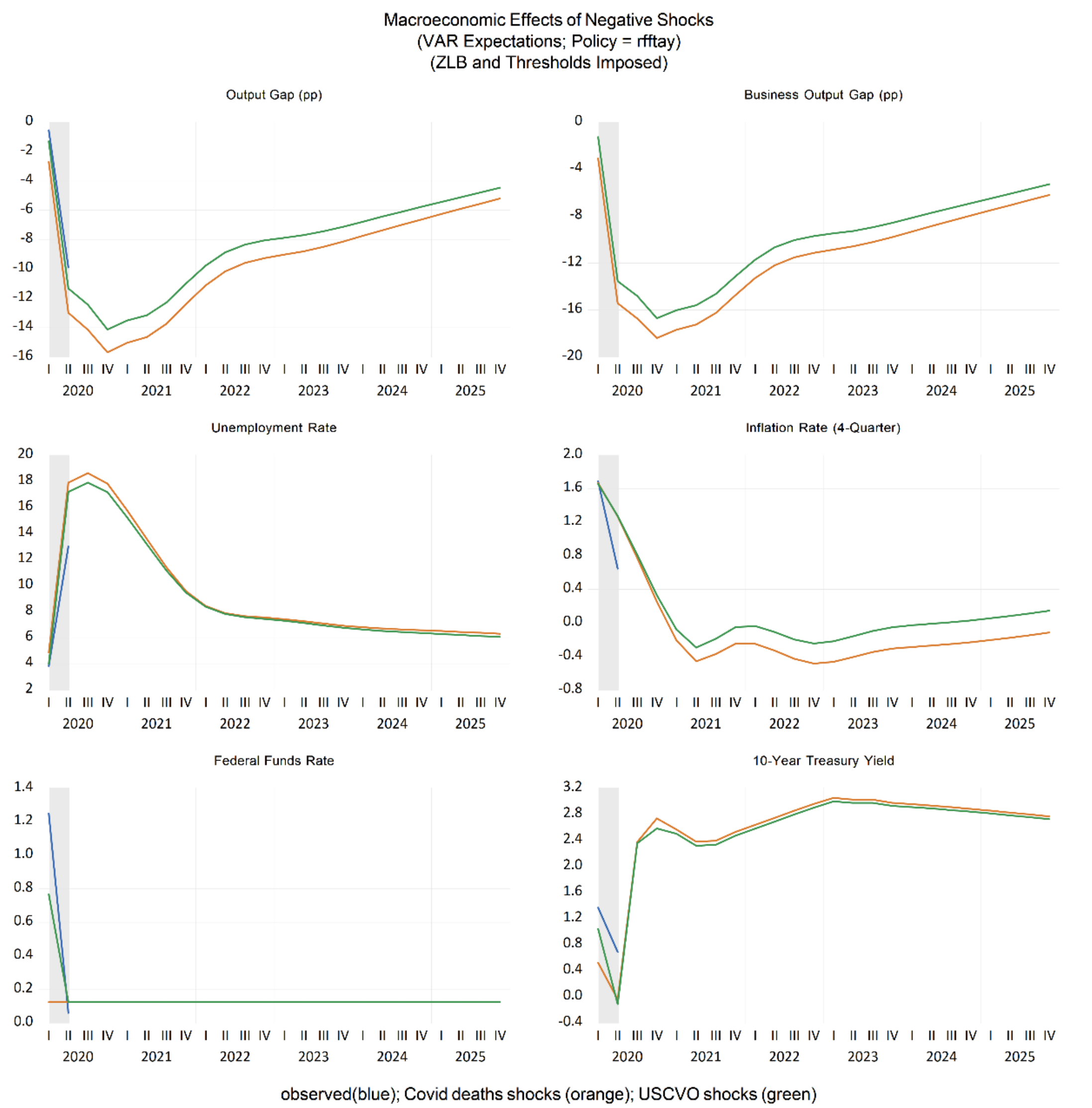
The signals of the Covid-19 impact on economic variables can be extracted, alternatively, from cross-country panels, since it has been a global, near synchronous event, according to the methods described in Baker et al. (2020a) and Fernandez-Villaverde & Jones (2020). One should mind the proper control of country idiosyncrasies. They can also be extracted from micro-level data, as it is also explored in Baker et al. (2020a). One should consider the proper identification of a cross-firm common factor since we have verified the great sectoral heterogeneity when we estimate (*eq 1*) on sectoral employment or price time series. They can also be extracted from financial cost measures of previous events and then extrapolated from the preliminary projection of the cost of fiscal responses as in Ludvigson et al. (2020). One should mind the imprecision of government commitment vis-à-vis fiscal response execution, and the imprecision of the liquidity and securitization mitigation effect, which prescinds expenditure. Our shock extraction approach, however, is less prone to arbitrary transposition of the past events, but only viable when there are at least few, present data points.

Confidence intervals are considered less informative and intentionally omitted in Figure 5 and all other graphs presented here. The reason is twofold: point estimation is close enough to be statistically indistinguishable, and the variance estimation upon which intervals are computed can no more be demonstrated to be reliable due to an increase in uncertainty.

Thus, considering only point forecast, both shock extraction techniques entail similar comparable levels and dynamics with respect to observed data about inflation, short- and long-term interest rates. The simulation with shocks extracted via GMM and via UCSVO overshoot the observed unemployment rate of 13% for 2020 Q2. While the simulation with shocks extracted through UCSVO overestimates by less the output gap fall of 10%. Hence, no approach perfectly fits the actual outline. An incomplete choice of which shocks might be to blame, tangled with difficulty of capturing unconventional monetary policy responses; liquidity provision and credit measures upon a crunch in financial conditions; job retention schemes; and the incompleteness of FRB/US model at last. By finding negative impacts beyond what where observed, the model consistently prescribes more sudden responses in terms of benchmark and 10-year interest rates. Nevertheless, the deflationary prices response was milder than what actually happened.

Note that we have selected only one price shock POIL - real crude oil price, because no other consumer or producer price in Fred-QD met our shock selection criteria presented in Section 4. The FRB/US model has a New Keynesian Phillips Curve (NKPC) for hourly compensation, but even if we augment Fred-QD with private hourly wage, the dynamics will not help explain the difference between observed and simulated consumer expenditure prices. One possible explanation would be that the FRB/US model is calibrated with an NKPC flatter than otherwise would capture a larger interplay between activity and prices. Such debated discussion is outside our scope, and the interested author shall be referred, for instance, to Hoover et al. (2020). Henceforth, we shall only assume that our exercises will tend to depict a smoother price response, both ways.

Figure 5: Contrasting responses to shocks extracted via GMM and UCSVO estimation



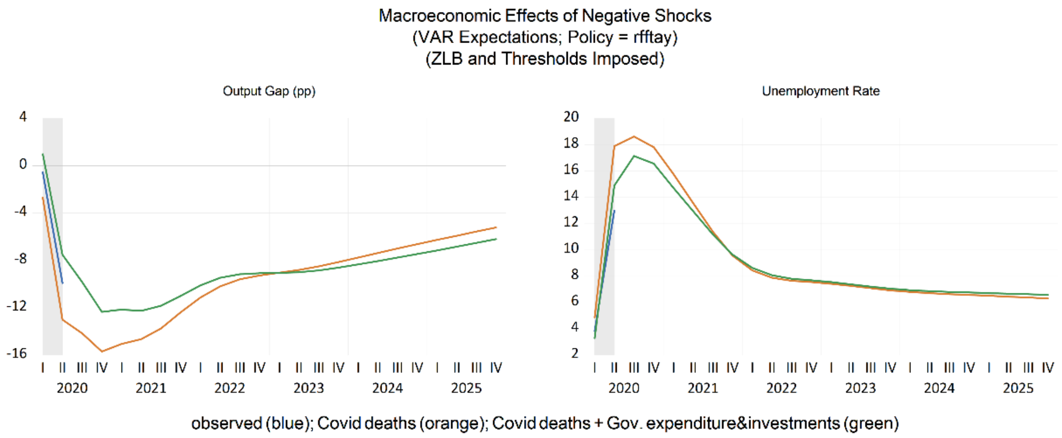
We shall return to this debate in the next section. Remind that our goal is to survey the challenges, rather than to provide accurate estimates. Therefore, we can more safely claim that it is worth having more than one approach to extract signal from such complex and large shocks. This is a valid robustness concern that is comparable to experimentation with distinct lag order and identification strategies usual for VAR-based estimations such as the ones in Section 3.

6. Challenge 3: Assessing the coherence of projections (level and dynamics)

Even believing that the shock extraction approach can be deemed useful, it begs the question about the difference between observed and simulated values for output gap and unemployment rate in 2020. According to CEA (2020), the US government bore the weight of economic responses unified in a package called CARES Act, approved for implementation in the final days of 2020 Q1. At a quarterly level, we fail to extract counterweights shocks with inferring from just a single data point against Covid-19 variables.

Regardless we repeated the simulation in Section 5, making the most out of FRB/US model fiscal block by adding an extra shock only: GCEC1 – Real Government Consumption Expenditures & Gross Investment, with the same magnitude of the observed values for 2020 Q1 and Q2. The results are depicted in Figure 6.

Figure 6: Assessing simulated variables level



This single, blunt move makes the level of simulated output gap and unemployment rate much more comparable with their respective observed values. However, we cannot use it to correct levels forward, because we cannot condition fiscal measure on Covid-19 variable since $(eq. 1)$ fails to establish such relation. In fact, we believe the fiscal nearcasting deserved a special attention considering political and geopolitical dimensions expected for the rest of 2020, outside the scope of this paper, which is intentionally narrowed to Covid-19 economic dynamics. Although we recognize the limitation in terms of data samples and macroeconomic model, we motivate the reader to appreciate the remaining exercises as counterfactuals: what would have happened and might happen if Covid-19 exogeneous took hold but without any fiscal or financial liquidity support response.

Despite level caveats, we still need to validate the coherence of the simulated paths. For that, the economic analysis of past effects can always rely on the contrast with the observed reality. For forecasts, one may benefit from simulating a benchmark extracted from previous "comparable" events. The features of Covid-19 pandemic may only resonate with those of the Spanish flu, a hundred years ago. However, the institutions and the economy are hardly comparable after hundred years. For past economic analysis, the causes and the anticipation matter more. Looking ahead, once the event has set in, one may argue the equivalent transmission channels, in turn, matter more to assess propagation. Alternatively, one can learn from the economic dynamics in the aftermath of previous natural disasters. Ludvigson et al. (2020) have chosen previous costly and deadly natural disasters, and Baker et. (2020a) have added extreme events like political coups, revolutions, and terrorist attacks also. However, note that here we propose to use previous events only as a validation benchmark, while these other works use past events in the estimation. Notwithstanding, one may still argue that no such event had fortunately had the depths and the breadth of Covid-19 pandemic over the global economy, or even over the US economy.

Despite valid, yet opposite arguments, we dare to take the Global Financial Crisis (GFC) of 2008-09 as the unlikely benchmark with which to compare the propagation of Covid-19 shocks, regardless of the fact that at least two aspects argue against such analogy: the endogenous nature of GFC shocks; the benefit of testing responses therefrom and learning from its lessons.

Extracting relevant shocks from 2008Q3-2009Q2 and reapplying them as if they were unfolded in 2020 Q1[18] allows for another simulation that outputs the FRB/US

[18] *Shock values provided in FRB/US and those extracted in this paper shown similar values.*

programmed response, as it is shown in Figure 7, together with those to the Covid-19 extracted shocks.

Figure 7: Contrasting responses to shocks extracted from Covid-19 and GFC

Contrasting responses, Figure 7 shows that Fed monetary reaction converged to ZLB much faster time than it did during the GFC[19], based on the observed data then and now, without delving into explaining the swiftness of policy makers this time. It also shows that responses in the short run for output gap and unemployment are more acute,

[19] *To prescribe Fed funds from 0-0.25 already in 2020 Q1 is a feature of the policy reaction function RFFTAY (the one in the graphs shown here), which has no interest rate smoothing term. For sake of robustness, we also experimented with RFFINTAY, RFFALT and RFFTLR, and we obtained qualitatively comparable conclusions.*

but not so different for consumer prices. However, in the medium to the long run, the FRB/US model simulation suggests a protracted recovery in terms of activity, employment, and a prolonged deflationary period.

In summary, these simulated dynamics seem consistent with the aftermath of a severe shock and with the insufficiency of the conventional interest rate policy to restore economic activity, thereby inflation. Such persistence is admissible since the possibility of long-term effects cannot be dismissed. Firstly, we expect some structural changes in terms of demand (what we buy), of supply (what in turn we make) and in terms of employment (how we work) as in Ramsden (2020). These changes can jointly alter consumer baskets, relative prices, and terms of trade, ensuing both allocative and measurement challenges. Secondly, there is evidence that the balance of the benefits and costs of unconventional monetary policy[20] is likely to deteriorate over time as Borio & Zabai (2016) claims. Thirdly, but more immediate, the pandemic may pick-up during the winter with additional economic drag.

This seems a pessimistic outlook, somewhat inconsistent with more recent data on higher frequencies. There are at least two possible ways to approximate the model outcome and the economic narrative. One is to revisit the model calibration, the other is to incorporate more recent, higher frequency information.

7. Challenge 4: Choosing now and near cast assumptions

There are several interesting sources of high frequency data. All of them come with their own drawbacks (Economist, 2020). Most often, those underrepresent the broad economy and underestimate substitution effects and rapid habit changes. For instance, lack of restaurant reservation matters for a sector, but consumption may dislocate from "food away from home" into "food at home", weakening its sectoral importance to activity and prices. Nevertheless, research with new data sources is worth.

In this paper, we based some conditional exercises on data plus projections about Covid-19 infection cases and deaths. Also, we explored the use of people mobility data. Despite possible criticisms, it pertains to the Covid-19 response recommendation of social distancing; it captures demand side without any sectoral link; it has professional

[20] *The FRB/US model captures ZLB binding effect, but no unconventional monetary policy.*

nearcasting for at least two more quarters. In these three variables observed values up to August are appended thereafter with the IHME projections, as shown in Section 2.

There are two opposite assumptions about how Covid-19 shall affect the economy dynamics from thereon[21]:

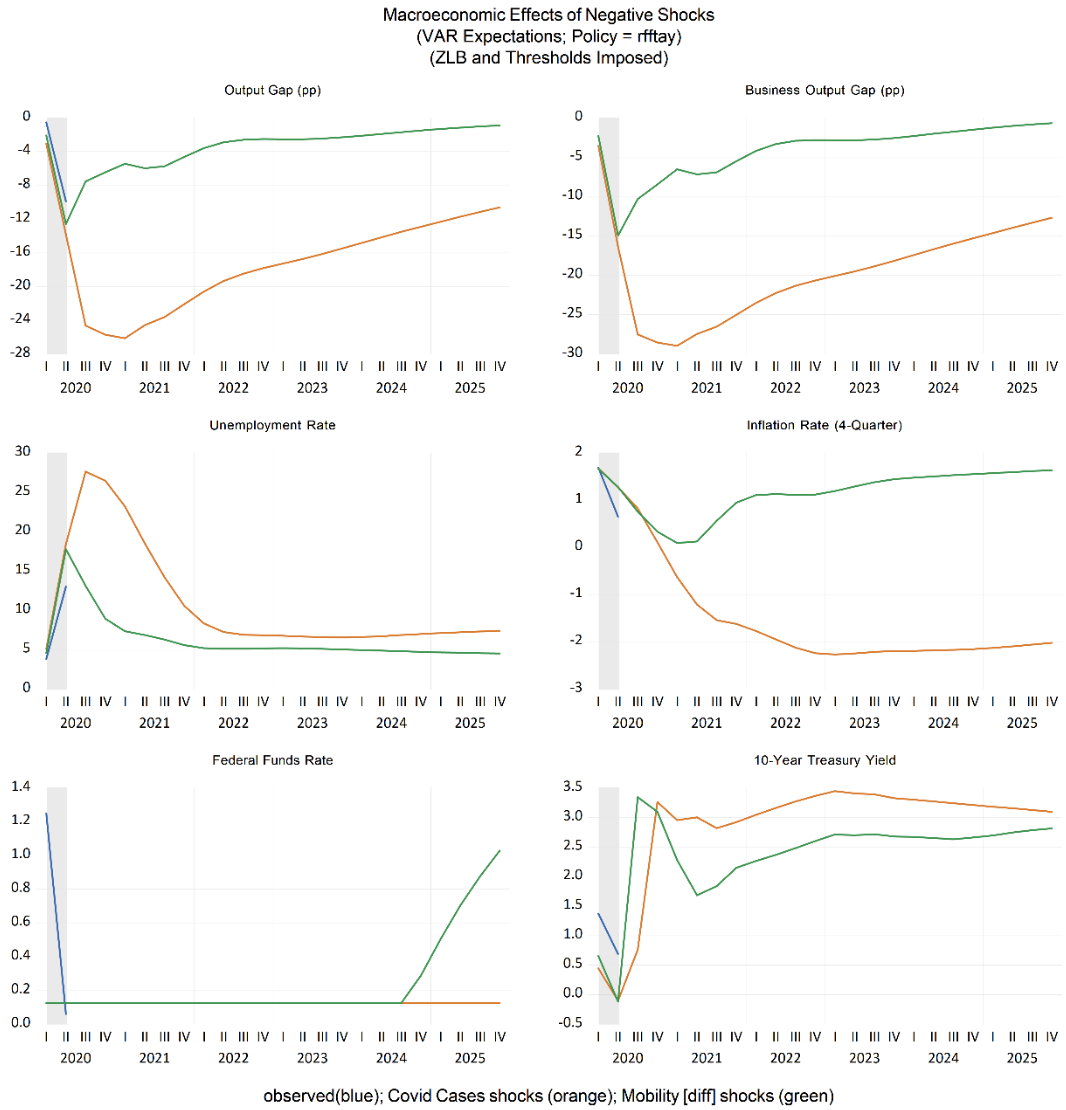
- Covid-19 keeps contributing negatively to the economy in the last two quarters in the same proportion that it did in the first two quarters of 2020;
- Covid-19 impact fades, although frequencies of infections and deaths still increase.

To outline the space of consequences given either assumptions, we followed the same procedure to extract the joint shocks.

We repeated the procedure for the three Covid-19 variables, both in log level and in first log difference, by feeding sets of joint shocks into the FRB/US model and running simulations. Among the six possible combinations, Figure 8 depicts the responses to shocks generated from Covid-19 infections in log level and mobility in first difference, because they provided a lower and an upper bound respectively to the persistent economic damage. On the one hand, the former denotes the downside scenario, when cases continue to mount, and their economic fallout keeps proportional to the frequency of cases. The economy reacts in a swoosh-shaped way. Observe in Figure 3 that IHME projects an increase in daily infections at least up to 2020 Q4. On the other hand, the later denotes the upside scenario, when mobility converge to pre-crisis level, its log difference (first derivate) increases. The economy reacts in a "V"-shaped way.

[21] No sudden stop shocks were assumed or simulated, for example, a large scale, successful vaccine.

Figure 8: Contrasting responses to shocks extracted from Covid-19 infections and mobility (Diff.) data and projections



The use of other data sources is valid and helpful, with due attention, for instance the use of people mobility. This is not new in economics, and in particular this is also explored in Fernandez-Villaverde & Jones (2020).

8. Challenge 5: Combining recent, partial data into conditional casting

Although the results discussed in Section 5 suggest that Covid-19 was the main driver of economic variables in the first half of 2020, one may argue that other factors may overtake Covid-19 shocks, e.g., policy measures, health measures, political and geopolitical factors etc. One may also argue against stating the Covid-19 will be still a relevant driver, but its contribution to economic variables variance may fade in the near future.

Assuming whichever argument recommends verifying whether recent, partial economic data already carry enough information to discern possible recovery paths. This exercise has a two-fold goal: to assess the rationality conditional scenarios based only on Covid-19 projections (those in Section 7); to assess how much 2020 Q3 can help untying the controversy about recovery shape. We believe that the composition of data sources in different frequencies can help untangle complex dynamics and relations between economic variables, even when we aim at long-term forecasts, provided that the noise of higher frequencies is properly smoothed out, as claimed in Galvao & Owyang (2020). Some works in Section 3 have opted to monthly, while some others to quarterly data. Baker et al. (2020a) resort also to weekly data.

Hence, we tried the following three nearcasting strategies for 2020 H2 to feed FRB/US model with the joint set of shocks extracted:

i. by assuming mobility in log difference (same as in Section 7);

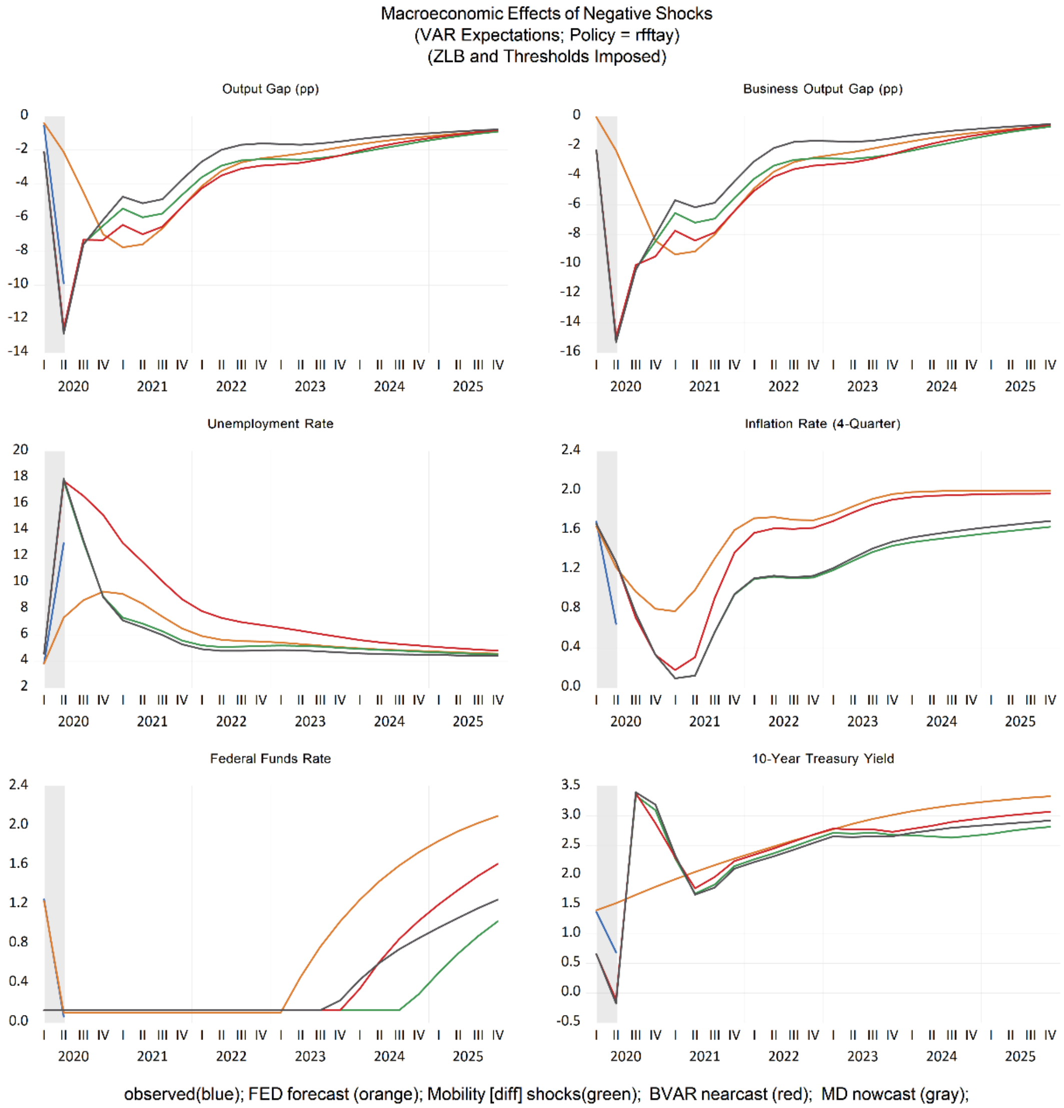
ii. through a standard Dynamic Factor Model Stock & Watson (2012) over Fred-MD dataset[22], but transforming data into quarterly frequency; and

iii. through a Bayesian Vector Autoregressive with prior selection based on Giannone et al. (2016) and a long lag structure (8), selected according to information criteria AIC[23].

Figure 9 depicts simulations of these three attempts, plus FRB/US **baseline** response for 2020 already embedded in FRB/US dataset.

[22] *Monthly Fred-MD presents only aggregated real personal expenditure (rPCE), but not its segments.*
[23] *With no commitment to accurate estimates, we have not invested in so many sampling, hyperparameter tuning and complex estimation techniques.*

Figure 9: Contrasting responses to shocks extracted through different techniques



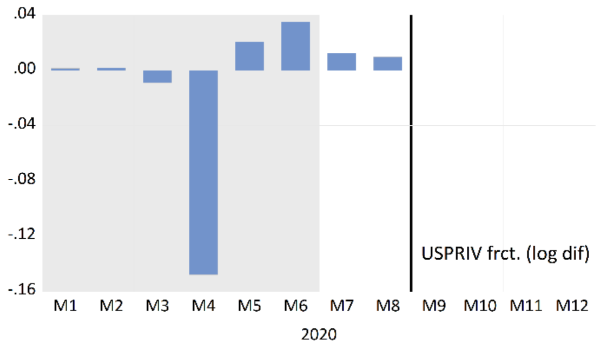
Three approaches ensue similar "V"-shaped dynamics. However, the one that incorporates observed monthly data from 2020 Q3 indicates a narrower "V" and less moderated recovery path from 2021 on. The current exercise also allows for comparisons between conditional and unconditional projection approaches.

Note that the addition of monthly data up to 2020M8 plus DFM forecasts up to the end of 2020 warrants the "V"-shaped recovery path with unemployment and inflation trajectories close to those obtained in Section 7 by conditioning nearcasting on the first difference of mobility data. These effects are mostly consequence of recent observations[24]

[24] *Vide sequence of four positive shocks from May to August of 2020.*

inasmuch as DFM projections outputs tiny future shocks to most variables. The typical low variance in US economic variables after the great moderation (after 1986), plus the mean-returning nature of this class of models may explain such outcome. For instance, the muted shocks that the DFM model outputs for the total of US private employees are portrayed in Figure 10 to a very keen eye.

Figure 10: DFM projections of USPRIV for 2020H2.



Not only for robustness but also for precision, different techniques may be employed, in particular when extreme variations (of orders of magnitude) risk distorting inferred projections. This issue may remain crucial even after the pandemic period, since future samples will also contain heteroskedastic breaks. Lenza & Primiceri (2020) introduce an innovative approach to estimate VARs that seeks to address such issues. However, it recognizes that the impulse responses are very similar whether one applies their technique or drops the observations after February 2020 from sample. The innovation merit still holds when one is concerned with uncertainty estimation. Thus, here we keep exercise simpler and we shall return to this debate in Section 11.

9. Challenge 6: Handling complex variable relationships (non-linear)

The magnitude of the Covid-19 caused economic shocks begs the question whether linearity and log approximations, usual to economic modelling, would imply meaningful imprecisions.

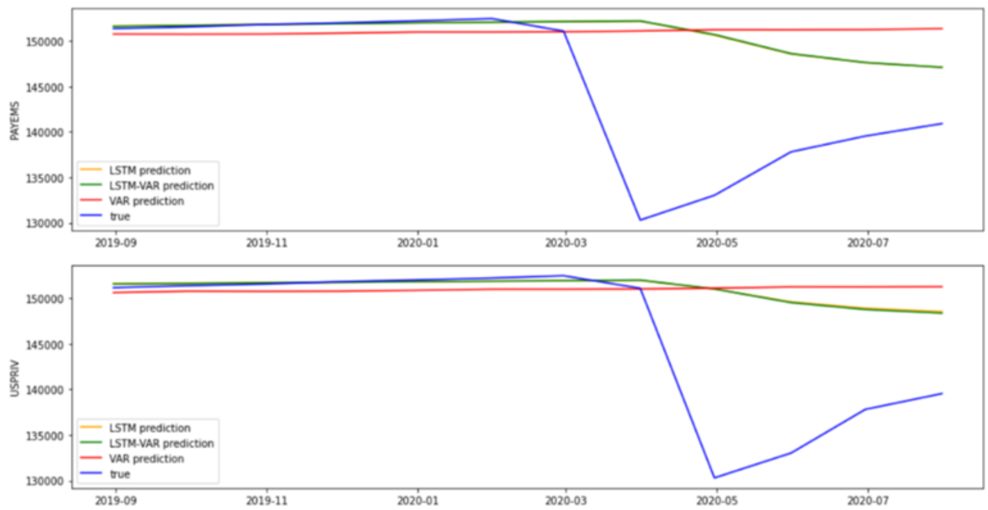
To address this challenge, we set a simple exercise over the same Fred-MD monthly mentioned in Section 8. We choose a different class of model, one that is claimed to tackle complex variable relationship patterns of higher order and of unknown length:

Long Short-Term Memory (LSTM[25]) subclass of Recurrent Neural Networks (RNN) (see Gers et al. (2001), and Malhotra et (2015)).

Figure 11 exhibits an illustrative exercise with LSTM model fitting and nearcasting. For two labor market variables: PAYEMS and USPRIV, the graph lines are: the actuals (blue); the fitted VAR values with Cholesky-identification (red); the path learned from a single step LSTM training; and the path learned from two-step LSTM training, where fitted VAR values augment the original time series. The optimal AIC lag order for the VAR also recommends the lag time series stacking for the LSTM model[26].

In contrast to the standard VAR and the DFM exercise in Section 8, both LSTM models learn about the downward trend, however slowly and parsimoniously[27]. This may be a desirable outcome for a nearcasting focus, and arguably an overfitting risk for a long-term structural trend inference. Yet such a leaning behavior resembles the one of the stepwise stochastic trend estimation (USCVO), despite their distinct theoretical underpinnings. In both cases, this less smooth trend capture can be overcome by frequent model reestimation and path revision.

Figure 11: RNN LSTM projections of PAYEMS and USPRIV for 2020H2.

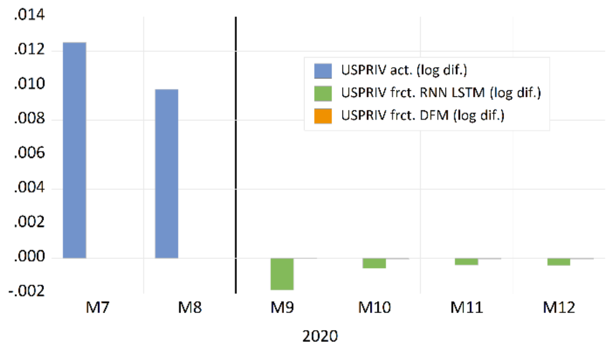


The LSTM learning generated some lagged, downward dynamic of aftershocks to private employment, in contrast to the aforementioned muted dynamic inferred by a DFM model, even over the same sample, as depicted in Figure 12. This may signal a higher

[25] *Any class of models comes with its own features and issues. This paper leaves outside of scope class comparations and competitions, to focus on the specificities of forecasting challenge.*
[26] *Adapting the code in https://github.com/cerlymarco/ to run on LIA https://lia.cloud-p.bcnet.bcb.gov.br/*
[27] *In this exercise, not as general rule, one- and two-step training yielded indistinguishable outcomes.*

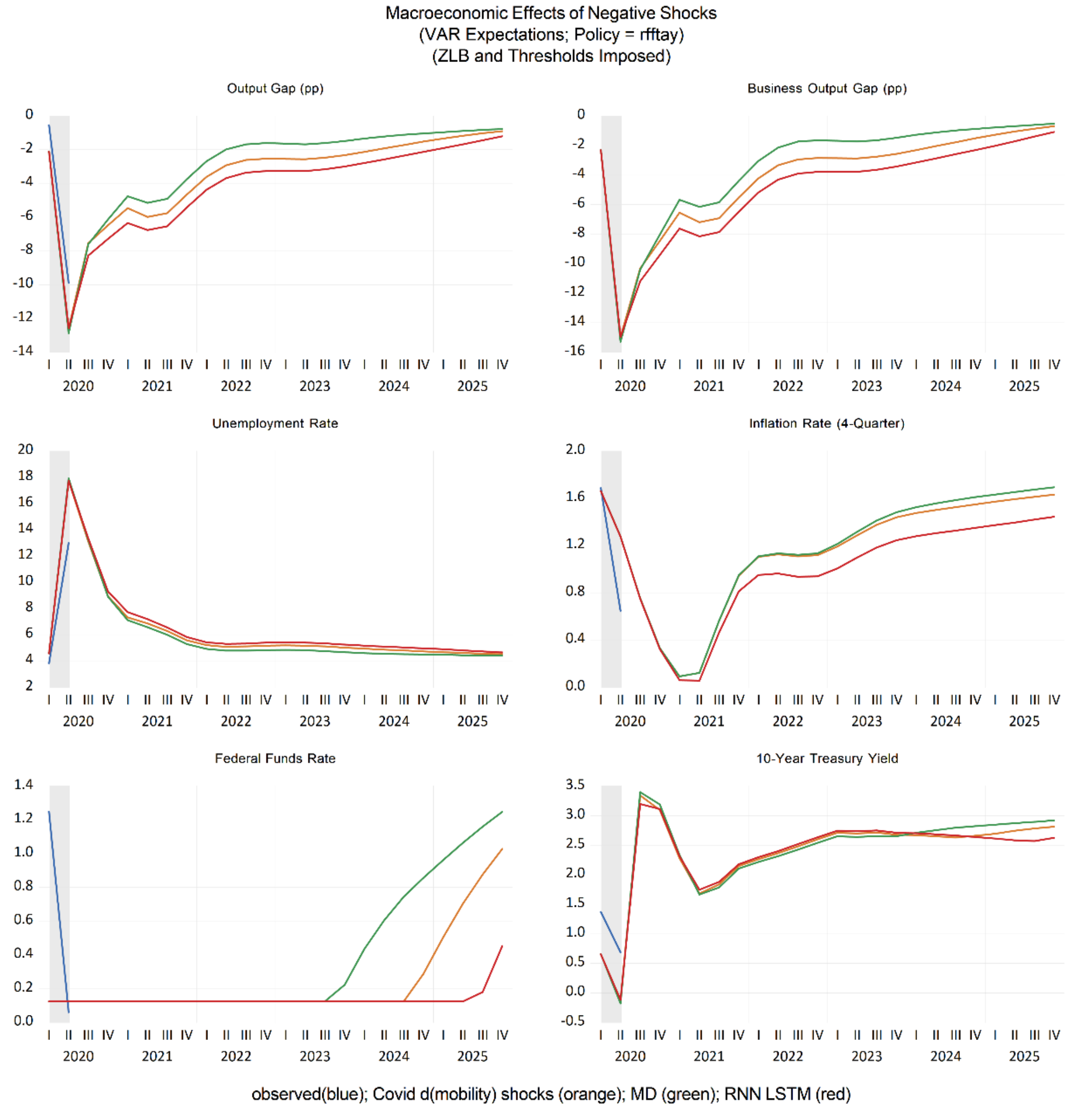
order, persistent economic drag or reveal an undesirable side-effect of the learning mechanics. Remind that LSTM belongs to a nonparametric, statistical, unconditional model class, that lacks background or theoretical knowledge about the economy and that hinges only on the provided sample. Hence, it inherently fails to capture, from past data only, the counterbalances of current policy responses.

Figure 12: Nearcast shocks inferred via DFM and via RNN LSTM on USPRIV



Repeating the exercise of feeding shocks to FRB/US, we aggregated those projected by the LSTM model into quarterly frequency and simulated the effects again from 2020 onwards. Figure 13 shows these simulation results. These show qualitatively similar dynamics, nonetheless closer to the conditional nearcasting based on the dynamics of people mobility (in first difference). Interestingly, both are bracketed with the simpler, conditional modelling assumptions. The DFM shocks simulation provides a more favorable dynamics by incorporating two positive months and almost no further deterioration. Whilst the LSTM shocks simulation provides a less favorable dynamics by hinting an additional higher order deterioration. Anyway, none contradicts the simulation out of a simpler assumption: economy recovers, and mobility normalizes.

Figure 13: Contrasting responses with additional shocks to expectation variables

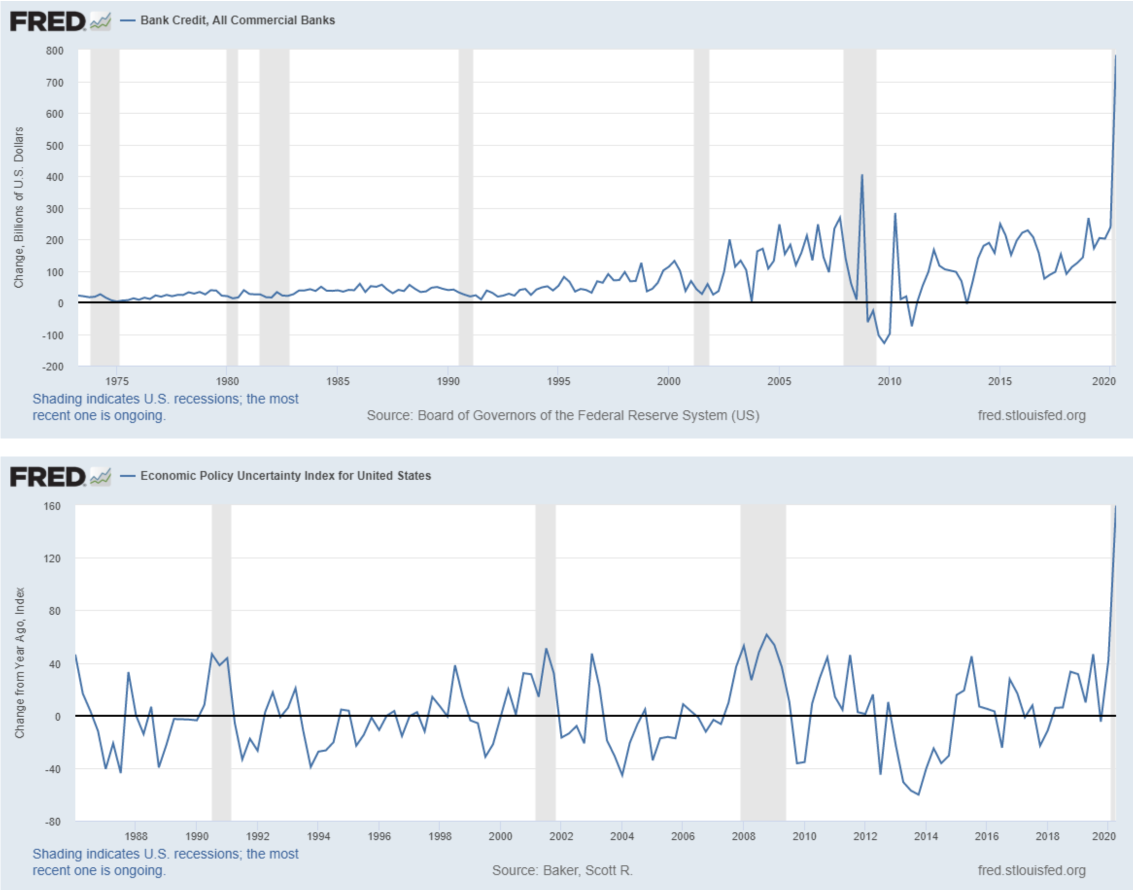


10. Challenge 7: Circumventing model incompleteness

Covid-19 variables explain relevant part of the variance of at least two other groups of economic variables; however, we have forsaken them in the previous exercises, because they do not match any of those 239 in the FRB/US model. These are soft data, including UMCSENTMx – University of Michigan Consumer Sentiment, USEPUINDMx – EPU economic policy uncertainty; and any of the financial credit data BUSLOANSx and CONSUMERx, real commercial and industrial loans, and real consumer loans, respectively.

Figure 14 depicts historical time series of two variables with unprecedented variation for 2020. Bank credit, moreover, displayed a growth instead of the typical contraction in previous, early recession periods.

Figure 14: Bank Credit and Economic Policy Uncertainty.



The FRB/US models private interest rates of common credit operations, but neither the stock of outstanding credit, nor the credit growth. The FRB/US models forward-looking expectations, but it does not model explicitly economic uncertainty.

One may argue that FRB/US, therefore all responses shown in the previous sections, overestimates the impact of Covid-19, because the transmission through "credit channel", i.e., the preferred conduit in current policy responses, has not been triggered. By the same token, one may argue that FRB/US, therefore all exercises here, underestimates the impact of Covid-19, because transmission through "expectations channel" is not captured. Remind that Baker et al. (2020a) tried to do just that, however, without taking other channels into account[28]. Perhaps, the lack of the net effect of these

[28] *To the best of present knowledge, Baker et al. (2020a) exercise in April, overstated the impact of Covid-19 over US GDP perhaps because only uncertainty transmission is modeled.*

two relevant channels help explaining the divergence of simulations mentioned in Section 5 and the observed data for 2020 Q2, i.e., this net effect might have ensued milder surge in both unemployment and output gap. Thus, the exercises described here might be interpreted as a counterfactual to an otherwise proactive FED.

There are two ways to address these shortcomings: to redesign FRB/US or to feed it with shocks from satellite econometric models, exactly as we did by using Covid-19 variables path. We tried to nearcast the expectation variables in Table 3 with a one-factor DFM model[29] wherein USEPUINDMx (US EPU index) path conditions expectation shocks.

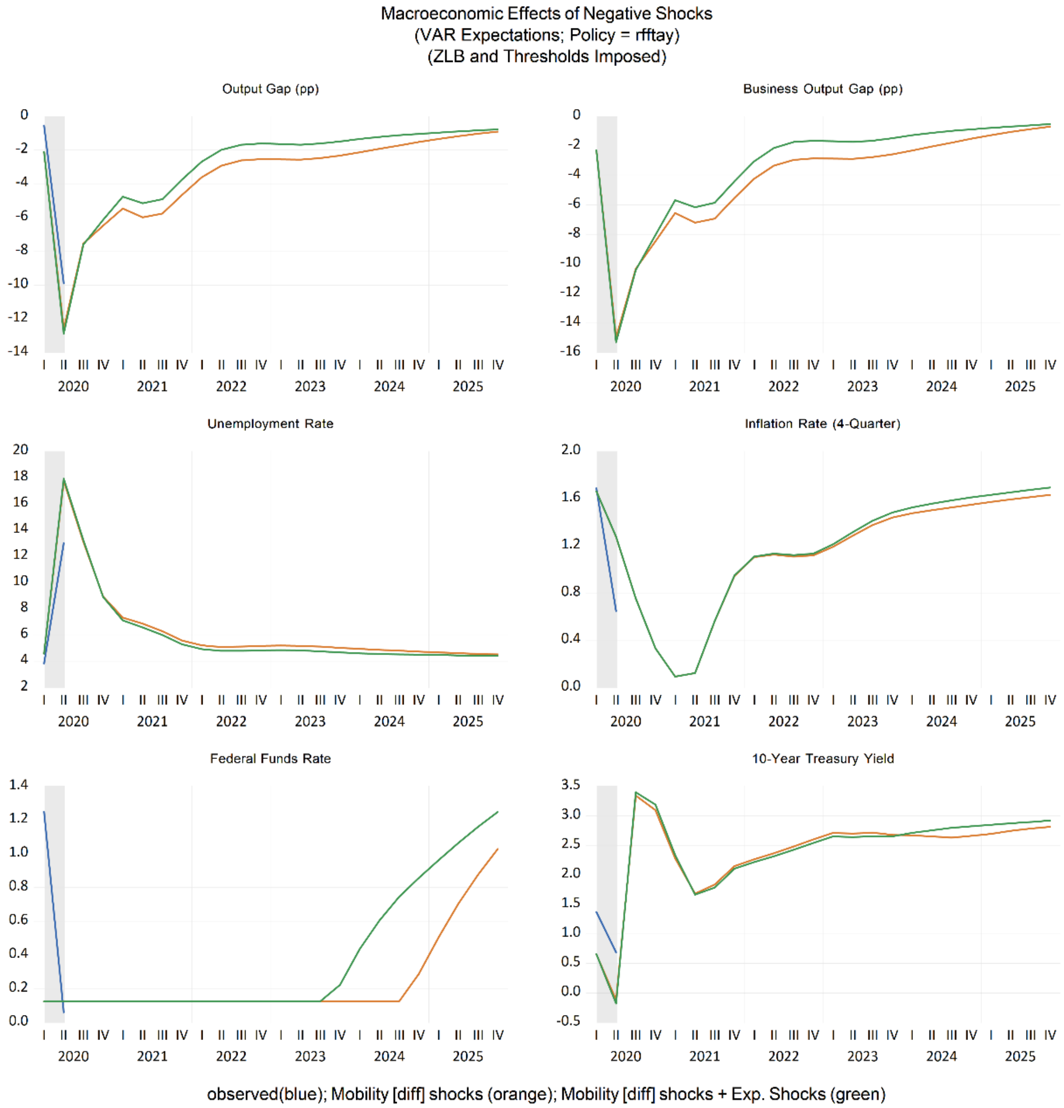
Table 3: Some expectation variables in FRB/US.

zebfi	Expected growth rate of business output EBFI
zecd	Expected growth rate of target durable consumption
zeco	Expected growth rate of target nondurables and nonhousing services
zlhp	Expected growth rate of target aggregate hours

The shocks (difference between FRB/US forward path and DFM projections) were fed and simulated though the relevant horizon of 2020. The results are depicted in Figure 15.

[29] *This strategy differs from the unconditional application of Kalman filter estimation of a DFM, as reported in 8, since an autoregressive path is assumed to the stabilization of the uncertainty level, thereby guiding the convergence of expectations in the second half of 2020.*

Figure 15: Contrasting responses with additional shocks to expectation variables



The presumed normalization of economic uncertainty level warrants positive shocks to expectations, in particular, to the one about fixed investment, thence an upside pick-up activity and eventually a return of policy rates (Fed funds) to historical levels[30].

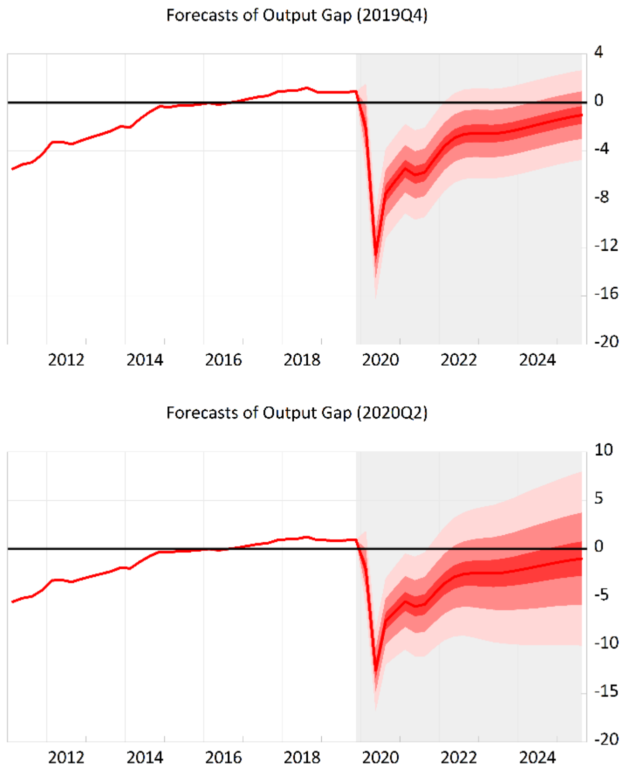
[30] *An analogous attempt to feed positive business loans shock into the IS curve, inspired by Borio (2014), has shown a drop attenuation in the business output gap. This exercise is omitted here since its results were less robust and dependent on estimation sample choice.*

11. Challenge 8: Measuring the uncertainty range around forecasts

The uncertainty around the previous forecasts is extraordinarily high and slightly asymmetric. Nonetheless, it should be measured to communicate the balance of risks ahead.

The standard representation of uncertainty is through confidence intervals computed out of previous forecast errors and series of historic volatility, and the standard notation to communicate it through a fan chart, like the ones drawn in Figure 16[31].

Figure 16: Fan charts for Output Gap forecasts



If the observed forecast errors in 2020 were to be included to compute uncertainty without any specific treatment, we would observe a widening of the density around the central (median) projection for the output gap. These results match similar findings in Lenza & Primicieri (2020) and the motivating example for their novel proposition.

The fan charts are usually informative to capture uncertainty, but in this context of heightened uncertainty, they may not suffice for showing such a wider range of

[31] *Considering the FRB/US estimated forecast errors up to 2019 Q4 and 2020 Q2.*

possible outcomes. Instead of debating how much of such uncertainty would last for how long, we propose that fan charts be supplemented with scenarios. Such scenarios can make underlying assumptions tangible and can anchor one's view against the excess volatility, thereby making balance of risks easier to be followed up.

We can resort to the social distancing proxy, the people mobility in first difference, to help assessing the range of economic impact of the exogenous shock, since it helped conditioning meaningful projections so far. Different assumptions about people mobility will lead to different economic scenarios.

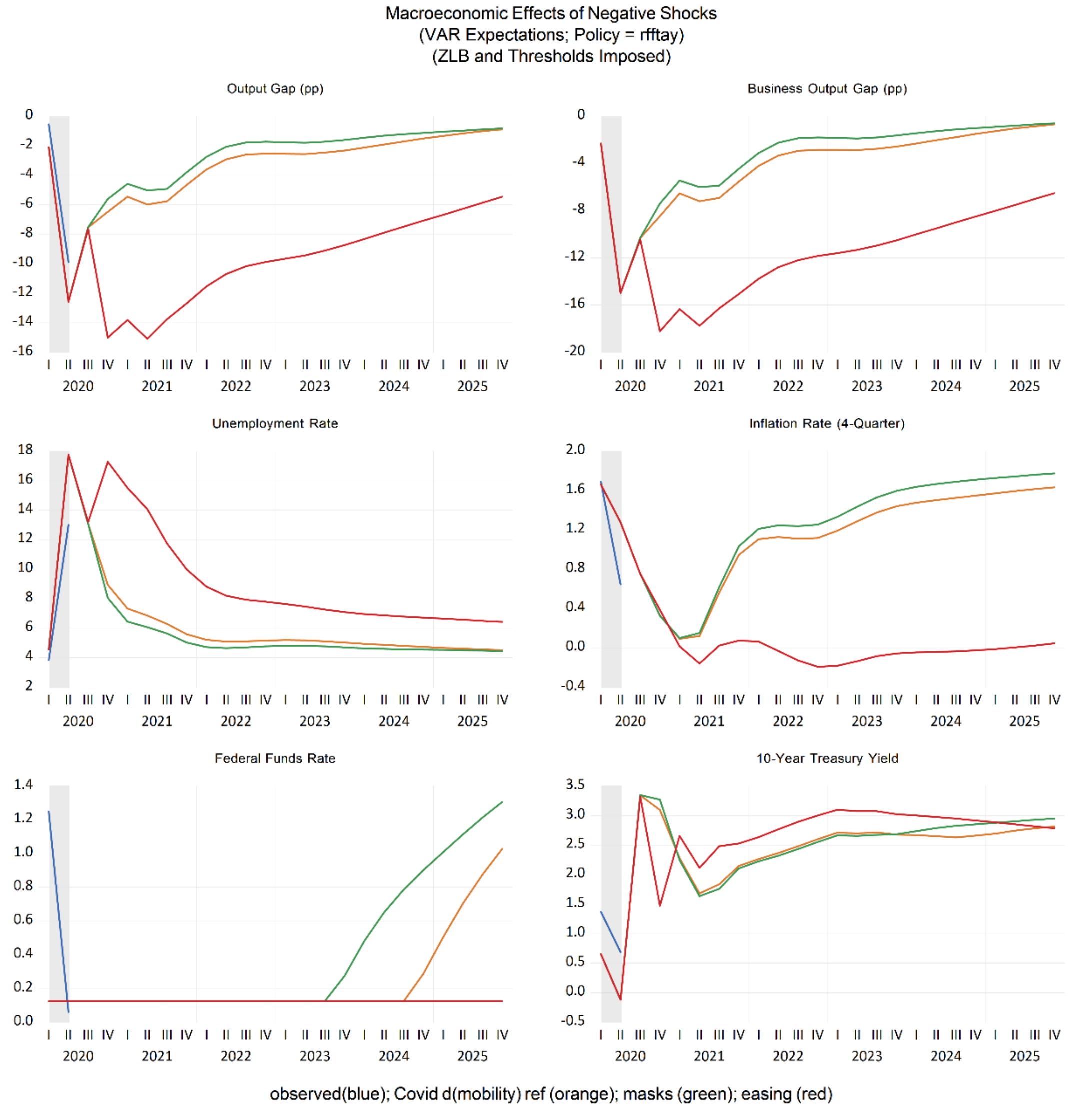
Given that there are specialized infection models, one can use one (or few) as a satellite to transform response policies hypothesis to people mobility paths, that, in turn, one can use to condition the FRB/US model. Section 3 includes two attempts by economists to estimate behavior models in epidemiology. As mentioned in Section 2, here we prefer to assume the two alternative scenarios, i.e., **masks** and **easing**, provided by the Institute for Health Metrics and Evaluation (IHME), and outlined in Section 3.

One is more benign for it assumes the increasing use of **masks** allowing for a pick on people mobility more safely. The other is more adverse for it assumes policy **easing**, and society complacency around restrictions allowing for another wave of infection, deaths, and reinstatement of mobility restrictions.

The same set of estimations for equation $(eq. 1)$ shown in Section 4 will then allow for calculating the near-term contribution of Covid-19 into the economic variables in each scenario, i.e., the same β_3 coefficient multiplies the average people mobility projection for third and fourth quarters. There are three caveats though: policy restrictions do not follow the same rationale; the shock passthrough might not hold constant and there can be many sensible reasons for that; and Covid-19 pandemic might compete with other driving forces, being political, financial or economic.

Figure 17 depicts simulation exercises for alternative people mobility paths: the **masks** and the **easing** scenarios. The baseline scenario is much closer to the benign scenario that it is from the adverse scenario. This entails a balance of risks tilted to the downside. For decision makers such approach is more informative than a symmetrical, statistically computed confidence intervals. Nevertheless, the exercise is a worthy complement to all point estimation shown before.

Figure 17: Economic Aftermath in People Mobility Alternative Conditional



At the end of Section 6, we hinted at the desirability of reestimating the semi structural model to find a better fit into the new time series to cater for the breaks in series and more permanent changes to its parameters. However, considering the information set of 2020 Q2, a model reestimation may not pay off, for the uncertainty about the persistence of recent observed values in the wake of the ongoing Covid-19 shock. However, we can still test hypothesis by fiddling with target model parameters that are central to the narrative. For instance, there is growing evidence in microdata and preliminary studies by Levine et al. (2020) that “as the pandemic deepened concerns about economic disruptions and layoffs, households boosted savings as a precaution against declines in future income, and some of those additional savings flowed into bank deposits".

This relevant hypothesis about the precautionary savings can be tested in the FRB/US model, indirectly. Assume that the elasticity of savings to expected income (**inc**.), or the elasticity of savings to wealth (**wth**.), or both, increase, turning the desired level of consumption more sensitive to business cycle. Thus, when the economy heats up, the propensity to consume accelerates, on the opposite, when the economy cools down, the propensity to consume decelerate by relatively more than otherwise estimated.

In this exercise, instead of triggering responses by adding shocks to selected variables, we arbitrarily change model parameters that govern the transmission channels from income and wealth to either household expenditures or to household savings.

Figure 18: Economic Aftermath in People mobility Alternative Conditional

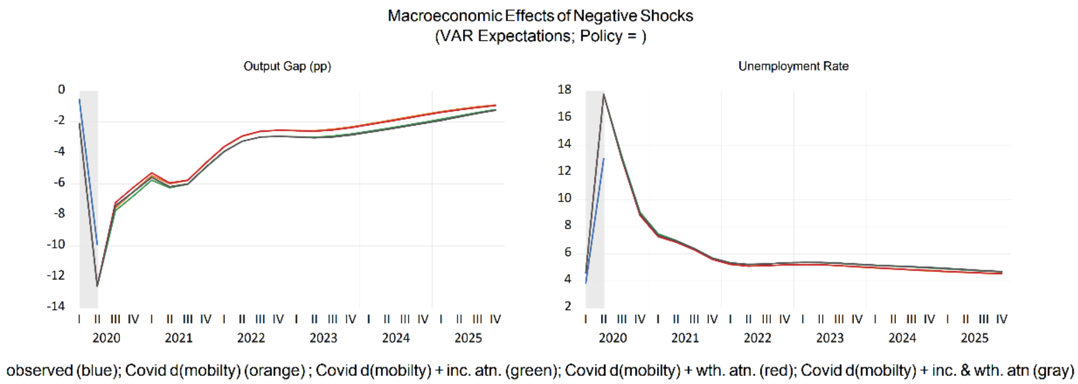


Figure 18 depicts the results of these simulations, plotting the same path seen in previous exercises (orange line) against changes to the elasticity of savings to work income, to property income and both by the same proportion. The simulated effects are small but cumulative. Households would demand more income to sustain the same level of expenditure, otherwise channeling more to savings. Subdued consumption means that the activity recovery would then be lower and take longer to converge to neutral levels. Therefore, these more permanent effects should be also accounted for when spawning the balance of risks.

12. Final Remarks

After reading through eight challenges, and few forecast exercises, the "crystal ball" is still blurred. Conscious of the inherent complexity and without the benefit of hindsight, this paper sets out to do just that: to explore the space of possibilities with its major concerns. That worries and must worry the policy maker and the forecaster.

The main contributions in our line of argumentations are the following:

- Keep open minded in the face of a new, ongoing, challenging outlook;
- Be ready to use different datasets, different techniques, and different tools;
- Keep it simple to communicate and to entail explainable policy decisions;
- But never oversimplify, one forecast path might be better than none if and only if the relevant issues and cares were catered for;
- Yet never overcomplicate with fancy apparatus, unless the gains exceed the issues; and
- Be prepared to judge among alternative scenarios, since certainty is never on you.

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13. Appendix

Figure 19 depicts GDP projections on the week that dataset used in this paper was collected.

Figure 19: *Professional forecasts from FED and private sector*