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ABSTRACT

The coronavirus is a global event of historical proportions and just a few months changed the time series properties of the data in ways that make many pre-covid forecasting models inadequate. It also creates a new problem for estimation of economic factors and dynamic causal effects because the variations around the outbreak can be interpreted as outliers, as shifts to the distribution of existing shocks, or as addition of new shocks. I take the latter view and use covid indicators as controls to 'de-covid' the data prior to estimation. I find that economic uncertainty remains high at the end of 2020 even though real economic activity has recovered and covid uncertainty has receded. Dynamic responses of variables to shocks in a VAR similar in magnitude and shape to the ones identified before 2020 can be recovered by directly or indirectly modeling covid and treating it as exogenous. These responses to economic shocks are distinctly different from those to a covid shock, and distinguishing between the two types of shocks can be important in macroeconomic modeling post-covid.

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1 Introduction

The 2019 coronavirus (hereafter COVID) is a once in a century global pandemic and remains very much active as of the first draft of this writing, one year after it surfaced in early 2020. It is a health disaster that has resulted in a loss of over half a million lives. It has also disrupted economic activities to such an extent that the three trillion dollar relief package passed by the Congress was not enough to offset the economic disruptions COVID has caused. Ludvigson et al. (2021) suggests that COVID constitutes a 192σ costly disaster shock.

In addition to social and economic disruptions, COVID has also created challenges for the modeling of economic time series. If we plot a randomly chosen series used in business cycle analysis, we will likely see a spike around March 2020 so large as to drawf five decades of observations preceding it. Without any adjustment, the post-covid observations will dominate to yield uninterpretable estimates, messing up the pre-covid fit. A case in point is factor estimation which is used in a variety of economic analysis. Without any adjustment, the first factor known to load heavily on real activity variables would be 19 standard deviations away from the mean of zero in March 2020 when by way of comparison, the financial crisis in 2008 registered four standard deviations.

There is no simple solution as there were only two pandemics in the post World War II era, and no lockdown was enforced in 1957-58 or 1968-69. As the historical data provide little guide to help understand the economic implications of global health shocks, how to econometrically handle pandemics is very much an open question. We may treat these irregular data points as temporary, but standard outlier adjustments would still leave the real activity factor 13 standard deviations below mean. It could be argued that the extreme values are not void of economic content and should not be 'dummied out'. Though treating the extreme observations as resulting from shifts to the underlying distributions may seem appealing, there are not enough post-COVID data to model the instabilities adequately. Introducing restrictions and information may help. Foroni et al. (2020) corrects post COVID forecasts using information from the 2008 financial crisis. Primiceri and Tambalotti (2020) assumes that COVID is a one-period shock that propagates differently from a typical macroeconomic shock, but whose trajectory can be approximated by a polynomial. Dynamic responses are then obtained by calibrating the polynomial to represent, for example, the scenario that the pandemic will dissipate by the end of 2020. Others incorporate information via priors. Lenza and Primiceri (2020) specifies a pareto distributed prior to the variance of the shocks while Huber et al. (2020) estimates an additive regression tree and uses flexible priors to deal with the extreme values during the pandemic. Many of these studies were prepared at the early stage of the pandemic and it is unclear whether the conclusions would hold up in an extended sample that include the subsequent waves.

The approach considered in this note also uses additional information, but I take as starting point that COVID is not an economic shock, but rather a large and persistent health event with pervasive economic consequences. Under this view, the variations in the post-COVID economic data are large not because of changes in distribution of variables already in the economic model, but because the economic data are no longer driven by economic shocks alone. The presence of a new, non-economic shock has implications for factor estimation as the principal components are no longer linear combinations of economic variations alone, for diffusion index forecasting as new predictors might be relevant, and for estimation of the dynamic causal effects of economic shocks as COVID now becomes a confounder.

To address these issues, I use COVID indicators either as controls in regressions to 'de-covid' the data so that economic factors and shocks can be identified, or as additional predictors to account for the persistent nature of COVID. In a nutshell, I use the COVID indicators to either remove or incorporate additional information relevant for the task. The COVID indicators also allow the trajectory of COVID to be determined by the data. Three measures of COVID indicators are considered: hospitalization ($\mathcal{H}$), positive cases ($\mathcal{P}$), and deaths ($\mathcal{D}$). They enter the de-covid regressions in four ways reflecting different assumptions about March and April of 2020. I study their implications in the context of updating the JLN measure of economic uncertainty developed in Jurado et al. (2015) since the exercise has a factor estimation step and a forecasting step. I also explore the impact of COVID for VAR modeling. In my set up, the issue COVID creates is that a n variable VAR now has COVID as the $n+1$-th shock.

The main findings can be summarized as follows. All four models find economic uncertainty in March/April of 2020 to be at a historical high but there is no corresponding decline in the level of real activity after controlling for COVID. A decomposition finds that while COVID uncertainty has subsided and real activity rebounded by the end of the year, economic uncertainty even after controlling for COVID remains high. But while the uncertainty estimates are qualitative similar across methods, the impulse response functions are strongly affected by the de-COVID method used. Dynamic responses to economic shocks similar to the ones identified pre-COVID can be obtained if we directly or indirectly remove the COVID variations prior to VAR estimation, essentially assuming that COVID is exogenous. These responses to economic shocks are distinctly different from those to a COVID shock, reinforcing the need to distinguish the two types of shocks in post-COVID estimation. The data support the exogeneity assumption.

2 Estimation of Common Factors

The JLN concept of uncertainty is based on the premise that uncertainty arises because of lack of predictability with respect to information available, and macroeconomic uncertainty occurs only when the lack of economic predictability is board based. Three ingredients are needed to make the uncertainty measure operational: factor estimation, forecasting, and volatility estimation.[1] Ludvigson et al. (2020) makes mean and standard deviation adjustments prior to factor estimation and add COVID variables as predictors. The procedure worked well for the August release of FRED-MD but the adjustments treat too much of the subsequent variations as predictable, making uncertainty counter-intuitively low. Moran et al. (2020) uses the same approach to update a Q2 measure of Canadian uncertainty. Quarterly data are less affected by spikes created by COVID because the month-to-month variations tend to average out, so the adjustments may perhaps not be necessary. My focus in what follows is the modeling of monthly data.

Generically let X be a panel of data with N columns. Let $T_o = 720$ be the size of the pre-COVID sample running from 1960:3-2020:2. The $T_0 \times N$ matrix of pre-covid data X are assumed to have a factor structure

$$X_{it} - \mu_i = \Lambda_i' F_t + e_{it}^X$$

where $F_t = (F_{1t}, \dots F_{rt})'$ is a vector of r common economic factors and e_{it}^X is an idiosyncratic error associated with variable i. Under conditions in Bai and Ng (2002) for example, the principal components of X will consistently estimate F and Λ up to a rotation matrix. In practice, the data are transformed by taking log and first or second difference, and adjusted for outliers data prior to estimation. The latter amounts to treating as missing those observations whose deviations from median are ten times larger than the difference between values at the top and bottom 25 percentiles, and imputing the missing values using the EM algorithm. Prior to COVID this procedure affects only a few observations during the financial crisis of 2008.

Let $T_1 = 730$ be the size of the full sample spanning 1960:3-2020:12, so observations $T_0 + 1$ to T_1 are post COVID. Instead of modeling COVID effects through shifts to F_t or e_{it}^X,

[1] In practice, $r_m = 8$ economic factors F_m are estimated from a large panel of N_m macro economic variables X_M, and $r_f = 4$ financial factors F_f from N_f financial time series X_F. In implementation, data for X_M are taken from FRED-MD and transformed as documented in McCracken and Ng (2016), and X_F are based on those used in Ludvigson and Ng (2007). The data are demeaned and standardized prior to factor estimation.

I allow for a virus factor V_t so that the factor representation of the extended sample is

$$X_{it} - \mu_i = \Lambda_i' F_t + \Gamma_i V_t + e_{it}^X$$

Assumption A

i. $V_t = 0$ when $t <= T_0$, and for $t > T_0 + 1$, V_t is a persistent process with innovations $v_t \sim (0, \sigma_v^2)$.

ii. Let $F_t = \Phi^F(L) u_t^F$ where $u_{kt}^F \sim (0, \sigma_{F_k}^2)$ and $e_{it}^X = \Phi_i^X(L) u_{it}^X$ where $u_{it}^X \sim (0, \sigma_{X_i}^2)$. The shocks (u_t^F, u_t^X, v_t) are serially and mutually uncorrelated.

Assumption (i) states that V_t is non-zero only after March 2020 and allows it to be persistent.[2] Assumption A.ii assumes that the shocks (u_t^F, u_t^X, v_t) are serially and mutually uncorrelated. Now V_t and F_t are both common factors in the sense that they affect a sufficiently large number of series indexed by i. Unlike the pre-COVID data, the principal components of X over the full sample will no longer be spanned by the economic factors F_t alone. Furthermore, as noted earlier, the full sample location and scale of the data will be dominated by the last few observations, creating spurious revisions to estimates obtained before COVID.[3]

I consider estimation of economic factors F_t from 'de-COVID' data

$$x_{it} = \begin{cases} X_{i,t} - \mu_{it}^0 & t \leq T_0 \\ X_{it} - \mu_{it}^1 & t > T_0 \end{cases}$$

for suitably defined μ_{it}^0 and μ_{it}^1. For the pre-COVID sample, one can let $\mu_{it}^0 = \mu_i^0$ for all $t \leq T_0$, and a consistent estimate of μ_i^0 is the mean of series i over the sample up to and including T_0. Estimation of μ_{it}^1 is more delicate as COVID is persistent and so its trajectory also needs to be specified. Even if V_t was observed, there are fewer than a year's worth of monthly data to work with. More problematic is that F and V are both latent, both pervasive, and both persistent. Thus recovering both from the post-COVID data would require additional information. I make use of COVID indicators.[4]

[2]We can also model the non-zero values for the 1968-69 pandemic, but its health and especially the economic impact were small relative to COVID. See Doshi (2008) and article in 'Solving the Mystery of the 1957 and 1968 Flu Pandemics in Bloomberg Opinion, March 11, 2021.

[3]The financial factors are much less impacted by the COVID observations. The first financial factor based on unadjusted data is -4.71, comparable to -4.73 in October 2008 and -6.15 in October 1987.

[4]Data are downloaded from `https://covidtracking.com/data/download/national-history.csv`. I use the February 21, 2021 vintage. The last release of data was March 7, 2021.

Table 1: Proxies for V_t and v_t

	V			v_t		
	$\mathcal{H}$	$\mathcal{P}$	$\mathcal{D}$	$\mathcal{H}$	$\mathcal{P}$	$\mathcal{D}$
2020-1	0	2	0	-	-	-
2020-2	0	16	5	-	-	-
2020-3	6700	196830	4326	8.809	9.4175	6.762
2020-4	38399	876304	55315	1.745	1.493	2.548
2020-5	73150	718191	41137	0.644	-0.199	-0.296
2020-6	31513	831681	19475	-0.842	0.147	-0.747
2020-7	63105	1900163	25249	0.694	0.826	0.259
2020-8	61144	1457252	30244	-0.015	-0.265	0.180
2020-9	37446	1192663	23329	-0.490	-0.200	-0.259
2020-10	53485	1892016	23545	0.356	0.461	0.009
2020-11	92675	4475990	37065	0.549	0.861	0.453
2020-12	126244	6323266	77112	0.309	0.346	0.732
2021-01	120837	6112572	95387	-0.043	-0.033	0.212
2021-02	61054	2374243	71058	-0.682	-0.945	-0.294

Note: $\mathcal{H}$ is HospitalizedIncrease, $\mathcal{P}$ is PostiveIncrease and $\mathcal{D}$ is DeathIncrease. Daily data are aggregated to monthly.
Source: `covidtracking.com/data/download/national-history.csv`.

Table 1 shows the daily data for $\mathcal{H}$ = 'hospitalizedIncrease, $\mathcal{P}$='positiveIncrease', and $\mathcal{D}$='deathIncrease' aggregated to monthly. The cumulative sum of $\mathcal{P}$ agrees with 11 million cases documented for the United States in February 2021, while the cumulative sum of $\mathcal{D}$ is 336802 in December 2020. Of the three proxies, $\mathcal{D}$ tends to lag $\mathcal{H}$ and $\mathcal{P}$, while $\mathcal{P}$ may overstate the situation because one could be tested positive and yet asymptomatic. From these COVID indicators, I construct three versions of v_t:

$$v_t = \log\left(\frac{V_t}{V_{t-1}}\right).$$

Notably, the V series trend up throughout 2020 but the v series are less persistent.[5] While the data show large increases in V in the summer and the fall, it is the extraordinary jumps at the outbreak of the pandemic that is problematic for estimation.

Given my presumption that COVID and economic shocks co-exist, the first task is to isolate the (predictable and unpredictable) COVID variations. It is natural to identify v_{T_0+1}

[5]The data for $\mathcal{H}$ vary across source but the v values are quite similar. Since there were zero hospitalizations in February but the March value for v_t is crucial, the calculation assumes $\mathcal{H} = 1$ in February.

by assuming (u_t^F, u_t^X)=(0,0) at $t = T_0 + 1$.[6] But COVID was spreading rapidly in April at the same time when the lockdown was in place, so different interpretations to April are possible. I consider four specifications of the following:

$$X_{it} = d_o + \gamma_i D_t + \beta_{i0} v_t + \beta_{i1} v_{t-1} + \beta_{iq} v_{t-q} + x_{it}.$$

t	Model1*	Model 2	Model 3	Model 4
$D_{t=T_0+1}$	1	1	1	-
$v_{t=T_0+1}$	0	v_{T_0+1}	v_{T_0+1}	v_{T_0+1}
β_{i0}	0	0	$\neq 0$	$\neq 0$

(*) data adjusted for outlier

In all models, $\beta_{i1}, \ldots, \beta_{iq}$ are unrestricted and differ in the treatment for March and April of 2020. Model 1 replaces the outliers by the pre-COVID means. Since the interquartile range is now computed on the full sample, the outliers are concentrated in the two months in question. Models 1, 2, and 3 pick up the jump at the outbreak using a one time dummy D_t, essentially modeling March as a pure COVID shock. By setting both v_{T_0+1} and β_{i0} to zero, Model 1 allocates all variations in April to economic sources and is expected to generate large (economic) residuals for that month. Models 2, 3, and 4 control the extreme values using COVID data. Model 2 allows v_t to enter only with a lag while Model 3 allows for contemporaneous effects. Model 4 allows for economic shocks in March by simply letting current and past effects of v_t be removed from X_{it} as determined by the regression. To be clear of what the models imply, I list the first few post-pandemic values of the regressors (from March to July of 2020) for the $\mathcal{P}$ version below.

$$\text{Model 1} \quad \begin{pmatrix} 1.000 & 1.000 & 0.000 & 0.000 \\ 1.000 & 0.000 & 0.000 & 0.000 \\ 1.000 & 0.000 & 1.493 & 0.000 \\ 1.000 & 0.000 & -0.199 & 1.493 \\ 1.000 & 0.000 & 0.147 & -0.199 \end{pmatrix} \qquad \text{Model 2} \quad \begin{pmatrix} 1.000 & 1.000 & 0.000 & 0.000 \\ 1.000 & 0.000 & 9.418 & 0.000 \\ 1.000 & 0.000 & 1.493 & 9.418 \\ 1.000 & 0.000 & -0.199 & 1.493 \\ 1.000 & 0.000 & 0.147 & -0.199 \end{pmatrix}$$

$$\text{Model 3} \quad \begin{pmatrix} 1.000 & 1.000 & 9.418 & 0.000 & 0.000 \\ 1.000 & 0.000 & 1.493 & 9.418 & 9.418 \\ 1.000 & 0.000 & -0.199 & 1.493 & 0.000 \\ 1.000 & 0.000 & 0.147 & -0.199 & 1.493 \\ 1.000 & 0.000 & 0.826 & 0.147 & -0.199 \end{pmatrix} \qquad \text{Model 4} \quad \begin{pmatrix} 1.000 & 9.418 & 0.000 & 0.000 \\ 1.000 & 1.493 & 9.418 & 0.000 \\ 1.000 & -0.199 & 1.493 & 9.418 \\ 1.000 & 0.147 & -0.199 & 1.493 \\ 1.000 & 0.826 & 0.147 & -0.199 \end{pmatrix}$$

[6] See, for example, Primiceri and Tambalotti (2020) and Chudik et al. (2020).

Estimation of the model on post-COVID data gives the fit, which is μ^1_{it}.[7] The mean adjustments for March 2020 are quite similar across methods. For example, based on Model 4, $\hat{\mu}_0$ NAPMNOI (new orders) changes from 55.440 in February to $\hat{\mu}_1 = 42.269$ in March, NAPM from 52.983 to 49.122, CUMFNS (capacity utilization) from -0.013 to -3.617, UMSCENT (consumder sentiment) from -0.10 to -12.68, UNRATE (unemployment rate) from 0.01 to 0.969, and CLAIMS (unemployment claims) from 0.0 to 2.515, while housing variables such as PERMIT as well as AWHMAN (average man hours) are much less affected. These results are representative of all four models. However, the April estimates for Model 1 are quite different from those for Models 2, 3, and 4. Model 1 gives (53.941, 0.005, -0.102) for NAPM, PAYEMS. and CLAIMS, while Model 4 yields much larger changes of (42.081, -0.146, and 0.651) respectively, with the implication that the adjusted data x for Model 1 will have more extreme values than the other three models.

Figure 1 plots the 2020 adjustments for eight selected series. The impact and subsequent adjustments vary significantly across series and over time. Compared to the Model 1 adjustments in the top panel, the Model 4 adjustments in the bottom panel tend to be more concentrated around April 2020. The differences are most notable for RPI, PAYEMS, BUSLOANS and CLAIMS.[8]. According to Model 4, many series are back to the Janurary/February levels shortly after April.

Once $x_{it} = X_{it} - \hat{\mu}^1_{it}$ is available, I proceed to estimate the factors. Though x_{it} is mean zero in the two respective subsamples, they may not be mean zero when pooled. The stacked data are demeaned and standardized prior to factor estimation by the method of principal components. In the 2020-02 (pre-COVID) vintage of FRED-MD which reports data up to 2019-12, F_1 explains 16% of the variation in the data. All three post-COVID estimates of F_1 continue to capture about 16% of the variations in the extended sample and are nearly identical up till 2020-02, with pairwise correlations exceeding 0.99.

Turning to the other factors, $\hat{F}_2$ in the pre-COVID data loads heavily on term spreads and explains 7% of variations pre-COVID, while $\hat{F}_3$ which loads heavily on prices and explains about 6.7% of the variations. In the post-COVID sample, $\hat{F}_2$ still loads heavily on term spreads while and $\hat{F}_3$ still loads heavily on prices. These two factor estimates, along with $\hat{F}_4$, $\hat{F}_7$, and $\hat{F}_8$ are nearly perfectly correlated with the pre-COVID estimates in the overlapping sample. However, the $\mathcal{H}$ and $\mathcal{P}$ correlations for $\hat{F}_5$ and $\hat{F}_6$ are less than 0.8, much lower than the $\mathcal{D}$ correlations which are over 0.95. Figure 2 plots the first three macros factors and the first

[7]An alternative is to estimate the model on the full sample with an additional dummy that equals one after T_0.

[8]The Model 1 adjustments do not include the outlier adjustments.

financial for Model 4. Interestingly, the February values of $\hat{F}_1$, $\hat{F}_2$ and $\hat{F}_3$ in the de-COVID data are more different from August/September than March/April when the lockdown started.

Figure 3 summarizes the different estimates of $\hat{F}_1$ in 2020 across models. All suggest a rebound in June presumably due to the stimulus package. However, only Model 1 suggests a sharp drop in April with the $\mathcal{D}$ version being the largest (-3.59), and ends the year on the negative side. Models 2, 3, and 4 differ in the magnitude of the rebound in June, but all three estimates of F_1 are above the February level at the end of the year.

3 Forecasting and Measuring Uncertainty Post-Covid

The second step of the JLN exercise involves generating h-step ahead prediction errors. Following Stock and Watson (2002), we form diffusion index forecasts by augmenting the estimated factors to an autoregression:[9].

$$y_{jt+h} = \phi^y_{jh}(L)y_{jt} + \gamma^F_{jh}(L)\hat{F}_t + \hat{\gamma}^W_{jh}(L)W_t + v^y_{jt+h}$$

Prior to COVID y_{jt} is one of the 134 series in FRED-MD (ie. X_{jt}) after standardization,

$$W_t = (\hat{F}'_{mt}, \hat{F}'_{ft}, \hat{F}^2_{m,1,t}, \hat{G}_{m,t})'.$$

where $\hat{F}_{mt}$ is a set of eight macro factors, $\hat{F}_{ft}$ is a set of four financial factors, G_m is the first factor in X^2_m. A t test with a threshold of 2.56 is used to screen predictors.

COVID changes this exercise in two ways. First, as there is now a new source of variation in the data, predictability of y_{jt+h} as measured by X_{jt+h} must be distinguished from predictability as measured by x_{jt+h}. Second, the lingering effects of COVID on economic activity are not entirely unpredicted after the initial outbreak. Schorfheide and Song (2020) finds it better to make forecasts shortly after COVID using the model estimated pre-COVID, but this cannot be a sustained solution.[10]. I expand the predictor set to include COVID indicators: Let

$$W^+_t = (\hat{F}'_{mt}, \hat{F}'_{ft}, \hat{F}^2_{m,1,t}, \hat{v}^P_t, \hat{v}^D_t)'. \tag{1}$$

Since y_{jt} has been transformed to be stationary, I use v_t instead of V_t which is not stationary. I enter two measures of v_t in W_t because the number of deaths tend to lag the number of positive cases, and the two may contain different information. However, G_m is no longer a

[9] For properties of a factor-augmented regression, see Bai and Ng (2006); Stock and Watson (2002, 2016)

[10] The authors consider a mixed (monthly-quarterly) frequency VAR of eleven variables and finds that for forecasts made in the end of January, April, and May of 2020, the model estimated using data up to the end of 2019 are reasonable than those based on recursive estimation that includes the post COVID data

potential predictor set. This factor would have to be estimated from the panel of X_{jt}^2 which necessitates additional adjustments. It is noteworthy that based on the t test criterion, the variables being selected are quite similar before and after COVID. The lags of $\hat{v}_t$ are selected with frequencies ranging from 0.3 to 0.54.

After an h period ahead diffusion forecast for series j is obtained from the factor-augmented regression, step three of the JLN exercise estimates stochastic volatility models for the one-period ahead predictor error $\hat{\varepsilon}_{j,t+1}^y$ for each series j and $\hat{\varepsilon}_{k,t+1}^F$ for each factor k. This volatility estimation step is unaffected by COVID though the volatility estimates will be higher after COVID. The three-steps yield N estimates of individual uncertainties which are then aggregated to form macro-economic uncertainty by equal-weighting. I will denote the macro-uncertainty measure based on predictability of x by $U(x)$, to distinguish it from the one based on predictability of X, which is denoted $U(X)$.

Figure 4 plots the $\mathcal{P}$ version of uncertainty for Models 1 and 4. $U(X)$ is higher than $U(x)$ because X retains the COVID variations which contribute to unpredicted forecast errors. Model 1 suggests higher uncertainty in 2020 than Model 4 because of the treatment of the April variations. But regardless of model and version, uncertainty is high in 2020 by historical standard. There are now four episodes of uncertainty that exceed 1.65 standard deviations: the 2007-09, the 1981-82 and 1973-74 recessions, and COVID.

The difference between $U_M(X)$ and $U_M(x)$ can be thought of as 'covid uncertainty'. This is plotted in the bottom panel of Figure 4 for Model 4. Though covid uncertainty' is high in March, it has subsided by the end of 2020. Also of note is that the COVID uncertainty series for Models 2, 3, and 4 are very similar, suggesting that the March dummy incorporated in Models 2 and 3 is unnecessary, and the agnostic approach used in Model 4 suffices. The next section shows that Method 4 is also useful in VAR analysis.

4 Implications for Estimation of Dynamic Causal Effects

The data issues created by COVID also apply to other forms of time series modeling. Prior to COVID, the model for the $n \times 1$ vector of variables Y_t is

$$Y_t = \alpha + A(L)Y_{t-1} + Be_t$$

where e_t is a vector of n economic shocks. Now extend the data to include ten months of COVID data. Under the view that COVID is a health shock, there are now $n+1$ shocks in the n variable VAR which cannot be expected to recover n economic shocks.

To illustrate, consider a VAR(p) in unemplyoment rate (UR) and log industrial production (IP). The top panel of Figure 5 shows the dynamic responses to a UR shock using parameters estimate over the sample 1961:1-2019:12 with $p = 6$ lags. Both responses have a hump shape shock, peak after eight months, and are persistent. The second panel of Figure 5 shows that the post-COVID responses are generally larger in magnitude and distinctively different in shape from the pre-covid responses in the top panel. In particular, they are no longer hump shaped. Presumably, results like this have prompted Lenza and Primiceri (2020) to scale up the variance of the shocks during the pandemic, and Carriero et al. (2021) to incorporate outliers in a VAR with stochastic volatility. Instead of assuming changes to the distributions of economic shocks, I assume that there is an additional shock.

Following the arguments above, the idea is to purge v from each of the $n \cdot p$ variables in the VAR. Note that this is not the same as running a VAR on n de-COVID variables. However, by Frish-Waugh arguments, it is simple to augment the n variable VAR in un-adjusted data Y with v and its lags as exogenous variables.

$$Y_t = \alpha + \gamma D_t + \delta 1_{t>T_0} + A(L)Y_{t-1} + \beta(L)v_t + Be_t \qquad \text{(VAR-E)}$$

where D_t and each row of $\beta(L)$ are defined as in Models 1 to 4 above. A mean shift dummy is needed since the de-COVID regressions are now run on the full sample. The role of v and its lags is to partial out the effects of COVID from the dependent variable and the regressors so that coefficients can be used to construct dynamic responses to economic shocks, holding v and its lags fixed. The third panel of Figure 5 shows the $\mathcal{P}$ version of the Model 4 impulse responses based on (VAR-E) along with the 95% confidence interval. Notably, they are very similar both in magnitude and in shape to the pre-COVID responses in the top panel. The results for $\mathcal{D}$ and $\mathcal{H}$ versions are similar. Methods 2 and 3 also retain the hump shaped responses but not quite as close the pre-COVID estimates as Model 4.

It is of interest to consider a three variable VAR that includes a COVID variable and ordered first. While VAR-E assumes no feedback from UR or IP to v, a three variable VAR allows for such feedback. The dynamic responses should be similar if COVID is indeed exogenous.[11] The bottom panel of Figure 5 verifies that the responses of the three variable VAR to a UR shock are similar to the ones plotted for VAR-E. However, these responses to a UR shock are distinctly different from the responses to a COVID shock. As seen from Figure 6, a COVID shock has much larger but shorter lived effects on economic activity. The unemployment rate returns to control after about one year. The effect on IP, while large, is statistically significant for only two months. A two variable VAR without controlling for

[11] A six-variable VAR finds likewise that adding the COVID indicators as exogenous variables recovers the pre-COVID impulse responses. The variables are unemployment rate (unrate), log of employment (payems), log real consumption of durables (cdur), log real consumption of services (cs), industrial production (ip), and log of the consumption expenditure deflator excluding food and energy.

COVID would confound the responses to the two different shocks, as seen from the second panel of Figure 5.

Table 2: Orthogonalized Shocks

	UNRATE shock						IP shock					
	M0	M1	M2	M3	M4	VAR3	M0	M1	M2	M3	M4	VAR3
march	0.81	0.00	0.00	0.00	-0.22	0.07	-4.30	0.00	0.00	0.00	-0.16	-0.07
april	9.62	19.56	0.00	-0.04	0.25	0.09	-11.84	0.68	-0.12	-0.14	-0.25	-0.16
may	-1.28	-2.43	0.34	0.09	0.14	0.04	3.22	1.40	-0.04	-0.20	0.01	-0.10
june	-0.71	-2.46	-1.90	-1.41	-0.23	-0.08	1.74	1.12	0.83	1.11	0.15	0.07
cor	0.83	0.81	0.96	0.97	0.97	1.00	0.95	0.96	0.97	0.98	0.98	1.00

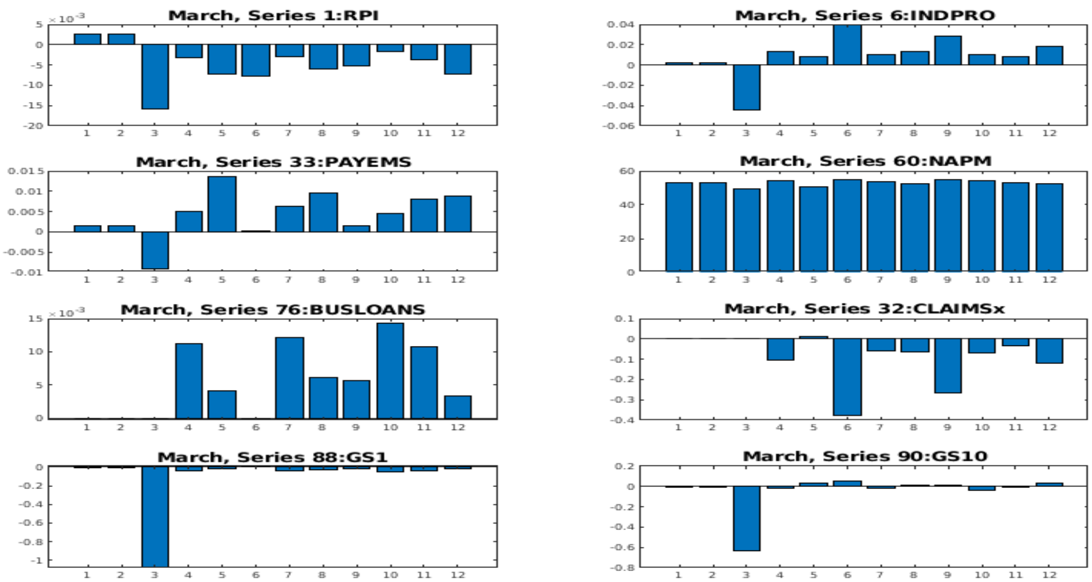
A look at the orthogonalized shocks highlights the identification problem that COVID creates. The column labeled M0 is based on post-COVID estimation without controls, while M1, M2, M2, M4 correspond to the four methods above. These are all bivariate VARs and to be distinguished from VAR3, which is a three-variable model for (v, UR, IP). The rows list the values of the identified shocks from March through June as well as the correlation with the corresponding shock identified pre-COVID data over the overlapping sample. Evidently, the M2, M3, M4 correlations are high and the shocks identified for UNRATE and IP in April are small. With no or inadequate adjustments, the M0 and M1 correlations are lower, and the shocks identified for UR and IP in April are large. The analysis lends support to treating COVID as exogenous which is the maintained assumption of Method 4 used to purge COVID effects from the data prior to factor estimation.

Our COVID variables are zero before March 2020 which can be approximated by time series with values arbitrarily close to zero except for the few spikes in 2020. Data with such extreme values have heavy tails, and one might wonder if our least squares used to estimate the three variable VAR or the de-COVID regressions are valid. Intuitively, the issue is that in a standard regression framework, the response variable should have heavy tails if one of the predictors has heavy tails. Yet, our economic data have fat but not heavy tails. For such problems, Davis and Ng (2021) uses a new (heavy-light) framework to dampen the coefficient on the heavy tailed predictor so that it can meaningfully affect the thin-tailed response variable. In that setup, the coefficient on the heavy tailed regressor is consistent at rate $T^{1/\alpha}$ where $\alpha \in (0, 2)$ is the tail index, implying that the estimated coefficient on the heavy-tailed regressors are super-consistent.

5 Conclusion

COVID can be treated as an outlier, a health shock with macroeconomic consequences, or an economic shock. I use COVID indicators to purge the data of their effects so that economic factors can be estimated. Adding COVID indicators to a VAR as exogenous controls also makes it possible to recover impulse responses to economic shocks similar to the ones estimated pre-COVID. This note draws attention to the need to control for COVID variations in macroeconomic modeling.

Figure 1: $\hat{\mu}^1_{it}$, $\mathcal{P}$ version: 2020:01-2020:12
Model 1



Model 4

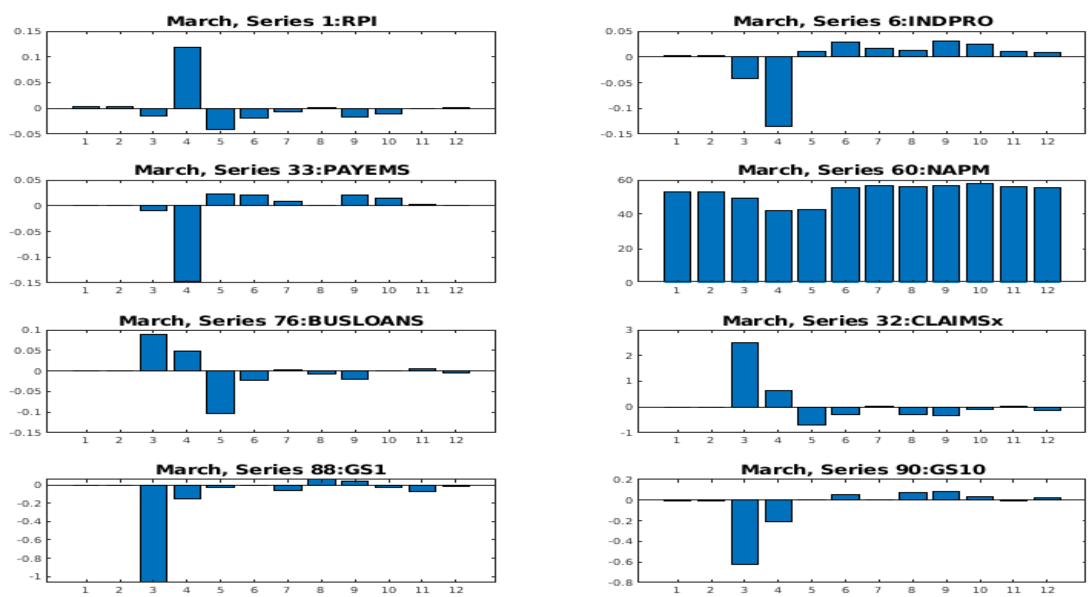


Figure 2: Factor Estimates: 2019:01-2020:12: Model 4

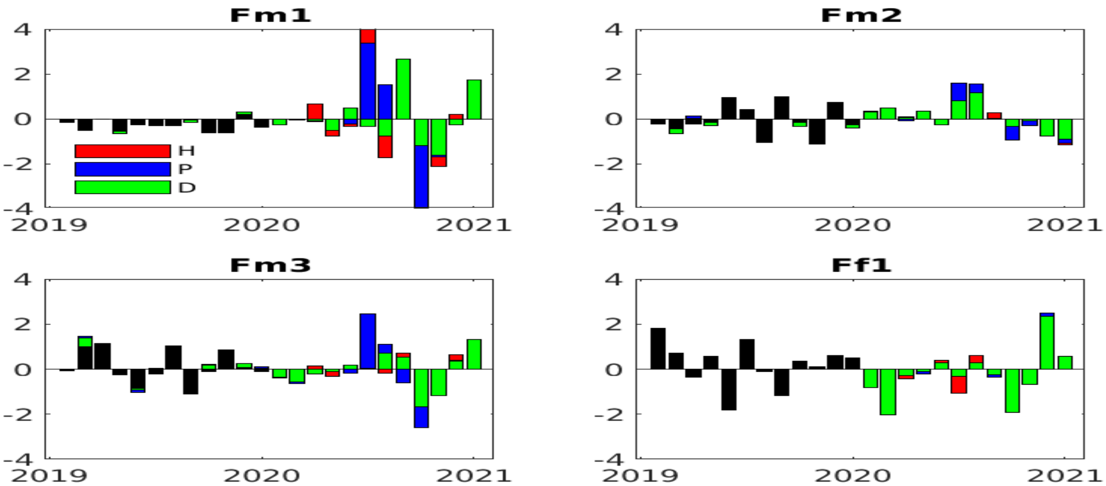
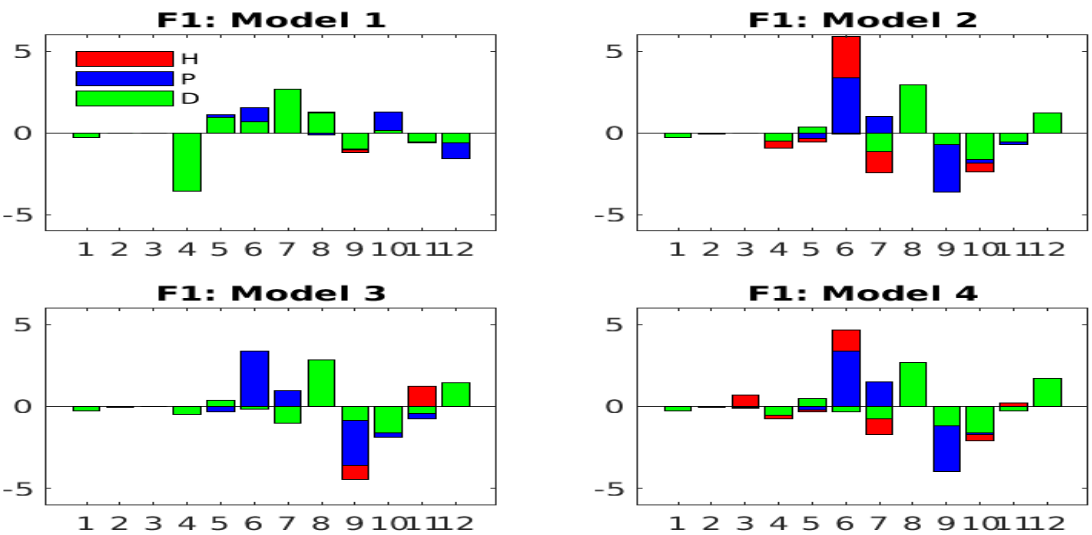
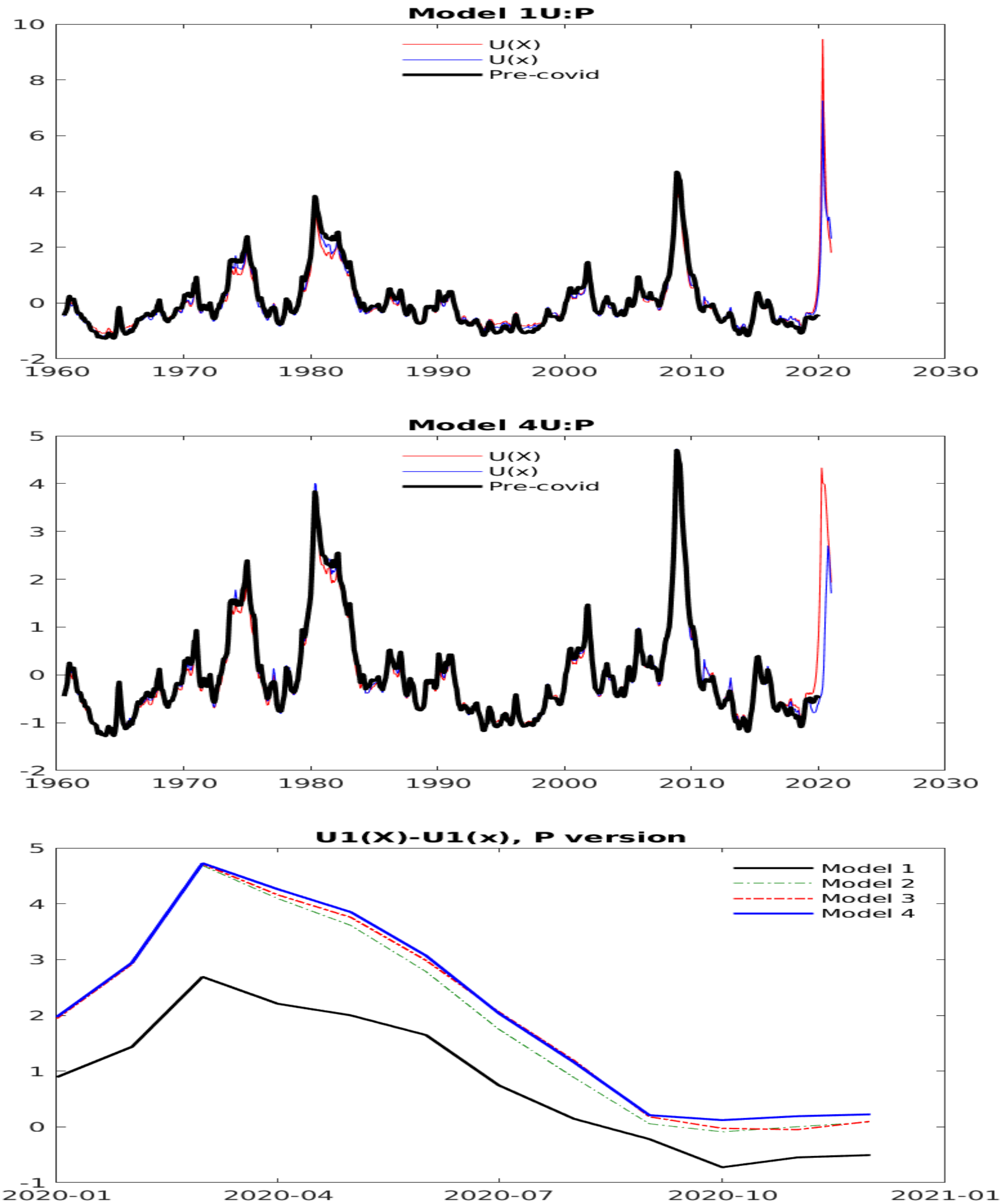


Figure 3: Estimates of F_1 in 2020:01-2020:12



Note: (H, P, D) uses hospitalization data, positive cases, and number of deaths as controls respectively.

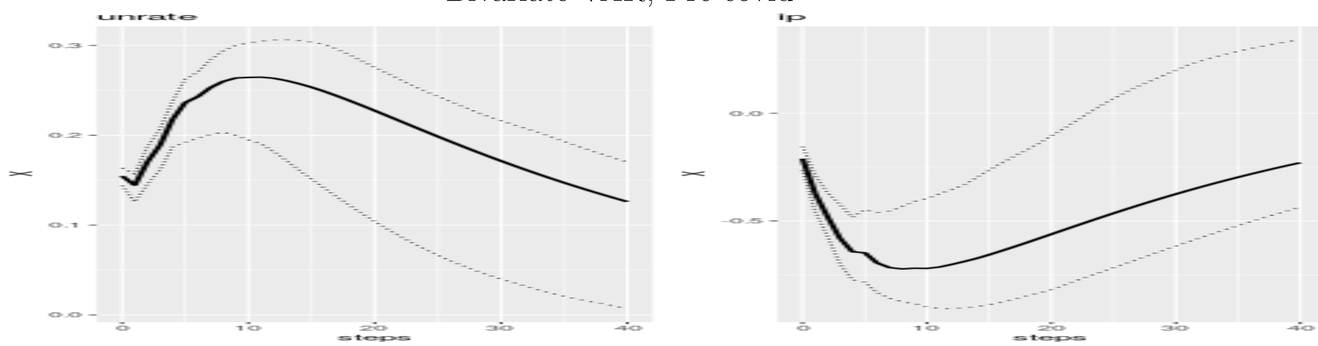
Figure 4: One Period Ahead Uncertainty Estimates



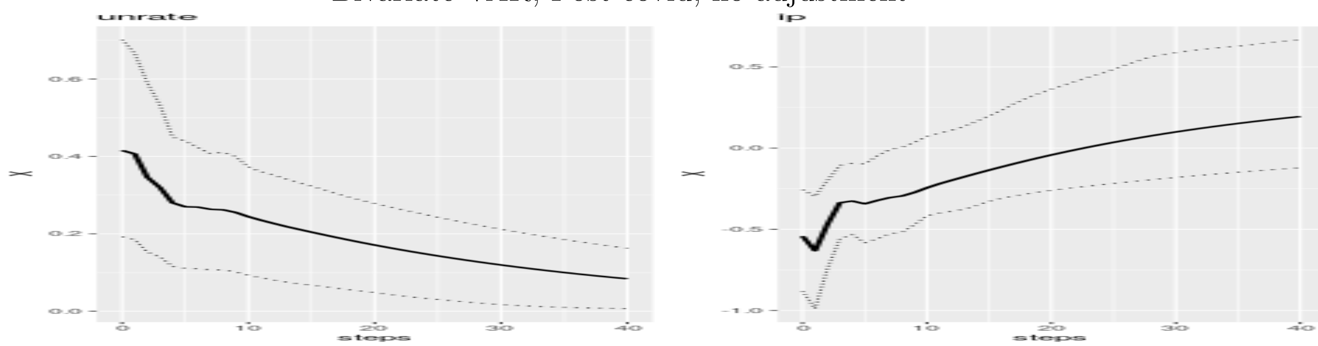
Note: U(X) is based on predictability of unadjusted data X. U(x) is based on predictability of the de-covid data, x.

Figure 5: Dynamic Responses to Unemployment (UR) Shock

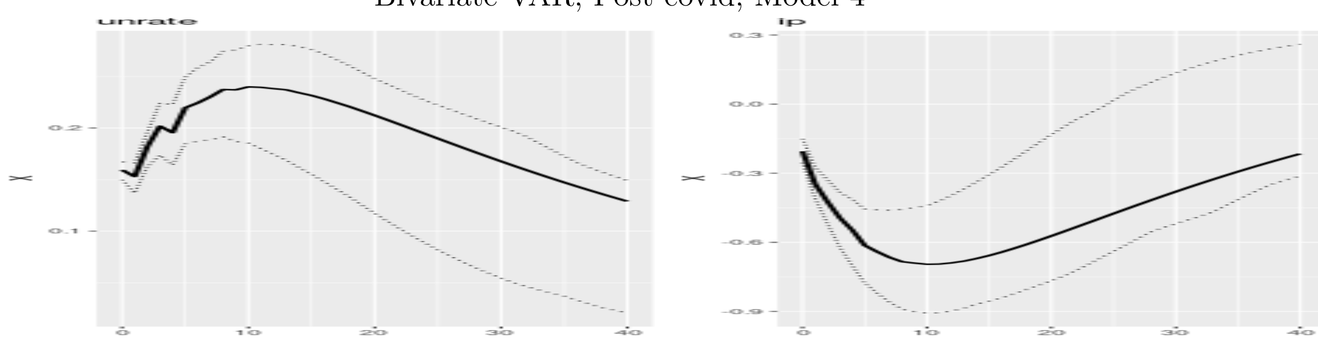
Bivariate VAR, Pre-covid



Bivariate VAR, Post-covid, no adjustment



Bivariate VAR, Post-covid, Model 4



Three variable VAR

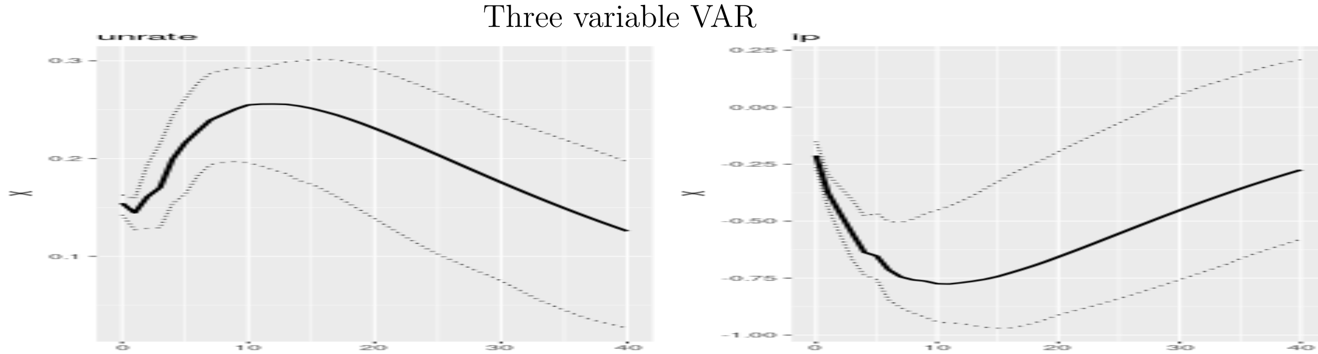
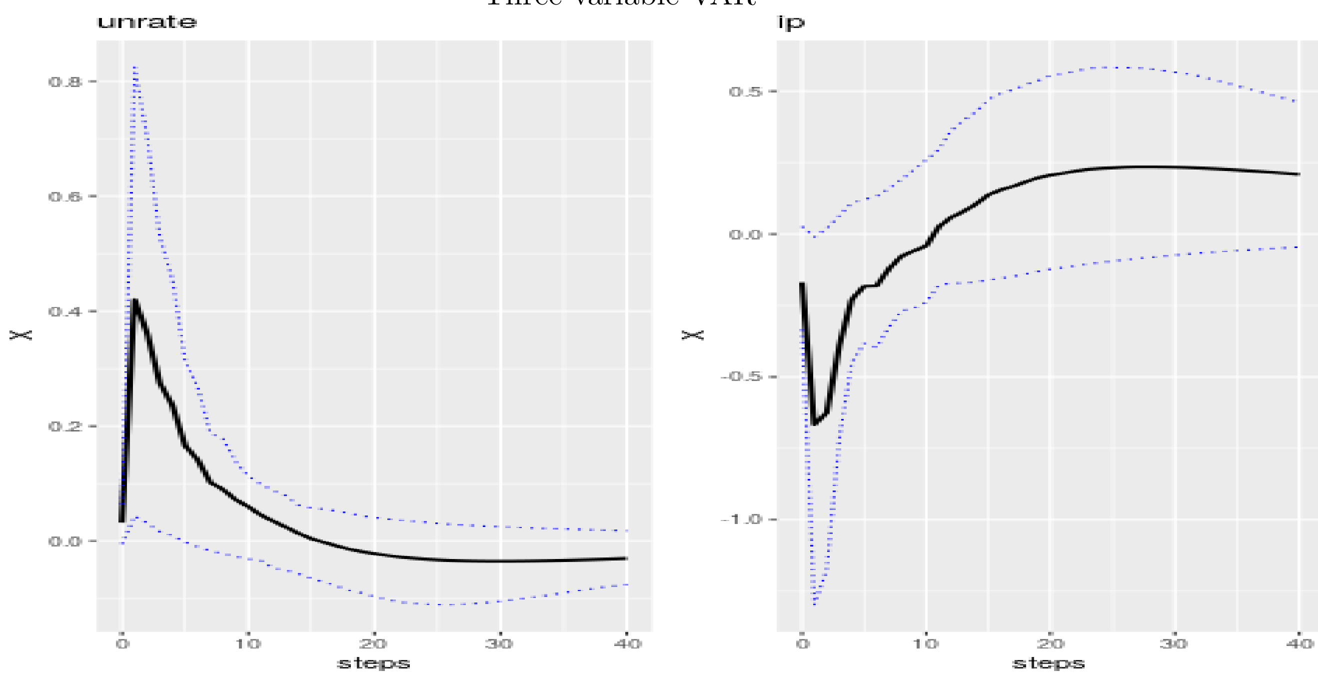


Figure 6: Dynamic Responses to Covid Shock
Three variable VAR



References

Bai, J. and Ng, S. 2002, Determining the Number of Factors in Approximate Factor Models, *Econometrica* **70**(1), 191–221.

Bai, J. and Ng, S. 2006, Confidence Intervals for Diffusion Index Forecasts and Inference with Factor-Augmented Regressions, *Econometrica* **74:4**, 1133–1150.

Carriero, A., Clark, T., Marcellino, M. and Mertens, E. 2021, Addressing COVID-19 Outliers in BVARs with Stochastic Volatility, mimeo.

Chudik, A., Mohaddes, K., Pesaran, M. H., Raissi, M. and Rebucci, A. 2020, A Counterfactual Economic Analysis of Covid-19 Using A Threshold Augmented Multi-Country Model, unpublished Manuscript.

Davis, R. D. and Ng, S. 2021, Time Series Estimation of the Dynamic Effects of Disaster-Type Shocks, arXiv: 2107.06663.

Doshi, P. 2008, Trends in recorded influenza mortality: United States, 1900-2004., *American journal of public health* **98 5**, 939–45.

Foroni, C., Marcellino, M. and Stevanovic, D. 2020, Forecasting the Covid-19 Recession and Recovery: Lessons from the Financial Crisis, unpublished Manuscript.

Huber, F., Koop, G., Onorante, L., Mfarrhofer, M. and Schreiner, J. 2020, Nowcasting in a Pandemic Using Non-Parametric Mixed Frequency VAR, *Journal of Econometrics*.

Jurado, K., Ludvigson, S. C. and Ng, S. 2015, Measuring Uncertainty, *The American Economic Review* **105**(3), 117–1216.

Lenza, M. and Primiceri, G. 2020, How to Estimate a VAR after March 2020, mimeo, Northwestern University.

Ludvigson, S. and Ng, S. 2007, The Empirical Risk Return Relation: A Factor Analysis Approach, *Journal of Financial Economics* **83**, 171–222.

Ludvigson, S., Ma, S. and Ng, S. 2020, Adjustments to JLN Uncertainty for Covid-19 Mean Shift, unpublished manuscript.

Ludvigson, S., Ma, S. and Ng, S. 2021, Covid-19 and the Costs of Deadly Disasters, *AEA Papers and Proceedings* **111**, forthcoming.

McCracken, M. and Ng, S. 2016, FRED-MD: A Monthly Database for Macroeconomic Research, *Journal of Business and Economic Statistcs* **36**(4), 574–589.

Moran, K., Stevanovic, D. and Toure, A. K. 2020, Macroeconomic Uncertainty and the Covid-19 Pandemic Measure and Impacts on the Canadian Economy, unpublished manuscript.

Primiceri, G. and Tambalotti, A. 2020, Macroeconomic Forecasting the Time of COVID-19, mimeo, Northwestern University.

Schorfheide, F. and Song, D. 2020, Real Time Forecasting with a (Standard) Mixed-Frequency VAR During a Pandemic, mimeo, University of Pennsylvania.

Stock, J. H. and Watson, M. W. 2002, Macroeconomic Forecasting Using Diffusion Indexes, *Journal of Business and Economic Statistics* **20:2**, 147–162.

Stock, J. H. and Watson, M. W. 2016, Dynamic Factor Models, Factor-Augmented Vector Autoregressions, and Structural Vector Autoregressions in Macroeconomics, *Handbook of Macroeconomics*, Vol. 2A, pp. 415–525.