

# Measuring the effectiveness of US monetary policy during the COVID-19 recession

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## Abstract

The COVID-19 recession that started in March 2020 led to an unprecedented decline in economic activity across the globe. To fight this recession, policy makers in central banks engaged in expansionary monetary policy. This paper asks whether the measures adopted by the US Federal Reserve (Fed) have been effective in boosting real activity and calming financial markets. To measure these effects at high frequencies, we propose a novel mixed frequency vector autoregressive (MF-VAR) model. This model allows us to combine weekly and monthly information within a unified framework. Our model combines a set of macroeconomic aggregates such as industrial production, unemployment rates, and inflation with high-frequency information from financial markets such as stock prices, interest rate spreads, and weekly information on the Fed's balance sheet size. The latter set of high-frequency time series is used to dynamically interpolate the monthly time series to obtain weekly macroeconomic measures. We use this setup to simulate counterfactuals in absence of monetary stimulus. The results show that the monetary expansion caused higher output growth and stock market returns, more favorable long-term financing conditions and a depreciation of the US dollar compared with a no-policy benchmark scenario.

## KEYWORDS

mixed frequency model, monetary policy effectiveness, unconventional monetary policy

## JEL CLASSIFICATION

E52; E58; H12

## 1 | INTRODUCTION

Worldwide restrictions to contain the spread of the novel coronavirus (COVID-19) triggered a sharp drop in global economic activity, a collapse in trade, and a severe rise in unemployment. First estimates for 2020 point at considerable contractions of gross domestic product (GDP) in most advanced economies (McKibbin & Fernando, 2020). As of now, the severity of the crisis for the US economy is comparable to that of the Great Depression in the 1930s. Policy makers responded swiftly, with unprecedented fiscal stimulus packages in the magnitude of nearly 15% of global GDP.<sup>1</sup> In the same vein, central banks provided stimulus by loosening their policy stance considerably. In many emerging economies, central banks successfully introduced forms of quantitative easing for the first time (Arslan et al., 2020; Hartley & Rebucci, 2020), while in advanced economies with policy space, easings took mostly the form of rate cuts, which further facilitated the use of fiscal stimulus packages.

In the United States, the economic impact of the pandemic was felt strongly on labor markets: employment dropped sharply and wages were cut (Cajner et al., 2020; Kurmann et al., 2020). This weakened demand and inflation considerably. To put these numbers into perspective, by most economic indicators, the contraction in the US economy is comparable to that of the Great Depression of the 1930s which constitutes the largest and longest slump in economic activity in US history.<sup>2</sup>

The negative business climate also deterred financial markets, with equity prices collapsing more strongly than in any previous crises triggered by infectious disease outbreaks (Baker et al., 2020). Relatedly, US Treasury markets experienced a sharp sell-off, leading to spikes in long-term yields (Schrimpf et al., 2020). The US Federal Reserve (Fed) responded with several measures including the opening of credit facilities to support malfunctioning markets and actions aimed at relieving cash-flow stress for small and medium-sized businesses, as well as municipalities. The most prominent actions, however, were moving the policy rate back toward the zero lower bound and resuming the monthly purchase of massive amounts of securities (80 billion US dollars immediately and up to 700 billion US dollars in total over the coming months).

This paper tries to give a first assessment of how successful the monetary easing in the United States was in stabilizing prices and providing stimulus to the economy. One concern when assessing effectiveness of policy responses in real time is the low-frequency nature of many macroeconomic aggregates (with most of them available on a monthly or quarterly frequency, at best). Even if we rely on monthly data, we are left with only very few observations that we can use to infer the effects of monetary policy during the COVID-19 crisis on several key quantities of interest for policy makers. For this purpose, we borrow strength from data which are available at higher frequencies. These time series are often sampled at daily or weekly frequency and allow us to construct weekly measures of industrial production, inflation, and unemployment. This is achieved within a coherent multivariate framework that allows for dynamic interactions between the macroeconomic and financial quantities considered.

<sup>1</sup>For an overview of these policy measures, see [bruegel.org/publications/datasets/covid-national-dataset](https://bruegel.org/publications/datasets/covid-national-dataset).

<sup>2</sup>Direct comparisons in terms of GDP are, however, fraught with measurement difficulties. Nevertheless, some rough comparisons can be made. First, current projections for the US economy point at a severe recession with a contraction of GDP of similar magnitude to that during the Great Depression but point at a quick recovery thereafter. By contrast, the Great Depression was a very persistent recession reaching a trough of economic activity after four years. The US unemployment rate, rose during 2020 from 3.5% in February to nearly 15% in April before declining in the subsequent months, to about 7.9% in September. During the Great Depression, unemployment did not rise as sharply in the early months of the recession, but gradually rose to 25% in 1933 and stayed above 10% throughout the 1930s (Wheelock, 2020).

The proposed econometric framework is a mixed frequency vector autoregression (MF-VAR, see Schorfheide & Song, 2015) which models all variables on a weekly frequency. Using a state-space representation of the multivariate system, we recast the lower-frequency quantities in terms of a weekly component with missings between monthly observed values. These missing observations are subsequently estimated by taking into account the properties of the model and using the higher-frequency time series dynamically. Such methods have been used heavily in recent years for improving predictive accuracy of nowcasts or forecasts, mostly by linking series such as gross domestic product to several higher-frequency series that possess predictive power for the low-frequency quantity (see Cimadomo & D'Agostino, 2015; Cimadomo et al., 2020; Schorfheide & Song, 2015, among many others).

Related econometric frameworks have also been used for structural analyses (see, for instance, Ferrara & Guerin, 2018; Foroni & Marcellino, 2014; Ghysels, 2016; Marcellino & Sivec, 2016; McCracken et al., 2015). Ghysels (2016) provides a comprehensive discussion of structural inference using mixed frequency data. He argues that using higher and lower frequencies simultaneously introduces several interesting cases of potential timing restrictions regarding latent and observed shocks and relates VAR-based approaches to mixed data sampling (MIDAS) regressions. McCracken et al. (2015), for instance, consider differences in the effects of monetary policy shocks conditional on which month during the quarter they have occurred. Foroni and Marcellino (2014) ask whether mixed frequency data help tracing the effects of monetary policy shocks in the context of dynamic stochastic general equilibrium (DSGE) models and answer this question in the affirmative.

Our approach is closest in spirit to Marcellino and Sivec (2016), in the sense that we rely on established structural methods in the context of a mixed frequency data environment. We use our model to simulate the effects of monetary policy shocks. Using these shocks, we can compute weekly historical decompositions and perform counterfactual scenarios to investigate the effects the monetary policy measures had on the US economy. The results indicate that without a monetary expansion, US economic activity would have been significantly lower. In other words, the US Fed, so far, has been successful in cushioning the economic consequences of the COVID-19 crisis. Positive effects on output growth are underpinned by a rise in stock market returns, an easing of long-term financing conditions and a depreciation of the US dollar. By contrast, effects on inflation and the unemployment rate are statistically insignificant.

The remainder of this paper is structured as follows. Section 2 briefly describes the dataset and econometric model used while Section 3 shows the main results. In this section, we discuss the dynamic reactions to a monetary policy shock and discuss the historical decompositions. Finally, the last section briefly summarizes and concludes the paper.

## 2 | EMPIRICAL FRAMEWORK

### 2.1 | A mixed frequency VAR model

As stated in the introductory section, one key issue with adequately assessing the impacts of COVID-19 related monetary policy measures is the extremely short time span of available data. To provide a timely estimate, one could focus on high-frequency variables such as interest rate spreads or stock prices. But these are typically not of direct interest for policy makers. In policy making circles, assessing the effects of monetary policy interventions on output, inflation, and labor markets is pertinent. Unfortunately, for all these variables we only have a handful of observations, rendering an adequate assessment of policy effectiveness difficult.

As a solution, we propose pairing a panel of weekly indicators, contained in an  $M_W$ -dimensional vector  $y_t^{(W)}$ , with monthly indicators stored in an  $M_M$ -dimensional vector  $y_t^{(M)}$  in a MF-VAR. These vectors run from  $t = 1, \dots, T$ , with  $T$  denoting the number of weeks in our sample. Following Schorfheide and Song (2015), we assume that  $y_t^{(W)}$  is a latent weekly measure of the low-frequency indicator.

One key objective is to infer  $y_t^{(W)}$  to obtain weekly measures of the low-frequency variables.

This is achieved by defining  $y_t = (y_t^{(M)}, y_t^{(W)})'$ , which is an  $M (= M_M + M_W)$ -dimensional vector, and assuming that it follows a VAR( $P$ ) process:

$$y_t = c + A_1 y_{t-1} + \dots + A_P y_{t-P} + \varepsilon_t, \quad \varepsilon_t \sim \mathcal{N}(0_M, \Sigma_t) \quad (1)$$

where  $c$  is an  $M \times 1$ -vector of intercepts, and  $A_p = (p = 1, \dots, P)$  are  $M \times M$  coefficient matrices associated with the  $p$ th lag of  $y_t$ .  $\varepsilon_t$  is a white noise Gaussian process with time-varying variance-covariance matrix  $\Sigma_t$ . To speed up computation and assume that the COVID-19 shock led to a sharp increase in the conditional variance of all elements in  $y_t$ , we introduce a common stochastic volatility (CSV) model originally proposed in Carriero et al. (2016).

Several papers discuss methods for estimating VAR models in light of huge-variance shocks such as during the pandemic (Huber et al., 2021; Lenza & Primiceri, 2020; Schorfheide & Song, 2020). Our approach is closest to Lenza and Primiceri (2020), who find that overall macroeconomic dynamics and cross-variable relationships during the pandemic months are consistent with those of the pre-pandemic period. They propose the variance-covariance matrix of the VAR to follow a mixture distribution, downweighting outlying observations to allow for stable estimation of the coefficient matrices.

We assume that  $\Sigma_t$  is driven by a scalar factor such that:

$$\Sigma_t = e^{h_t} \times \Sigma,$$

and  $h_t$  evolves according to an AR(1) process:

$$h_t = \mu_h + \rho_h (h_{t-1} - \mu_h) + \sigma_h v_t, \quad v_t \sim \mathcal{N}(0, 1).$$

Here,  $\mu_h$  denotes the unconditional mean,  $\rho_h$  the autoregressive parameter and  $\sigma_h^2$  the error variance.  $h_t$  simply scales the time-invariant variance-covariance matrix  $\Sigma$ . This allows us to capture sudden common shifts in variances while leaving the contemporaneous relations unchanged over time. The common scaling factor  $e^{h_t}$  acts similarly compared with the framework proposed in Lenza and Primiceri (2020) and shows a large spike during the pandemic. This reduces the weight of the pandemic observations in the posterior of all other coefficients, thereby allowing for estimating the MF-VAR with constant coefficients (without affecting estimates significantly) even when facing the large outliers produced by the pandemic. Equation (1) can be cast in its companion form:

$$z_t = F z_{t-1} + \eta_t, \quad (2)$$

with  $z_t = (y_t', \dots, y_{t-p+1}', 1)'$  and  $F$  being the  $K \times K$  companion matrix (for  $K = PM$ ) with the first  $M$  rows given by  $(A_1, \dots, A_P, c)$ . The remaining rows are defined to return an identity such that  $y_{t-j} = y_{t-j}$  for  $j = 1, \dots, P - 1$ . The first  $M$  elements of  $\eta_t$  are equal to  $\varepsilon_t$ , while all other elements are equal to zero.

The missing values in  $y_t$  can be obtained by interpreting Equation (2) as a state evolution equation that provides information on how the elements in  $z_t$  (and thus  $y_t$ ) are related over time.

Consistent with Mariano and Murasawa (2003), we assume that the observed monthly values of  $y_t^{(M)}$ , which we denote by  $\tilde{x}_t^{(M)}$ , are related to  $y_t^{(M)}$  as follows:

$$\tilde{x}_t^{(M)} = (y_t^{(M)} + y_{t-1}^{(M)} + y_{t-2}^{(M)} + y_{t-3}^{(M)})/4. \quad (3)$$

This is the so-called intertemporal restriction. The specific restriction is inherently tied a priori transformations of the underlying data. Data in log-levels often use a restriction via averages as in Schorfheide and Song (2015), while this translates to a triangular scheme for data modeled in period-by-period log-differences, see Mariano and Murasawa (2003) for details. For our empirical analysis, all variables enter the model as year-on-year log

differences. Restriction Equation (3) is derived by assuming that the monthly observations on the log-level are the average of the corresponding latent weekly observations of the respective month (for details, see Appendix A).

Notice that this assumption implies that each month features exactly four weeks (and thus we drop four weeks per year to arrive at 48 weeks).<sup>3</sup> Define a selection matrix  $S_t^{(M)}$  that equals an identity matrix in time  $t$  only in the last week of a month while being equal to a zero matrix for the initial three weeks, and  $\Lambda^{(M)}$  is a matrix such that:

$$x_t^{(M)} = S_t^{(M)} \bar{x}_t^{(M)} = S_t^{(M)} \Lambda^{(M)} z_t.$$

For the weekly indicators, we assume that the identity  $x_t^{(W)} = y_t^{(W)}$  holds if the dataset is balanced. If some weekly values are missing, we introduce a separate selection matrix  $S_t^{(N)}$  with  $x_t^{(N)} = S_t^{(N)} y_t^{(N)}$ . Following Schorfheide and Song (2015), the observation equation that relates the observed to the latent quantities is:

$$x_t = \mathcal{M}_t \Lambda z_t. \tag{4}$$

Here,  $x_t = (x_t^{(M)'} , x_t^{(W)'})'$ , is a selection matrix and  $\Lambda$  is composed of  $\Lambda^{(M)}$  and appropriate selection vectors to single out the high-frequency quantities in  $z_t$ .

Following the related literature on medium to large-scale VARs and MF-VARs, we estimate the model using well-established Bayesian methods (Bańbura et al., 2010; Carriero et al., 2015, 2016; Koop et al., 2020; Schorfheide & Song, 2015). This implies that we need to specify priors on all parameters of the model. Let  $s_m^2$  for  $m = 1, \dots, M$  denote the residual variances of independent AR(4) regressions of the variables in  $y_t$ . In this paper, we use the following prior setup:

- For the VAR coefficients, we rely on a conjugate Minnesota-type prior (similar to Schorfheide & Song, 2015). We stack the coefficients in  $A = (A_1, \dots, A_p, c)'$  in an  $M(M_p + 1) \times 1$ -vector  $a = \text{vec}(A)$ . The prior takes the form  $a \sim \mathcal{N}(a, \Sigma \otimes \Xi)$ , with  $a, \Xi$  denoting hyperparameters. The prior mean is  $\underline{a} = 0_{[M(M_p+1)]}$ . The diagonal elements of  $\Xi = \text{diag}(\{\xi_i\}_{i=1}^{M(p+1)})$ , are set as follows:

$$\xi_i = \begin{cases} \lambda_1^2 / (p^{\lambda_2} \times s_m^2), & \text{for lag } p \text{ of variable } m, i = M(p-1) + m\xi_i \\ \lambda_3^2, & \text{for } M_p + 1 \text{ (intercept).} \end{cases}$$

The hyperparameters are  $\lambda_1 = 0.2$  (governing overall tightness of the prior),  $\lambda_2 = 1$  (lag-decay) and  $\lambda_3 = 10$  (intercept).

- On the parameters of the state equation of  $h_t$ , we use a Beta prior on the transformed autoregressive coefficient  $(\rho_h + 1) / 2 \sim \mathcal{B}(5, 1.5)$ , a normally distributed prior on the unconditional mean  $\mu_h \sim \mathcal{N}(0, 100)$  and a Gamma prior on  $\sigma_h^2 \sim \mathcal{G}(1/2, 1/2)$ .
- Finally, we use a weakly informative inverse Wishart prior on  $\Sigma \sim \mathcal{IW}(\underline{S}, \underline{v})$ , with prior moments given by  $\underline{S} = (\underline{v} - M - 1) \times \text{diag}(s_1^2, \dots, s_M^2)$  and  $\underline{v} = M + 2$ .

Estimation is carried out using the Markov chain Monte Carlo (MCMC) algorithm discussed in Schorfheide and Song (2015) and efficiently implemented in the R package **mbfvar** (Ankargren & Yang, 2019).

<sup>3</sup>We use this practicable solution to obtain a balanced weekly-dataset by using data on the first four weeks of each month and drop additional weeks afterwards. Due to the fact that weeks sometimes cover two months, we allocate them based on the assigned weekday at the time of publication of the respective series. For aggregated daily series per week, we allocate weeks overlapping two months based on into which month the majority of weekdays fall.

## 2.2 | Data

Our analysis focuses on the reaction of the consumer price index (CPIAUCSL), the unemployment rate (UNRATE) and industrial production (INDPRO) to a monetary policy easing. All of these focal variables are on a monthly frequency. Higher-frequency variables consist mainly of financial indicators. In particular, we include the money supply (M2) as the policy variable, the *five-year forward inflation expectation rate* (T5YIFR) to gauge market-based inflation expectations, the NASDAQ composite indicator (NASDAQCOM), the *US dollar/euro foreign exchange rate* (DEXUSEU) and the *ten-year treasury constant maturity rate* (WGS10YR). As measures of financial stress, we rely on the *CBOE volatility index* (VIX, VIXCLS).

The sample period runs from the first week of 2011 to week 24 of 2020 (end of week: June 8, 2020) and is taken from the FRED database of the Federal Reserve Bank of St. Louis. If the raw data for financial variables is on a higher frequency than weekly (that is, daily for T5YIFR, NASDAQCOM, DEXUSEU, VIXCLS), we take end-of-week values. All variables enter the model as year-on-year log-differences. We choose  $p = 12$  lags (3 months' worth of weekly lags).

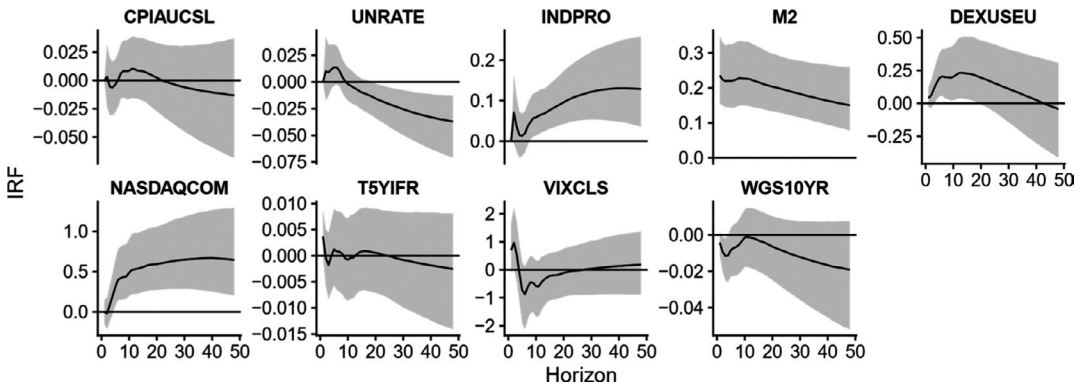
## 3 | SCENARIO AND COUNTERFACTUAL ANALYSIS

In this section, we examine the effects of an expansion of the US money supply on output, inflation, the unemployment rate and several financial indicators. In what follows, we proceed in two steps.

First, we look at the overall plausibility of our model by examining impulse response functions. For that purpose, we rely on a simple recursive identification scheme with ordering the monthly variables first, followed by M2. Last, we put all other weekly indicators. Note that this simple recursive scheme implies zero restrictions on the low-frequency variables. In particular, in our application the Cholesky decomposition states that there are no contemporaneous effects of the high-frequency indicators on inflation, output and the unemployment rate, an assumption with which most economists would agree upon. This also relates to our previous discussion of structural inference in mixed frequency data models. Ghysels (2016) states that high-frequency shocks are typically well-identified in mixed frequency VAR models, but identifying impacts of low-frequency series is harder. Our focus is on identifying shocks to a high-frequency series, and the restrictions we impose imply that shocks to the low-frequency variables induce contemporaneous responses in high-frequency variables.<sup>4</sup> This is consistent with the notion that latent series can be interpreted as capturing expectations of the low-frequency variables with respect to the high-frequency dataset in real time.

We take a broad stance on how monetary policy is measured in our model by looking at an expansion of M2. This captures both measures the Fed has recently undertaken, a massive cut in interest rates accompanied by a commencement of their asset purchase program. While conventional monetary policy mainly works through stimulating aggregate demand, the latter affects the economy through the portfolio re-balancing channel. In a nutshell, if the central bank buys financial assets from the market, the yields on these assets decline and investors with the aim to restore the duration of their portfolio will seek assets from other markets. This results in a broad easing of overall financing conditions which boosts firm and household investment, aggregate demand and hence price growth. For an excellent summary, see Joyce et al. (2012). Indeed, the empirical literature examining the effects of quantitative easing during the global financial crisis suggest positive effects on equity prices, mainly because they reduce term or risk premia through portfolio balance effects (Gagnon et al., 2011; Rogers et al., 2014), market liquidity (Christensen & Gillan, 2013; Christensen & Krogstrup, 2015), real GDP and inflation (Chung et al., 2012).

<sup>4</sup>Note that shocks to other series than the high-frequency measures of M2 are only of indirect interest. It is, however, worth mentioning that relying on MF-VARs with latent shocks may result in potential issues with timing restrictions, which may alter impulse response functions (for a discussion and alternative approaches, see Ghysels, 2016).



**FIGURE 1** Impulse response functions to a one-standard deviation shock to M2. Notes: Median response alongside the 90 percent posterior credible set. The black horizontal line marks zero

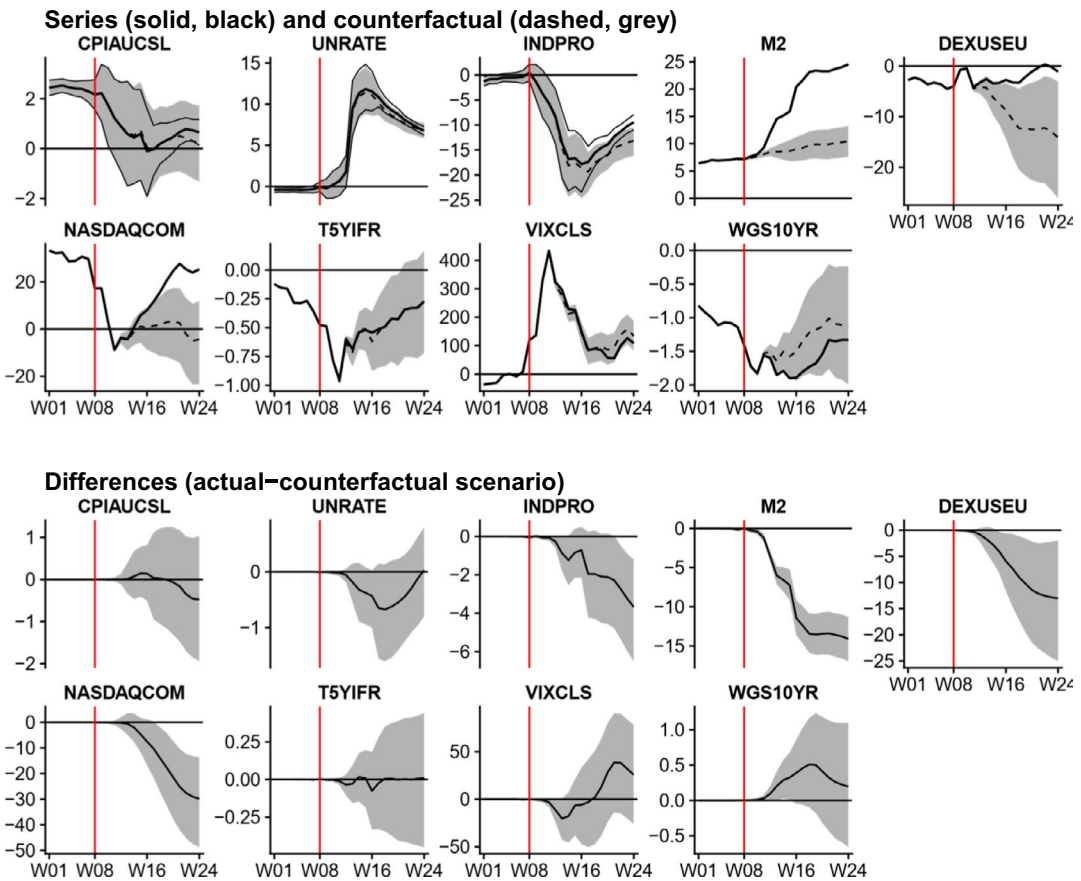
The results are depicted in Figure 1 which shows the posterior median (solid line) along with 90% credible intervals. The figure demonstrates that the expansionary shock to the money supply (M2) significantly drives up output growth and lowers the unemployment rate. These effects are rather persistent and take place with a lag. We do not find a significant upward effect on inflation, although we have included inflation expectations which in general should help mitigating the price puzzle (Castelnuovo & Surico, 2010) often encountered in empirical studies. This finding can be explained by the time period under consideration, which was characterized by low interest and inflation rates. As regards financial variables, we see a significant and persistent upward effect on equity returns, a front-loaded depreciation of the US dollar and a decrease of long-term yields. Also the VIX increases immediately, which could be related to the positive and pronounced shoot-up of equity returns. Summing up, the mixed-frequency approach generates impulse response functions that are in line with predictions of the bulk of empirical studies on the effects of monetary policy.

Next, we generate counterfactual scenarios. For that purpose, we construct historical decompositions that explain deviations of time series from their trend by shocks to the equations in the system. Neutralizing shocks to money supply after the onset of the COVID-19 crisis thus yields a counterfactual scenario to answer the question how output growth, unemployment, and inflation would have evolved without the Fed having provided monetary stimulus. We choose the last week of February (week eight of 2020) as the first observation in the pandemic period.

The results are depicted in Figure 2. In the upper panels, we show the evolution of actual series (black thick lines) and responses under the counterfactual scenario (gray shaded area, dashed line) along with 90% credible intervals. Since high-frequency movements of low-frequency variables are estimated within the MF-VAR framework, we also depict credible intervals for the historical weekly evolution of inflation, the unemployment rate and output growth (black thin lines).

The results indicate that output growth would have been weaker without monetary policy stimulus provided by the US Fed. This finding could be driven by the strong effect monetary policy exerted on financial variables: equity returns would have been considerably lower and long-term yields higher under the no-policy scenario. The analysis also suggests that monetary policy triggered a stronger depreciation of the exchange rate and hence a boost to external competitiveness of the US economy. By contrast, the counterfactuals show no significant effect on unemployment and inflation. Considering the delayed response of unemployment discussed in the context of the impulse response functions, this might be an artifact of the considered counterfactual period being too short to detect effects of the expansion yet.

To investigate the significance more systematically, the bottom panel of Figure 2 presents the differences of the responses under the no-policy and the policy scenario along with 90% credible intervals. That analysis



**FIGURE 2** Counterfactual analysis for 2020 based on setting identified shocks to M2 after the onset of the COVID-19 crisis (last week of February 2020, week eight) to zero. Notes: The black solid lines depict the actual evolution of the series (alongside the 90 percent posterior credible set for monthly variables), the dashed line alongside the gray shaded area (90 percent posterior credible set) shows the counterfactual (upper panel). Posterior of the differences between the actual and counterfactual scenario (lower panel). The horizontal black line marks zero, and the vertical red line is the beginning of the pandemic period [Colour figure can be viewed at [wileyonlinelibrary.com](http://wileyonlinelibrary.com)]

corroborates the findings from above that monetary policy led to higher output growth, a pick up in equity returns and an easing in long-term financing conditions. It also led to a significantly lower value of the US dollar.

## 4 | CLOSING REMARKS

In this note, we gave a first empirical investigation of the effects of US monetary policy to stimulate growth in response to COVID-19. For that purpose, we have estimated a MF-VAR on monthly and weekly data. This model allows us to estimate weekly measures of industrial production, inflation, and the unemployment rate. We then simulate the effects of expansionary monetary policy and assess its effects on the endogenous variables in the model.

The results suggest that the US Fed was successful in stimulating growth on the back of higher equity prices and more favorable long-term financing conditions. Also, monetary policy triggered a depreciation of the US dollar supporting external competitiveness of the US economy. By contrast, we do not find significant effects on unemployment and inflation, both variables that typically react more sluggishly to economic stimulus.



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APPENDIX A

DERIVATION OF THE INTERTEMPORAL RESTRICTION

Let  $\log(\tilde{x}_t^{(M)})$  denote the log-level of the respective lower-frequency quantities that are observed each month and denote the latent weekly process that is never observed (in log-levels) by  $\log(Y_t^{(W)})$ .

The log-levels of the observed weekly series are collected in the vector  $\log(Y_t^{(W)})$ . All of these series are included in our model as year-on-year differences. Recall that we assume that each year is composed of 48 weeks. This implies that  $\tilde{x}_t^{(W)} = \log(\tilde{x}_t^{(W)}) - \log(\tilde{x}_{t-48}^{(W)}) = \Delta_{48}\log(\tilde{x}_t^{(W)})$ , and accordingly,  $y_t^{(W)} = \Delta_{48}\log(Y_t^{(W)})$  and  $y_t^{(M)} = \Delta_{48}\log(Y_t^{(M)})$ .

Consistent with the restriction assumptions for log-level data in Schorfheide and Song (2015) and the derivations in Mariano and Murasawa (2003), our restriction is as follows:

$$\log \tilde{x}_t^{(M)} = (\log Y_t^{(M)} + \log Y_{t-1}^{(M)} + \log Y_{t-2}^{(M)} + \log Y_{t-3}^{(M)}) / 4,$$

that is, the monthly measures are linked to the unobserved weekly measures by averaging over the respective weeks in the month. Taking year-on-year differences results in

$$\log \tilde{x}_t^{(M)} - \log \tilde{x}_{t-48}^{(M)} = ((\log Y_t^{(M)} - \log Y_{t-48}^{(M)}) + (\log Y_{t-1}^{(M)} - \log Y_{t-49}^{(M)}) + (\log Y_{t-2}^{(M)} - \log Y_{t-50}^{(M)}) + (\log Y_{t-3}^{(M)} - \log Y_{t-51}^{(M)})) / 4.$$

Using the notation for year-on-year growth rates introduced above, this results in the exact specification of the intertemporal restriction in Equation (3):

$$\tilde{x}_t^{(M)} = (y_t^{(M)} + y_{t-1}^{(M)} + y_{t-2}^{(M)} + y_{t-3}^{(M)}) / 4.$$