
“Monitoring daily unemployment at risk”

Helena Chuliá, Ignacio Garrón and Jorge M. Uribe

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Abstract

Using a high-frequency framework, we show that the Auroba-Diebold-Scotti (ADS) daily business conditions index significantly increases the accuracy of U.S. unemployment nowcasts in real-time. This is of particular relevance in times of recession, such as the Global Financial Crisis and the Covid-19 pandemic, when the unemployment rate is prone to rise steeply. Based on our results, the ADS index presents itself as a better predictor than the financial indicators widely used by the literature and central banks, including both interest and credit spreads and the VXO.

JEL classification: C54,E23,E24, E27,E32.

Keywords: Quantile regressions, Mixed-data sampling, Nowcast, Unemployment rate.

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1. Introduction

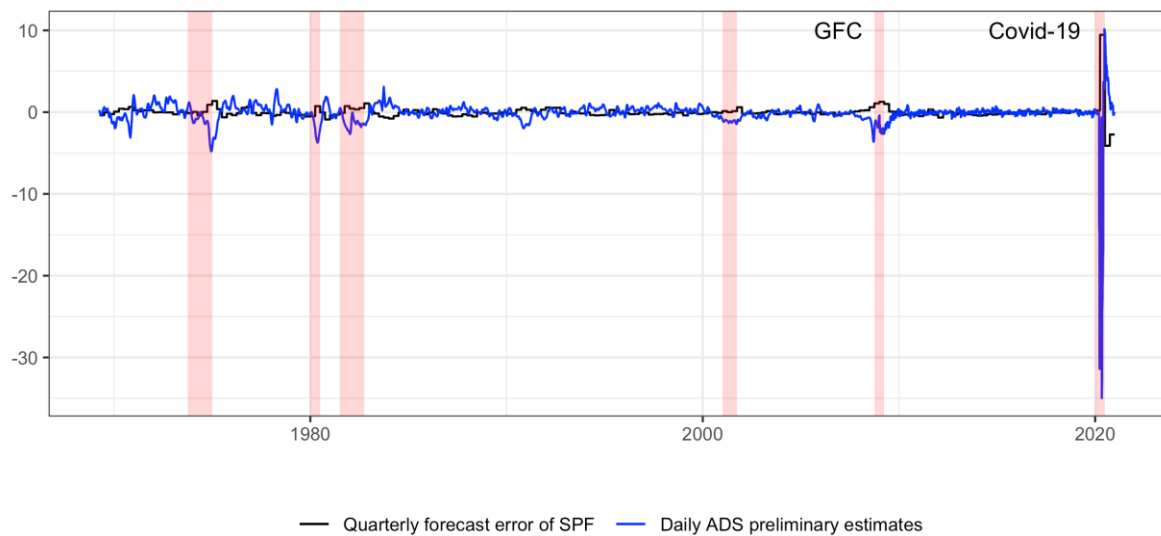
A primary task of macroeconomic policymaking is to provide accurate forecasts of the unemployment rate so governments can decide on the most appropriate monetary policy stance to adopt at any given time. This is particularly challenging during episodes of market distress. For instance, at the onset of the Covid-19 pandemic, the Federal Open Market Committee (FOMC) reported that job gains were solid and the U.S. unemployment rate could be expected to remain low (FOMC, 2020). However, during the next quarter, the average unemployment rate spiked at 13%, the highest increase recorded since 1948. This paper seeks to provide real-time daily unemployment nowcasts to inform policymakers at the highest possible frequency about the tail-risks surrounding current or near-future unemployment and, in so doing, contribute to the literature of ‘unemployment at risk’ (URisk) pioneered by Kiley (2021) and Adams et al. (2021).

We extend the framework developed by Adams et al. (2021). These authors use quantile regressions to construct quarterly predictive distributions of unemployment around the median forecasts of the Survey of Professional Forecasters (SPF), conditional on a quarterly National Financial Conditions Index. This approach has two limitations: i) it fails to incorporate daily flows of information, which have proven to be valuable for monitoring macroeconomic risks in real time (Ferrara et al., 2021); and ii) it ignores the stable relationship between unemployment and economic activity – Okun’s Law – widely documented in the literature (Okun, 1962; Ball et al., 2017).

We address these two issues by means of a mixed data sampling quantile (Q-MIDAS) model, which conditions unemployment density on the ADS index, a daily indicator of real economic activity developed by Aruoba et al. (2009) and regularly updated by the Federal Reserve Bank of Philadelphia (FRBP). We center our analysis on the Global Financial Crisis (GFC) and the Covid-19 pandemic.

Our primary motivation here is captured by Figure 1, which shows the relationship between quarterly SPF’s forecast errors and the real-time daily ADS index. As can be observed, there is a negative relationship between the two variables, which is more evident in crisis episodes and we show that this relationship can be used to significantly improve the accuracy of nowcasting exercises to inform policy making.

Figure 1. Quarterly SPF's forecast errors and real-time daily ADS index



Sources: FRBP and authors' computation.

Note: Time span 1969-04-01 to 2020-12-31. The daily ADS index is calculated using preliminary estimates as they were released at each point in time, so that nowcast can be made in real-time. Shaded areas represent NBER recessions.

2. Data

We draw on data from real-time survey forecasts of unemployment provided by the quarterly SPF, as conducted by the FRBP. This survey, carried out since 1990:Q3, publishes its forecasts in the middle month of each quarter. For each survey, participants provide quarterly point forecasts for a particular variable for the next five quarters, including the current quarter. Specifically, we use the one-quarter-ahead forecasts for the median unemployment rate from the survey corresponding to the current quarter. For the unemployment rate, which is the target variable, we use the average unemployment rate obtained from the Federal Reserve Bank of St. Louis database (FRED). As for the ADS index, we use weakly vintages starting from November 30, 2008 from the FRBP to conduct the nowcasting exercise. Table 1 shows the description of the daily variables used as additional conditioning variables to construct unemployment nowcasts. Our data sample spans the period from 1969-01-01 to 2020-12-31.

Table 1. Daily variables

| Variable | Description | Source |
|-------------------------------------|-----------------------------------------------------------------------------------------|--------|
| Interest rate spread (ISPREAD) | Interest rate spread between the 10-year government bond rate and the federal fund rate | |
| CBOE S&P 100 Volatility Index (VXO) | Option-based implied volatility measure of S&P100 | FRED |
| Credit spread (CSPREAD) | BAA-AAA corporate bond yield credit spread | |
| ADS | ADS index vintages collected in real-time from November 30, 2008. | FRBP |

Source: Authors' elaboration.

3. Methodology

We extend the methodology developed by Adams et al. (2021) to accommodate daily predictors in a Q-MIDAS framework⁵.

Let $e_{t+1|t}^{SPF}$ denote the one-step-ahead median SPF forecast error, such that $e_{t+1|t}^{SPF} = y_{t+1} - y_{t+1|t}^{SPF}$, where y_{t+1} is the unemployment rate at quarter $t + 1$ and $y_{t+1|t}^{SPF}$ is the one-step-ahead median SPF forecast of y_{t+1} , given the survey conducted at quarter t . Also, $\tilde{\mathbf{X}}_{t+1-h_d}^D$ is a vector of the transformed⁶ high-frequency variable, which contains one-year daily lags up to the latest available information of quarter $t + 1$ (minus h_d days).

In the first step, we estimate a Q-MIDAS model using quantile regressions (Koenker and Bassett, 1987):

$$e_{t+1|t}^{SPF} = \alpha_0(\tau) + \tilde{\mathbf{X}}_{t+1-h_d}^D \boldsymbol{\phi} + \epsilon_t, \quad (1)$$

where $\beta(\tau) = (\alpha_0(\tau), \boldsymbol{\phi})'$ denotes the vector of parameters corresponding to the τ -th quantile, and $\epsilon_t(\tau)$ is a random noise. Notice that the forecast error only depends on the vector of daily information $\tilde{\mathbf{X}}_{t+1-h_d}^D$ which is updated until the last day of the next quarter minus h_d days. In this formulation, the forecast horizon is expressed in high-frequency terms, that is, a given day between quarters t and $t + 1$.

⁵ Details about Q-MIDAS estimation are provided in the Appendix.

⁶ We consider a third-degree Almon lag polynomial with restrictions on the value and slope of the lag polynomial.

The predictive value of Equation 1,

$$\widehat{Q}_\tau(e_{t+1|t}^{SPF} | \widetilde{\mathbf{X}}_{t+1-h_d}^D) = \alpha_0(\tau) + \widetilde{\mathbf{X}}_{t+1-h_d}^D \boldsymbol{\phi}, \quad (2)$$

produces an estimate of the conditional quantile of $e_{t+1|t}^{SPF}$ conditional on the information contained in the high-frequency variable $\widetilde{\mathbf{X}}_{t+1-h_d}^D$ for different $\tau = 0.05, 0.25, 0.75, 0.95$. Then, to construct the predicted quantiles for the target variable y_{t+h} , we add the forecast point $y_{t+h|t}^{SPF}$ available at time t :

$$\widehat{Q}_\tau(y_{t+h} | \widetilde{\mathbf{X}}_{t+1-h_d}^D) = \widehat{Q}_\tau(e_{t+1|t}^{SPF} | \widetilde{\mathbf{X}}_{t+1-h_d}^D) + y_{t+h|t}^{SPF}. \quad (3)$$

In the second step, to construct the full conditional probability distribution from our quantile regression estimates, we follow the methodology proposed by Adrian et al. (2019). We consider Azzalini and Capitanio's (2003) four-parameter skew t-distribution with the probability density function given by:

$$f(y; \mu, \sigma, \alpha, \nu) = \frac{2}{\sigma} t\left(\frac{y-\mu}{\sigma}; \nu\right) * T\left(\alpha \left(\frac{y-\mu}{\sigma}; \nu\right) \sqrt{\frac{\nu+1}{\nu + \frac{y-\mu}{\sigma}}}; \nu + 1\right), \quad (4)$$

where $t(\cdot)$ and $T(\cdot)$ denote the probability density function and cumulative distribution function of the Student's t-distribution, respectively. This distribution is specified by its location μ , scale σ , shape α , and fatness ν . In essence, this distribution allows us to capture fat tails and skewness (see Azzalini and Capitanio, 2003).

Finally, for each quarter, we fit a skew-t distribution by choosing the parameters $(\widehat{\mu}_{t+1}, \widehat{\sigma}_{t+1}, \widehat{\alpha}_{t+1}, \widehat{\nu}_{t+1})$ that minimize the squared differences between our quantile regression estimates and the skew t-implied quantiles for $\tau = 0.05, 0.25, 0.75$, and 0.95 :

$$(\widehat{\mu}_{t+1}, \widehat{\sigma}_{t+1}, \widehat{\alpha}_{t+1}, \widehat{\nu}_{t+1}) = \underset{\mu, \sigma, \alpha, \nu}{\operatorname{argmin}} \sum \left(\widehat{Q}_\tau(y_{t+h} | \widetilde{\mathbf{X}}_{t+1-h_d}^D) - F^{-1}(y; \mu, \sigma, \alpha, \nu) \right)^2. \quad (5)$$

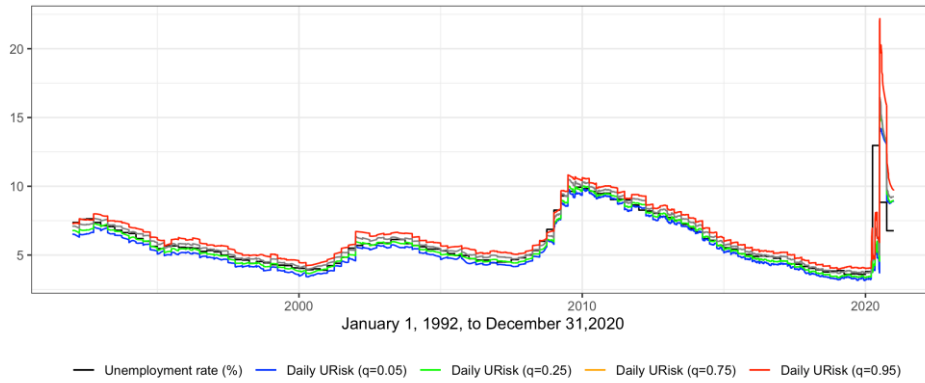
In addition, as a natural benchmark for our estimates, we construct the unconditional predictive distributions based only on the current $y_{t+1|t}^{SPF}$ and the distribution of historical forecast errors (see Reifschneider and Tulip, 2019)⁷.

4. Nowcasting unemployment at risk

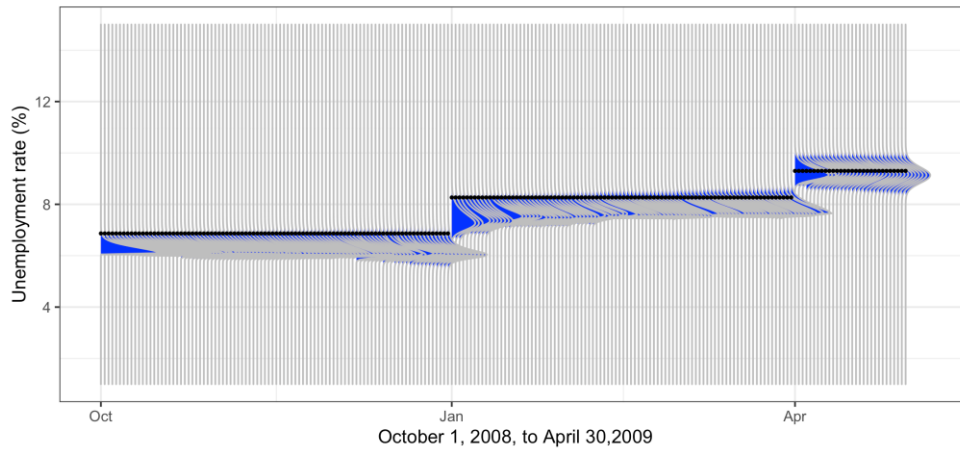
Using the ADS index collected in real-time our nowcasting exercise starts on January 1, 1992. Figure 2 displays the nowcasts results for the historical quantile estimates, the density nowcasts during the GFC, approximately from 2008:Q3 to 2009:Q1, and the Covid-19 pandemic, from 2020:Q1 to 2020:Q3. The historical nowcasts show that our daily quantile estimates capture the dynamic of the unemployment rate (Figure 2a). Particularly, during the first of these events, we observe that the model conditioning on the ADS index precisely captures the upside risks in the unemployment rate as the distribution of our model (blue line) moves to the right (Figure 2b). Likewise, during the second of these events, the density distribution moves significantly to the right after the onset of the pandemic, coinciding with the Federal Reserve Press Release (FOMC, 20). Importantly, in the second quarter, the average unemployment rate spiked at 13%, the highest increase recorded since 1948 (Figure 2c). Also, the asymmetry of shifts in the density forecasts highlights the differences in unemployment risk over the time span of each event. In the appendix, we show the results for the alternative indicators ISPREAD, VXO and CSPREAD.

⁷ Following Adams et al. (2021), we estimate quantile regressions in Equation 1 with only a constant term included in the set of conditioning variables. We then center these estimates around the current $y_{t+1|t}^{SPF}$, and fit the skew t-distribution as in Equation 5.

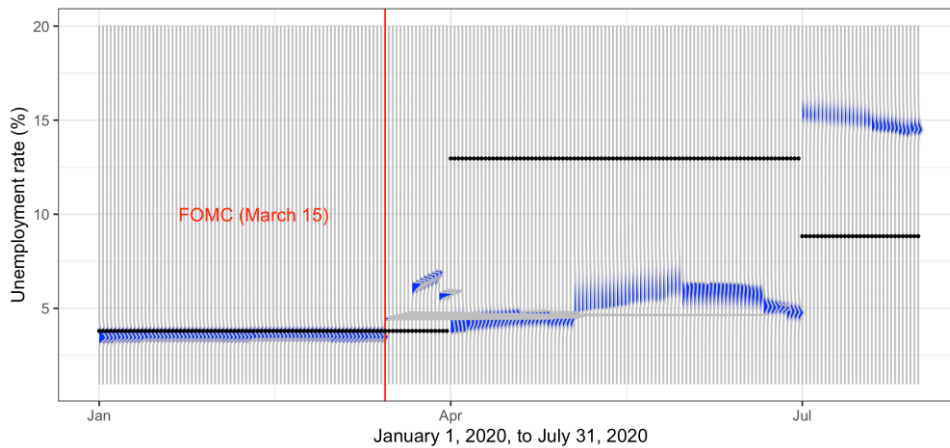
Figure 2. Daily nowcasts of ADS index in real time
a. Historical quantile estimates



b. GFC



c. Covid-19



Sources: FRED and authors' computation.

Note: The blue daily density nowcasts correspond to the model that incorporates the ADS as the high-frequency indicator. The black dots indicate the realized value of the unemployment rate in the given quarter.

To assess the accuracy of our daily unemployment nowcasts, we calculate predictive scores by evaluating the model's density at the realized value of the unemployment rate. Table 2 reports differences in average log predictive scores between the predictive densities

that considers daily predictors and the benchmark distribution of historical forecast errors, for different daily horizons. Positive values indicate a superior average forecasting performance of the densities that incorporate the corresponding daily predictor.

Overall, we find strong support for the superior predictive ability of the ADS index to nowcast the conditional probability distribution of unemployment rate when compared to other daily predictors, for both periods the pre-Covid 19 period and the period including the Covid-19 pandemic (both periods include the GFC). More specifically, it is the only indicator that manages to gauge the increase in unemployment with 40 days' lagged information when the sample period includes the Covid-19 pandemic.

Table 2: Evaluation of out-of-sample nowcasts for different daily horizons

| | $h_d = 0$ | $h_d = 10$ | $h_d = 20$ | $h_d = 40$ | $h_d = 60$ |
|---------------------------------------|--------------|--------------|--------------|--------------|--------------|
| Before COVID-19 (1992Q1 to 2019Q4) | | | | | |
| ISPREAD | -0.025 | -0.026 | -0.021 | -0.021 | -0.029 |
| VXO | -0.296 | -0.385 | -0.142 | -0.100 | -0.118 |
| CSPREAD | -0.023 | -0.016 | -0.011 | -0.018 | -0.011 |
| ADS | 0.157 | 0.169 | 0.178 | 0.143 | 0.152 |
| Including COVID-19 (1992Q1 to 2020Q4) | | | | | |
| ISPREAD | -0.571 | -0.555 | -0.527 | -0.517 | -0.392 |
| VXO | -0.862 | -0.979 | -0.770 | -1.441 | -1.528 |
| CSPREAD | -0.039 | -0.033 | -0.030 | -0.057 | -0.194 |
| ADS | -0.162 | -0.426 | -0.898 | 0.047 | -0.983 |

Note: This table reports differences in average log predictive scores. Column names h_d represent the lag of the high frequency daily information (i.e., minus h_d days before the quarter ends).

4. Conclusions

We construct daily unemployment at risk around consensus forecasts conditional on the ADS business conditions index, using a Q-MIDAS model. Our results suggest that this indicator i) has better nowcasting properties than those provided by daily financial conditioning variables, and ii) provides early signal of unemployment rate increases, especially during episodes of distress. Our results are relevant for risk monitoring and nowcasting purposes of central banks and other institutions.

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APPENDIX

1. Description of the Data

Table A1 presents a detailed description of the daily indicators used from January 1, 1970 to December 31, 2020. In the case of the VXO and CSPREAD, pre-1986 information is unavailable in the corresponding websites. Thus, in the first case, following Bloom (2009), the daily VXO is calculated as the 20-day standard deviation of the S&P500 index normalized to the same mean and variance as the VXO index when they overlap from 1986 onward. In the second case, we use the information provided in the online appendix of Lima et al. (2020).

Table A1. Daily variables

| Variable | Description | Source |
|-------------------------------------|-----------------------------------------------------------------------------------------|-----------------------------------|
| Interest rate spread (ISPREAD) | Interest rate spread between the 10-year government bond rate and the federal fund rate | |
| CBOE S&P 100 Volatility Index (VXO) | Option-based implied volatility measure of S&P100 | Federal Reserve Bank of St. Louis |
| Credit spread (CSPREAD) | BAA-AAA corporate bond yield credit spread | |
| ADS | ADS index vintages collected real-time from November 30, 2008. | FRBP |

Source: Author's elaboration.

2. Methodology

2.1. Parameter proliferation problem

Let $e_{t+1|t}^{SPF}$ denote the one-step-ahead median forecast error from the SPF, such that $e_{t+1|t}^{SPF} = y_{t+1} - y_{t+1|t}^{SPF}$, where y_{t+1} is the unemployment rate at quarter $t + 1$ and $y_{t+1|t}^{SPF}$ is the one-step-ahead median SPF forecast of y_{t+1} , given the survey conducted at quarter t . $\mathbf{X}_{t+1}^D = (x_{t+1}^1, x_{t+1}^2, \dots, x_{t+1}^p)'$ is a $p * 1$ vector of the high-frequency variable available on a daily basis, with $x_{t+1}^j, j = (1, 2, \dots, p)$, which is observed d times between quarter $t + 1$ and t . In this setup, we consider that conditional quantile of $e_{t+1|t}^{SPF}$ is affected by up to one year ($q = 4$ quarters) of past daily shocks of \mathbf{X}_{t+1}^D , giving a total number of parameters (including the

constant) approximately equal to $K = q * d + 1 = 4 * 60 + 1 = 241$, assuming a five-day working week ($d = 60$ days); that is, $\mathbf{X}_{t+1}^D = (x_{t+1}^1, x_{t+1-\frac{1}{60}}^2, \dots, x_{t+1-\frac{239}{60}}^{240})'$. Note that the number of parameters K is relatively larger than the total number of observations T , so we are faced with a parameter proliferation problem, which invalidates the standard estimation procedure of the quantile regression.

2.2. MIDAS quantile

In this context, the mixed data sampling quantile (Q-MIDAS) model offers an effective solution to incorporate high-frequency indicators, which relies on a restriction of the form in which the distributed lags of the high frequency variable are included in the regression. Specifically, we consider the Almon lag polynomial⁸ as in other recent works (Lima et al., 2020; Mogliani and Simoni, 2021; Ferrara et al., 2021).

Let X_{t+1}^D follows the Almon lag polynomial given by:

$$B(L\bar{a}; \boldsymbol{\theta}_j(\tau)) = \sum_{i=0}^{p-1} b(i; \boldsymbol{\theta}_j(\tau)) L\bar{a}^i x_{t+1}^j, \quad (1)$$

where $L\bar{a}^i x_{t+1}^j = x_{t+1-\frac{i}{d}}^j$ works as a daily lag operator and $b(i; \boldsymbol{\theta}_j(\tau)) = \sum_{k=0}^{c-1} \theta_{k,j} i^k$ is the weighting function that depends on the vector of parameters $\boldsymbol{\theta}_j(\tau)$, the lag order $i = (1, 2, \dots, p)$, and the order of the Almon lag polynomial given by c .

Thus, the $p * 1$ vector of the high-frequency variable X_{t+1}^D , can be transformed based on the following polynomial weighting matrix:

$$Q = \begin{pmatrix} 1 & 1 & 1 & \dots & 1 \\ 1 & 2 & 3 & \dots & p^1 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 1^{c-1} & 2^{c-1} & 3^{c-1} & \dots & p^{c-1} \end{pmatrix}.$$

By multiplying $Q * X_{t+1}^D$ we get the vector of transformed daily predictors $\tilde{\mathbf{X}}_{t+1}^D$, which enters into our quantile framework. In our specification, we set $c = 3$ (third degree Almon lag), and

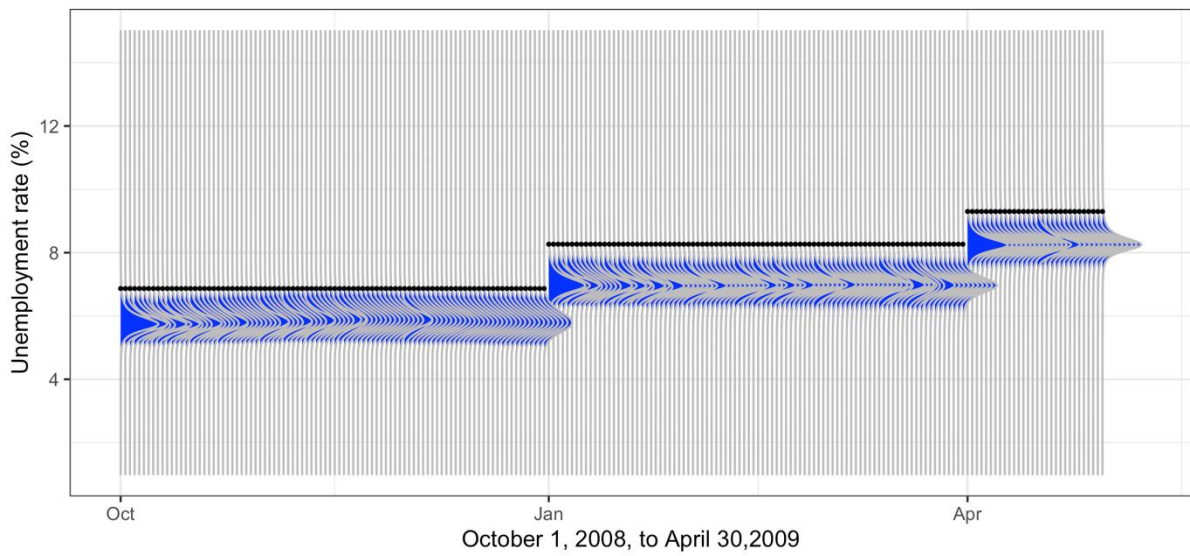
⁸ Since at least Pettenuzzo et al. (2016) many works in the literature have chosen to use the Almon lag polynomial for MIDAS, since it is parsimonious and linear in the parameters (Pettenuzzo et al., 2016; Lima et al., 2020; Mogliani and Simoni, 2021; Ferrara, 2021).

we impose two zero restrictions ($r = 2$) on the slope and value of the lag polynomial, following Mogliani and Simoni (2021). This last causes the weighting structure to slowly reduce to zero. Consequently, the number of parameters to be estimated reduces substantially from $p + 1$ to $c + 1 - r$ parameters.

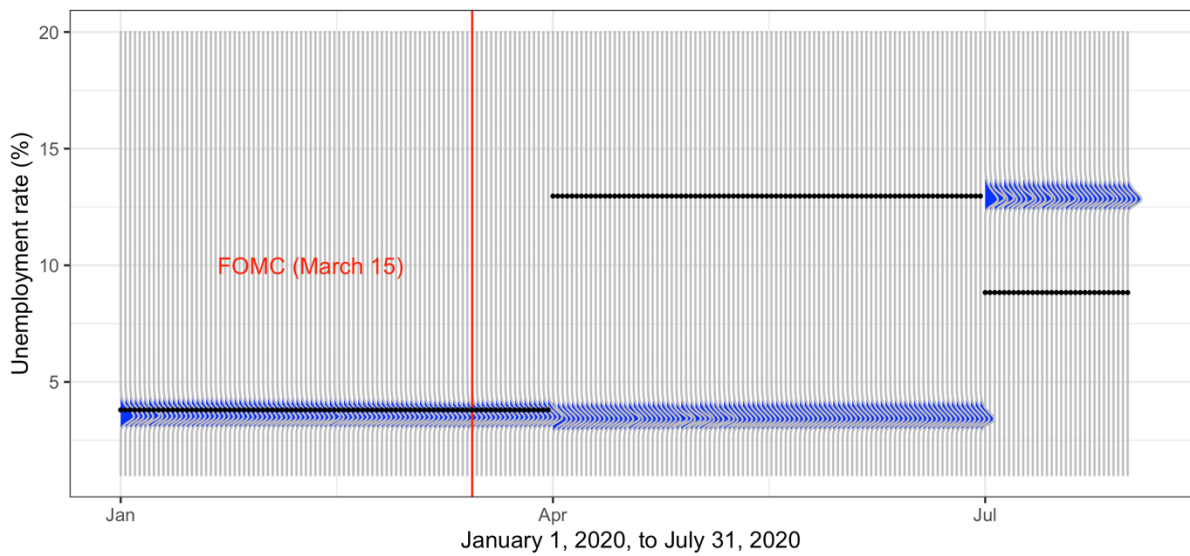
3. Results

Figures A1 to A3 display the daily density nowcasts for the model that incorporates either the ISPREAD, VXO or CSPREAD as the high-frequency indicator around two events, respectively: i) the Global Financial Crisis (GFC) from 2008Q1 to 2009Q4 and, ii) the Covid 19 pandemic from 2019Q4 to 2020Q4 (the last date in our sample).

Figure A1. Nowcasts for ISPREAD model
a. GFC



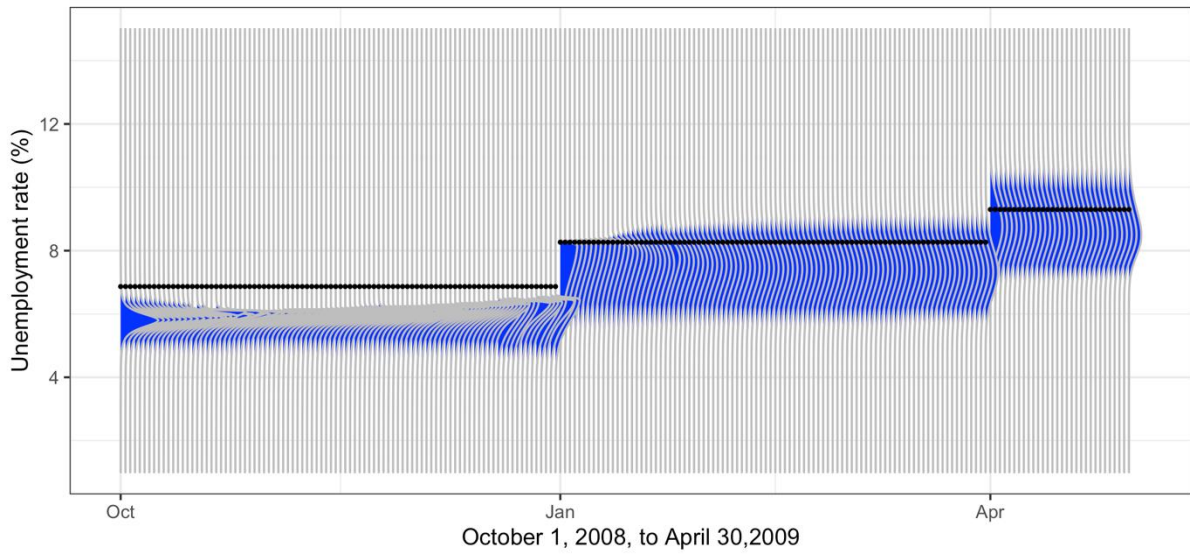
b. Covid-19



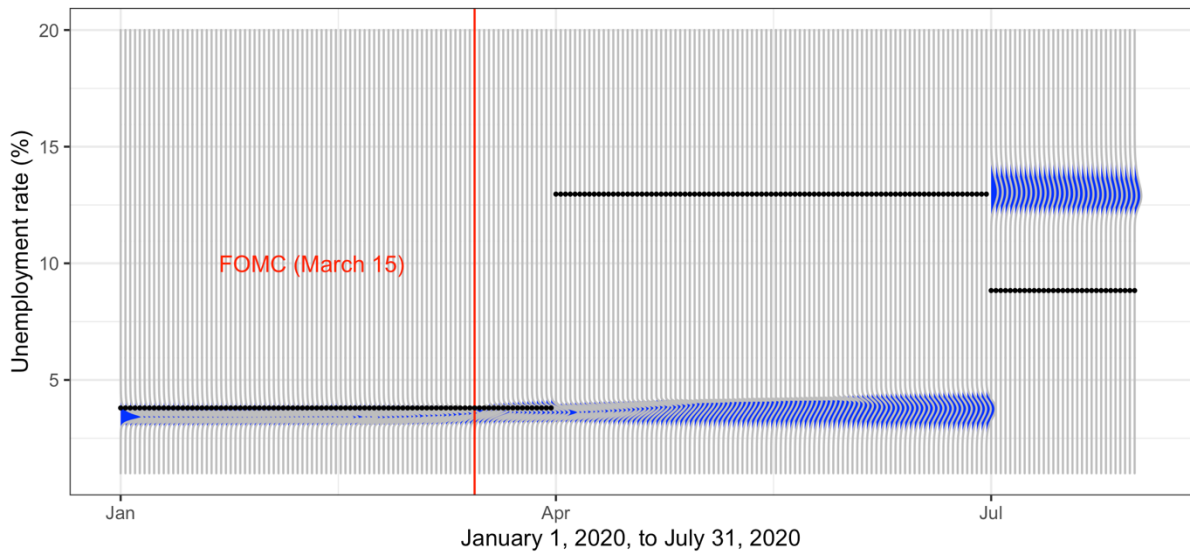
Sources: FRED database and author's computation.

Note: The blue daily density nowcasts correspond to the model that incorporates the ISPREAD as the high-frequency indicator. The black dots indicate the realized value of the unemployment rate in the given quarter.

Figure A2. Nowcasts for VXO model
a. GFC



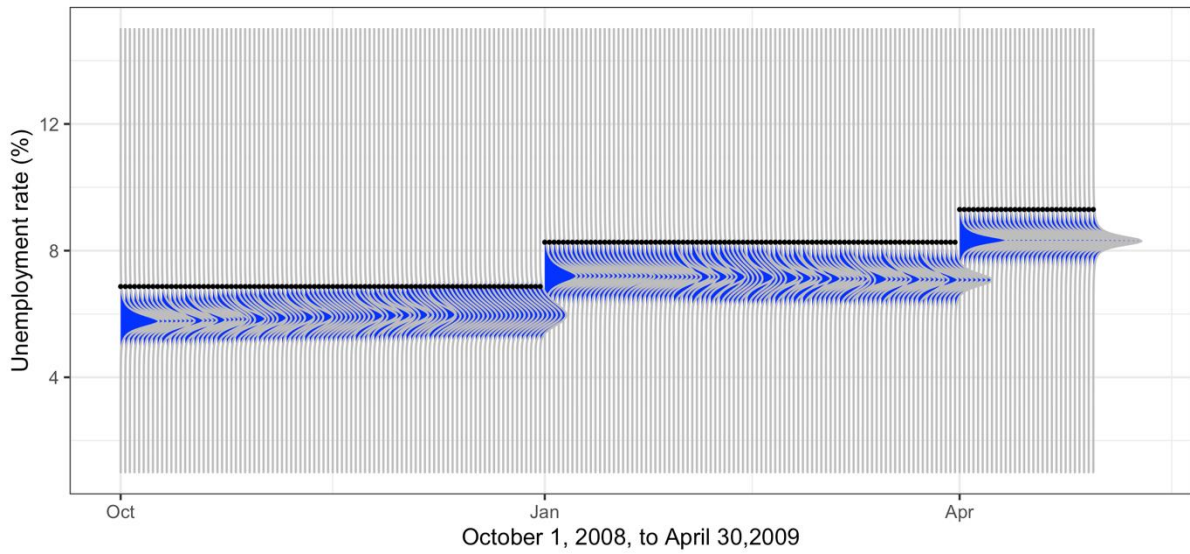
b. Covid-19



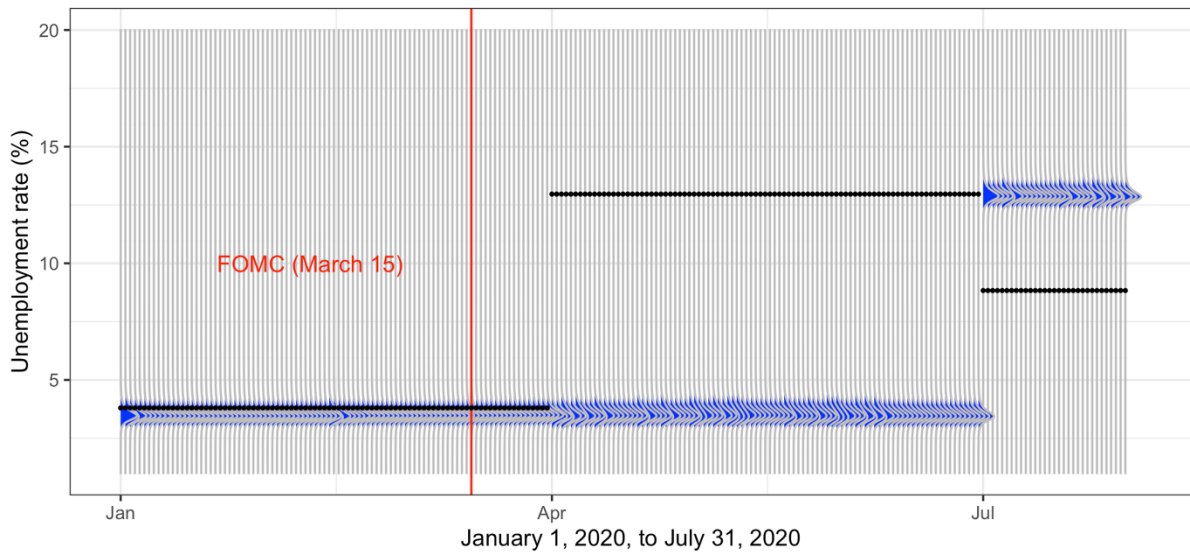
Sources: FRED database and author's computation.

Note: The blue daily density nowcasts correspond to the model that incorporates the VXO as the high-frequency indicator. The black dots indicate the realized value of the unemployment rate in the given quarter.

Figure A3. Nowcasts for CSPREAD model
a. GFC



b. Covid-19



Sources: FRED database and author's computation.

Note: The blue daily density nowcasts correspond to the model that incorporates the CSPREAD as the high-frequency indicator. The black dots indicate the realized value of the unemployment rate in the given quarter.

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A large, decorative background pattern consisting of numerous thin, parallel lines that form a circular shape, centered in the lower half of the page. The lines are light blue and create a subtle, textured effect against the darker blue background.