This appendix provides additional details and supporting evidence for "Tracking Weekly State-Level Economic Conditions." Section A describes the estimation algorithm for the mixed-frequency dynamic factor model and specifies the prior choices. Section B takes a closer look at the benefits of using a rich cross section of indicator variables for the construction of state-level economic conditions indices and examines the role of newly available high-frequency data that provide timely information but have been available only since January 2020. Section C presents an illustration of how the time-varying posterior density of economic weakness can be used for risk assessment.

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A Dynamic Factor Model with Three Mixed Frequencies

Let $\theta = (\psi^q, \psi^m, \psi^w, \sigma^q, \sigma^m, \sigma^w, \lambda^q, \lambda^m, \lambda^w, \phi)'$ be a vector containing all the parameters involved in the dynamic factor model described by equations (5)-(7) in Section 2.1, where superscripts $q$, $m$, and $w$ indicate parameters associated with quarterly, monthly, and weekly indicators. In particular, $\psi_j^q = (\psi_{j,1}^q, ..., \psi_{j,p_q})'$, $\psi_j^m = (\psi_{j,1}^m, ..., \psi_{j,p_m})'$ and $\psi_k^w = (\psi_{k,1}^w, ..., \psi_{k,p_w})'$ contain the autoregressive coefficients of the idiosyncratic terms associated with $i^{th}$ quarterly, $j^{th}$ monthly, and $k^{th}$ weekly variables, respectively, and $\sigma^q$, $\sigma^m$, and $\sigma^w$ denote the corresponding innovation variances. Accordingly, we have that $\psi^q = (\psi_1^q, ..., \psi_n^q)'$, $\psi^m = (\psi_1^m, ..., \psi_n^m)'$ and $\psi^w = (\psi_1^w, ..., \psi_n^w)'$ for the autoregressive coefficients, and $\sigma^q = (\sigma_1^q, ..., \sigma_n^q)'$, $\sigma^m = (\sigma_1^m, ..., \sigma_n^m)'$ and $\sigma^w = (\sigma_1^w, ..., \sigma_n^w)'$ for the innovation variances. Similarly, the factor loadings linking the quarterly, monthly, and weekly variables with the common factor $f_t$ are collected in $\lambda^q = (\lambda_{1}^q, ..., \lambda_{n}^q)'$, $\lambda^m = (\lambda_{1}^m, ..., \lambda_{n}^m)'$, $\lambda^w = (\lambda_{1}^w, ..., \lambda_{n}^w)'$, respectively. The autoregressive coefficients of the common factor are collected in $\phi = (\phi_1, ..., \phi_p)'$.

Let $Y = [y_1, y_2, ..., y_T]$ denote the entire set of information on the data of economic variables at the quarterly, monthly, and weekly frequencies, in that order. $\xi_t$ is the state vector defined in (8) that collects all the latent variables in the model. The Bayesian method used to estimate the proposed dynamic factor model is based on the Gibbs sampler and can be summarized in two broad steps. First, generate a draw of $\xi_t$, conditional on $\theta$ and $Y$. Second, generate a draw of $\theta$, conditional on $\xi_t$ and $Y$. These two steps are sequentially repeated for a large number of iterations. The collection of those draws constitutes the posterior density associated with each element of the model. From these posterior densities, point estimates of the parameters and latent variables, along with the corresponding credible sets, can be easily obtained. In what follows, we describe in detail each step of the estimation algorithm and the chosen priors.

1. Sample latent variables

Conditional on the parameters $\theta$ and the data $Y$, the Carter and Kohn (1994) algorithm is used to generate inferences on $\xi_t$ by using the state-space representation (9)-(10). The time-varying matrix of coefficients corresponding to the observation equation is given by

$$H_t = \begin{bmatrix} H_{qt}^q \\ H_{mt}^m \\ H_{wt}^w \end{bmatrix},$$

where the first entry contains the rows associated with indicators at the quarterly frequency,

$$H_{qt}^q = \begin{bmatrix} \frac{\lambda_{q1}^q}{d(q_1)} 1'_{[d(q_1)]} & 0'_{[D-d(q_1)]} & 0'_{[D-d(q_1)]} & \cdots & 0'_{[d(q_1)]} & 0'_{[D-d(q_1)]} & 0'_{[C_n^m+p_w+n^w]} \\
\frac{\lambda_{q2}^q}{d(q_2)} 1'_{[d(q_2)]} & 0'_{[D-d(q_2)]} & 0'_{[D-d(q_2)]} & \cdots & 0'_{[d(q_2)]} & 0'_{[D-d(q_2)]} & 0'_{[C_n^m+p_w+n^w]} \\
\vdots & \vdots & \vdots & \ddots & \vdots & \vdots & \vdots \\
\frac{\lambda_{qN}^q}{d(q_N)} 1'_{[d(q_N)]} & 0'_{[D-d(q_N)]} & 0'_{[D-d(q_N)]} & \cdots & 1'_{[d(q_N)]} & 0'_{[D-d(q_N)]} & 0'_{[C_n^m+p_w+n^w]} \end{bmatrix}.$$
Recall that \( d(q) \) indicates the number of weeks falling in quarter \( q \) and \( D \equiv \max(d(q)) \) denotes the largest number of weeks in a quarter. Similarly, \( c(m) \) indicates the number of weeks falling in month \( m \) and \( C \equiv \max(c(m)) \) denotes the largest number of weeks in a month.\(^2\)

The second entry of \( \mathbf{H}_t \) contains the rows associated with monthly indicators,

\[
\mathbf{H}_t^m = \begin{bmatrix}
\frac{\lambda_1^n}{c(m)} \mathbf{1}^{c(m)} & \mathbf{0}^{[D(1+n^n)-c(m)]} & \frac{1}{c(m)} \mathbf{0}^{[C-c(m)]} & \cdots & \mathbf{0}^{[c(m)]} & \mathbf{0}^{[C-c(m)]} & \mathbf{0}^{[\text{period}]} \\
\frac{\lambda_2^n}{c(m)} \mathbf{1}^{c(m)} & \mathbf{0}^{[D(1+n^n)-c(m)]} & \mathbf{0}^{[C-c(m)]} & \cdots & \mathbf{0}^{[c(m)]} & \mathbf{0}^{[C-c(m)]} & \mathbf{0}^{[\text{period}]} \\
\vdots & \vdots & \vdots & \ddots & \vdots & \vdots & \vdots \\
\frac{\lambda_n^n}{c(m)} \mathbf{1}^{c(m)} & \mathbf{0}^{[D(1+n^n)-c(m)]} & \mathbf{0}^{[C-c(m)]} & \cdots & \mathbf{0}^{[c(m)]} & \mathbf{0}^{[C-c(m)]} & \mathbf{0}^{[\text{period}]} \\
\end{bmatrix},
\]

while the third entry refers to the rows associated with indicators at the weekly frequency,

\[
\mathbf{H}_t^w = \begin{bmatrix}
\lambda_1^w & \mathbf{0}^{[D(n^w+1)+Cn^w+\text{period}]} \\
\lambda_2^w & \mathbf{0}^{[D(n^w+1)+Cn^w+\text{period}]} \\
\vdots & \vdots \\
\lambda_n^w & \mathbf{0}^{[D(n^w+1)+Cn^w+\text{period}]} \\
\end{bmatrix}.
\]

The matrix of coefficients corresponding to the state equation can be defined as follows,

\[
\mathbf{F} = \begin{bmatrix}
\mathbf{F}^f \\
\vdots \\
\mathbf{F}^m \\
\end{bmatrix},
\]

where the entry that contains the law of motion of the common factor is given by

\[
\mathbf{F}^f = \begin{bmatrix}
\phi_1 & \phi_2 & \cdots & \phi_p & \mathbf{0}^{[D-p]} \\
1 & 0 & \cdots & 0 & \mathbf{0}^{[D-p]} \\
\vdots & \vdots & \ddots & \vdots & \vdots \\
0 & 0 & \cdots & 1 & \mathbf{0}^{[D-p]} \\
\mathbf{0}^{[p]} & 1 & \mathbf{0}^{[D-p]} \\
\mathbf{0}^{[p+1]} & 1 & \mathbf{0}^{[D-p]} \\
\mathbf{0}^{[p+(D-p-2)]} & 1 & \mathbf{0}^{[D-p]} \\
\end{bmatrix}.
\]

\(^2\)The terms \( \mathbf{0}_{[a]} \) and \( \mathbf{1}_{[b]} \) denote vectors of zeros and ones of size \( a \) and \( b \), respectively.
The entries that involve the autoregressive coefficients of the idiosyncratic terms are given by

\[
F_{i}^q = \begin{bmatrix}
\psi_{i,1}^q & \psi_{i,2}^q & \cdots & \psi_{i,pq}^q & 0'_{D-pq}
1 & 0 & \cdots & 0 & 0'_{D-pq}
\vdots & \vdots & \ddots & \vdots & \vdots
0 & 0 & \cdots & 1 & 0'_{D-pq}
0'_{pq} & 1 & \cdots & \cdots & \cdots
0'_{pq+1} & 1 & \cdots & \cdots & \cdots
\vdots & \vdots & \ddots & \vdots & \vdots
0'_{pq+(D-pq-2)} & 1 & 0 & \cdots & \cdots
\end{bmatrix},
\]

for the \(i^{th}\) quarterly indicator, by

\[
F_{j}^m = \begin{bmatrix}
\psi_{j,1}^m & \psi_{j,2}^m & \cdots & \psi_{j,p_m}^m & 0'_{C-p_m}
1 & 0 & \cdots & 0 & 0'_{C-p_m}
\vdots & \vdots & \ddots & \vdots & \vdots
0 & 0 & \cdots & 1 & 0'_{C-p_m}
\end{bmatrix},
\]

for the \(j^{th}\) monthly indicator, and by

\[
F_{k}^w = \begin{bmatrix}
\psi_{k,1}^w & \psi_{k,2}^w & \cdots & \psi_{k,p_w}^w
1 & 0 & \cdots & 0
\vdots & \vdots & \ddots & \vdots
0 & 0 & \cdots & 0
\end{bmatrix}
\]

for the \(k^{th}\) weekly indicator.\(^3\)

2. Sample parameters

Conditional on the state variable \(\xi_t\) and the data \(Y\), draws for each set of parameters are generated as follows.

2.1 Sample idiosyncratic autoregressive coefficients

To sample \(\psi_{k}^{w}\) we use a Normal prior distribution, \(N(\alpha_{\psi}, \Sigma_{\psi})\), with \(\alpha_{\psi} = 0_{p_w}\) and \(\Sigma_{\psi} = I_{p_w}\), and generate draws from the posterior density

\[
\psi_{k}^{w} | \sigma_{k}^{w}, u_{k,t}^{w}, Y \sim N(\overline{\alpha}_{\psi}, \overline{\Sigma}_{\psi}),
\]

where the expressions for the posterior mean and variance are given by

\[
\overline{\alpha}_{\psi} = (\Sigma^{-1}_{\psi} + X^{*}X^{*})^{-1}(\Sigma^{-1}_{\psi} \alpha_{\psi} + X^{*}Y^{*})
\]

\[
\overline{\Sigma}_{\psi} = (\Sigma^{-1}_{\psi} + X^{*}X^{*})^{-1},
\]

\(^3\)The term \([0]\) makes reference to all the zero entries required to make the matrix conformable.
with \( Y^* = \{ y_t \}^T_{t=p_w+1}, X^* = \{ x_t \}^T_{t=p_w} \), and 
\( y_t^* = \frac{u_{w,t}^*}{\sqrt{\sigma_k^w}}, x_t^* = \left( \frac{u_{w,t-1}^*}{\sqrt{\sigma_k^w}}, \ldots, \frac{u_{w,t-p_w}^*}{\sqrt{\sigma_k^w}} \right)^T \).

Note that conditional on the generated draws of the idiosyncratic terms associated
with the quarterly and monthly variables, the same procedure can be applied to sample \( \psi_k^m \) and \( \psi_k^q \). We use the same prior distribution to sample \( \psi_k^m \) and \( \psi_k^q \), that is, \( N(\alpha_k, \Sigma_k) \), with \( \alpha_k = 0 \) and \( \Sigma_k = I \).

2.2 Sample idiosyncratic innovation variances

To sample \( \psi_k^w \) we use an Inverse Gamma prior distribution, \( IG(\tau, \eta) \), with \( \tau = 10 \) and \( \eta = 0.1 \), and generate draws from the posterior density

\[
\sigma_k^w | \psi_k^w, u_{k,t}, Y \sim IG(\tau, \eta),
\]

where the corresponding shape and scale parameters are given by

\[
\tau = \frac{\tau + T}{2}, \quad \eta = \left( \frac{\eta + \varepsilon_k^w}{2} \right)^{-1}
\]

with \( \varepsilon_k^w = u_{k,t} - \psi_k^w u_{k,t-1} - \cdots - \psi_k^w u_{k,p_w} \) and where \( T \) denotes the sample size.\(^5\) Similar to Step 2.1, the same procedure used to generate \( \sigma_k^w \) is employed to sample draws of \( \sigma_j^m \) and \( \sigma_j^q \), using the same prior distribution.

2.3 Sample factor loadings

Conditional on the common factor and idiosyncratic terms, the factor loadings contained
in \( \lambda^w \) are sampled independently for each weekly variable using a Normal prior distribu-
tion \( N(\alpha_\lambda, \Sigma_\lambda) \) with \( \alpha_\lambda = 0 \) and \( \Sigma_\lambda = 1 \). The draws are generated from the posterior density

\[
\lambda_k^w | f_t, u_{k,t}, \psi_k^w, \sigma_k^w, Y \sim N(\bar{\alpha}_\lambda, \bar{\Sigma}_\lambda)
\]

where the posterior mean and variance are given by

\[
\bar{\alpha}_\lambda = \left( \Sigma_\lambda^{-1} + X^T Y \right)^{-1} \left( \Sigma_\lambda^{-1} \alpha_\lambda + X^T Y \right), \quad \bar{\Sigma}_\lambda = \left( \Sigma_\lambda^{-1} + X^T Y \right)^{-1}
\]

with \( Y^T = \{ y_t \}^T_{t=p_w+1}, X^T = \{ x_t \}^T_{t=p_w+1} \), and 
\( y_t^T = \frac{u_{w,t}^*}{\sqrt{\sigma_k^w}}, x_t^T = \frac{u_{w,t-1}^*}{\sqrt{\sigma_k^w}}, \ldots, \frac{u_{w,t-p_w}^*}{\sqrt{\sigma_k^w}} \). Following Antolín-Díaz, Drechsel, and Petrella (2017), draws for \( \lambda^m \) and \( \lambda^q \) are generated using GLS, and relying on the same prior distribution as for the case of \( \lambda^w \).

\(^4\)A similar approach is pursued by Antolín-Díaz, Drechsel, and Petrella (2017) when estimating a factor model that includes variables at the quarterly and monthly frequencies.

\(^5\)In the empirical application, we choose slightly different values for \( \tau \) and \( \eta \) for a few U.S. states to accommodate state-specific idiosyncracies.
2.4 Sample factor autoregressive coefficients

To generate draws of $\phi$, we use the Normal prior distribution $N(\alpha_\phi, \Sigma_\phi)$ where $\alpha_\phi = 0_{p_f}$ and $\Sigma_\phi = I_{p_f}$. Accordingly, draws are sampled from

$$\phi | f_t, Y \sim N(\bar{\alpha}_\phi, \bar{\Sigma}_\phi)$$

where the moments of the posterior distribution are given by

$$\bar{\alpha}_\phi = \left( \Sigma_\phi^{-1} + X^T Y \right)^{-1} (\Sigma_\phi^{-1} \phi_\phi + X^T Y)$$

$$\bar{\Sigma}_\phi = \left( \Sigma_\phi^{-1} + X^T Y \right)^{-1}$$

with $Y = \{ f_{t+1} \}_{t=p_f+1}^T$, $X = \{ x_{t+1} \}_{t=1}^{T-p_f}$, and $x_{t+1} = (f_{t-1}, \ldots, f_{t-p_f})'$.

**B A Closer Look at the Composition of Economic Conditions Indices and the Role of New Series**

Apart from providing a more timely assessment of ongoing economic developments, indices constructed from variables that cover various forms of economic activity also offer a more complete characterization of latent "economic conditions." As emphasized by Stock and Watson (1989), the selection of variables to use as the components of activity indices is key to producing a reliable summary measure of the current state of the economy.

**B.1 The Benfits of a Rich Cross Section of Data**

To fully appreciate the value of a broader cross section of data that spans multiple dimensions of state economies, we compare our state-level economic conditions indices to a weekly equivalent of the Philadelphia Fed’s state-level indices. Specifically, we mimic the composition of the Philadelphia Fed indices by relying on the following four input series: quarterly real wage and salary income, monthly total nonfarm employment, the monthly unemployment rate, and weekly initial unemployment insurance claims. While the first three series are the same as in the Philadelphia Fed state indices, we replace the fourth series, monthly average hours worked in manufacturing, with weekly initial jobless claims for several reasons. First, with the switch from the Standard Industrial Classification System (SIC) to the North American Industrial Classification System (NAICS) in January 2001, average hours worked in manufacturing are no longer publicly available before 2001 at the state level. While our estimation framework is designed to handle series entering mid-stream, by excluding average hours worked, we obtain a balanced panel which corresponds to the setting used in Crone and Clayton-Matthews (2005) that forms the blueprint for the Philadelphia Fed indices.\(^\text{7}\)

\(^6\)Note that the variance of the factor innovations is set to $\omega = 1$ for identification purposes (see Bai and Wang, 2015).

\(^7\)It is quite common in this literature to work with a gradually expanding cross section of underlying economic variables over time in both single- and mixed-frequency settings (see, e.g., Aruoba et al., 2009; Camacho and Pérez-Quirós, 2010; Antolin-Díaz et al., 2017, 2021; Baumeister et al., 2020).
Second, since our empirical approach requires an observed indicator at the base frequency, we select weekly initial jobless claims given that this series was chosen as the key weekly indicator variable in the mixed-frequency model of Aruoba, Diebold, and Scotti (2009) at the national level.

Figure 1A plots our weekly economic conditions indices (ECIs) against the weekly replica of the Philadelphia Fed indices for a selected set of U.S. states from April 1987 to February 2021. The cyclical dynamics implied by the smaller and larger datasets are qualitatively similar for the most part. However, the indices obtained with the smaller cross section of input series track economic developments with some delay compared to our broad-based indices. Some higher-frequency divergence stemming from the different information content of both indices is also readily apparent for New York and Pennsylvania, but less so for other states over this extended period of time.

Since we are not only interested in the overall cyclical movements, but mainly in the timely and reliable assessment of state-level economic performance week-by-week, we zoom into some subperiods to get a better sense of how much the composition of the information set matters for that. Figure 2A compares the weekly ECIs for Texas, Oklahoma, and California with the Philadelphia Fed replica during three specific periods. The first period focuses on the economic collapse triggered by the COVID-19 pandemic and the initial recovery phase (2020.1-2021.2); the second period covers the financial crisis, the Great Recession, and the recovery (2007.1-2011.1); and the third period spans the boom-and-bust years of the U.S. shale oil revolution (2011.6-2017.6).

During the COVID-19 episode, the main difference between the two indices lies in the magnitude of the contraction. While labor market developments played a central role during the pandemic, they are insufficient to capture the full extent of the economic fallout experienced by Texas (panel A) and California (panel C). In contrast, the additional information on which the ECI is based makes little difference for Oklahoma (panel B) during this period. This is not entirely surprising given the evidence presented in Figure 2 which shows that the key driver of Oklahoma’s downturn was indeed the labor market. The feature that stands out during the period of the Great Recession is that our economic conditions indices signal slowdowns and troughs earlier relative to the labor-based indices on a weekly basis. For example, the ECI for Texas shows a rapid deterioration in the second half of 2008 and reaches its trough at the end of the recession while the labor-only index lags behind by several months. The ECI for California also reaches the trough earlier and displays a faster rebound with economic conditions being about half a percentage point better compared to the alternative index throughout 2010. The value of an extended dataset that includes measures for state-specific characteristics (e.g. resource richness) is particularly evident during the shale oil cycle. The small-scale indices miss the beneficial effects of rising oil production for economic conditions both in Texas and Oklahoma during 2012-2013. The timing of worsening economic conditions reflected in the ECI for Texas is also more in line with developments in oil markets compared to the labor-only index. In sum, the more diversified cross section provides a more nuanced picture of weekly variations in economic conditions across states.

The analysis so far suggests that moving beyond variables pertaining to the labor market is critical for accurately assessing the severity of downturns and the speed and magnitude of recoveries.
Among the indicators missing from the Philadelphia Fed replica, real GDP is arguably a particularly informative variable since it is the most comprehensive measure of economic activity at the state level. It is therefore likely that some of the differences between our economic conditions indices and the ones based exclusively on labor market variables can be attributed to information contained in real GDP. One way to assess this is by looking at the correlation of the small-scale indices with state-level real GDP growth. We find that for states where the labor-based indices are weakly correlated with GDP, the differences between the two indices are larger compared to the case where the labor-based indices are highly correlated with GDP. For example, among the six states, California, which displays the smallest overall difference across both indices, has the highest correlation coefficient of 0.87. For Oklahoma, Illinois, and Texas, deviations of the Philadelphia Fed replica from our economic conditions indices are more visible in accordance with considerably lower correlations with real GDP which range from 0.66 to 0.77. Pennsylvania and New York show notable differences between the two indices that can again be linked to the low correlation with real GDP, which for Pennsylvania is 0.59 and for New York is -0.11. While it might seem surprising that the labor-based index is negatively correlated with real GDP for New York, this finding is consistent with evidence provided by Chinn and LeCloux (2018). They attribute this finding to the prevalence of the financial service industry in the greater New York City area that is not well captured by traditional labor market indicators. This analysis points in favor of including state-level real GDP into our dataset despite the fact that it only becomes available in 2005.

A related question is how well the model performs in dealing with the missing observations for real GDP over the period 1987-2005. Given that the Kalman filter provides an optimal estimate of the state vector, we can replace the missing observations with projections using equation (10). Figure 3A presents estimates of weekly real GDP growth at an annual rate for the same set of states as in Figure 1 together with weekly national real GDP growth at an annual rate for the entire sample. The estimated weekly series for state-level real GDP before and after 2005 are well aligned with the broad cyclical patterns at the national level. This evidence lends credibility to the estimates of the missing observations for real GDP as well as the economic conditions indices.

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8 Since we obtain a weekly estimate of real GDP growth using our baseline model, we compute correlation coefficients between the weekly small-scale indices and weekly real GDP. We restrict the sample to start in 2006Q1, when the first actual observation for annual growth of state-level real GDP becomes available, and to end in 2019Q4 to exclude the COVID-19 period, which uniformly increases the correlation for obvious reasons.

9 They report a correlation coefficient of -0.28 for New York between the standard Philadelphia Fed coincident index aggregated to a quarterly frequency and quarterly state-level real GDP growth at an annual rate over the period 2005-2017. They argue that New York and other states whose economies feature a high concentration in finance do not show any significant correlation between the labor-based coincident indicators and real GDP.

10 While real gross state product at the annual frequency is available further back in time and our mixed-frequency framework could be extended to include variables with yearly observations, Crone and Clayton-Matthews (2005) note that annual data are useful for assessing trend growth but do not lend themselves as indicators of business cycles.
B.2 The Value Added of High-Frequency Data on Mobility and Consumer Spending

One of the unique aspects of our state-level dataset is that it contains newly available high-frequency indicators, namely a weekly mobility index derived from the relative volume of direction requests in Apple Maps and a weekly measure of consumer spending based on credit and debit card transactions. Chetty et al. (2020), Fernández-Villaverde and Jones (2020), and Lewis et al. (2021) provide convincing evidence that mobility measures and credit card spending carry valuable information about the rapid economic decline in the early stages of the COVID-19 crisis. Given the unusual nature of the economic forces at work during the pandemic, these non-standard series potentially allow for a more timely reading of economic conditions compared to more traditional indicators. However, both series have an extremely short history, becoming available only in the week ending on January 18, 2020. This raises two related empirical questions. The first question is whether adding two time series with such a short time span of observations exerts an undue influence on the estimates of state-level economic conditions before these data were available. The second question is how much value their inclusion adds to quantifying state-level economic conditions after the onset of the pandemic.

To provide an answer to both questions, we re-estimated the models for all 50 U.S. states excluding these two input series and compared the resulting weekly indices to our baseline economic conditions indices. Figure 4A shows a scatter plot of the average absolute difference between the two weekly indices for the period before and after the availability of the two novel variables. For about half of the U.S. states, the absolute deviations across indices with and without these high-frequency data are small on average for both periods—with most points being concentrated in the lower left corner—but they are always larger for the more recent period when these data are observed. There are several states that display larger average variation as a result of the inclusion of data on mobility and credit card spending, but mostly in the post-2020 period when this information is expected to matter. In other words, while the points are somewhat spread out along the x-axis, which reports the differences after January 18, 2020, they are all well below the 45-degree line.

We now examine in greater detail how the inclusion of these novel indicators impacts our assessment of the prevailing economic conditions. We do so by comparing the weekly indices with and without the data on mobility and consumer spending for a subset of U.S. states, singled out by the various shapes in red in Figure 4A, over the period 2020.2-2021.2. Figure 5A illustrates that adding these high-frequency variables proves to be extremely useful for accurately tracking the magnitude and speed of economic developments across states over the course of the pandemic. For example, for North Carolina, the state with the largest average absolute difference post-2020, the plot shows that this difference derives from the asynchronous behavior of both indices. The index that is missing the information contained in the mobility index and consumer spending declines only gradually and reaches the trough with a delay of several weeks. It also is more sluggish during the recovery phase. While the average differential for New York and Rhodes Island is similar over this period (see Figure 4A), the pattern of their economic conditions indices differs. While for New
York both indices fall in sync by a similar magnitude, the mobility and spending data imply a faster bounceback during the reopening period. Instead, for Rhodes Island only the index with the high-frequency data captures the full extent of the massive deterioration in economic conditions compared to the one without those data despite their short time span. A similar picture emerges for Missouri and Iowa. Both states show a more rapid downturn thanks to the timely information encapsulated in mobility data and credit card spending, whereas this additional information matters little during the rebound. For Missouri we also observe a much greater economic loss at the height of the crisis for the baseline economic conditions index. California is representative of the group of states that display smaller variations in the scatter plot and for which the new data contribute relatively little to the estimates of economic conditions. Overall, our analysis suggests that there is no harm in including these variables, whereas omitting them can result in an inaccurate assessment of the depth and timing of state-level business cycles. It is also highly likely that these and other new high-frequency variables will gain in importance going forward.

\section{Risk Analysis}

It is useful to look at the entire distribution of economic weakness to obtain a probabilistic assessment of the build-up of risks. Figure 6A shows the weekly evolution of risks over a two-year period from February 2019 to February 2021. Throughout 2019, economic weakness is low with the densities concentrated around a mode of 0.1 or less, placing essentially no mass on values of the EWI above 0.25. Moving into early 2020, these densities gradually shift to the right attaching increasingly more weight to downside risks. By the middle of March 2020, the density signals mounting risks of widespread economic weakness, with the share of states facing a contraction between 50\% and 60\%. One week later, the likelihood of entering a phase of high national weakness rises further, with the density assigning considerable weight to the possibility that at least 75\% of the states will experience a recession. The week thereafter, all mass essentially piled up near one and risks remained elevated for the remainder of the year. By the end of February 2021, risks had not substantially subsided. This analysis illustrates how the time-varying densities of the EWI could be used in real time for risk assessment to inform policymakers.
References


Figure 1A. Weekly Economic Conditions Indices Based on Different Information Sets for Selected States 1987.4-2021.2

NOTES: The gray shaded areas indicate NBER recessions.
Figure 2A. Comparison of Weekly ECI and Philly Fed Replica for Selected States and Subperiods

Panel A: Texas
2007.1 – 2011.1

Panel B: Oklahoma
2007.1 – 2011.1

Panel C: California
2007.1 – 2011.1

Panels A, B, and C show the comparison of Weekly ECI and Philly Fed Replica for selected states and subperiods. The grey shaded areas indicate NBER recessions.

NOTES: The gray shaded areas indicate NBER recessions.
Figure 3A. Estimates of Weekly Real GDP for the US and Selected States 1987.4-2021.2

NOTES: The gray shaded areas indicate NBER recessions. The black dashed line indicates 2006Q1 when the first observation for state-level real GDP in annual growth rates becomes available.
Figure 4A. The Role of Including Data on Mobility and Credit/Debit Card Spending

NOTES: The scatter plot shows the average absolute difference between the state-level ECIs with and without data on mobility and credit/debit card spending over two periods. Pre-2020 refers to the period before the data on mobility and credit/debit card spending became available in the week ending on January 18, 2021 and post-2020 refers to the period thereafter. The red entries highlight U.S. states shown in Figure 5A with the symbols indicating the following states: x – California, cross – Iowa, pentagram – Missouri, triangle – New York, dot – North Carolina, diamond – Rhode Island. The blue squares refer to the remaining 44 states.
Figure 5A. Comparison of Weekly Economic Conditions Indices with and without Data on Mobility and Credit/Debit Card Spending for Selected States 2020.2-2021.2

North Carolina

Iowa

New York

Missouri

Rhode Island

California
Figure 6A. Time-varying Densities of the Weekly Economic Weakness Index
2019.2-2021.2

NOTES: The figure shows the evolution of the posterior density of the Weekly Economic Weakness Index over time. Distributions with darker colors are associated with more recent time periods.
Figure 7A. Weekly Economic Conditions Indices for all 50 U.S. States, 1987.4-2021.2
Figure 8A. Weekly Economic Conditions Indices for all 50 U.S. States
2020.1-2021.2
Figure 9A. Weekly Economic Conditions Index for the U.S. Economy 1987.4-2021.5

Panel A: Comparison of weekly U.S. Economic Conditions Index with WEI

Panel B: Decomposition of weekly U.S. Economic Conditions Index

NOTES: WEI is the Weekly Economic Index proposed by Lewis et al. (2020) and available from FRED from 2008-01-05 onward. Note that WEI is not normalized such that zero corresponds to long-run average growth, which is why we do not apply this normalization to the U.S. Economic Conditions Index in panel A for comparability; however, in panel B a value of zero indicates long-run average growth for comparability with the state-level indicators. The U.S. Economic Conditions Index is constructed based on 25 indicators that are listed in Table 1A, which mimic as closely as possible the state-level dataset.
Table 1A. Dataset for Weekly U.S. Economic Conditions Index

<table>
<thead>
<tr>
<th>Data category</th>
<th>Variables</th>
<th>Frequency</th>
<th>First observation</th>
<th>Tcode</th>
<th>Data source</th>
<th>Seasonal adjustment</th>
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<tbody>
<tr>
<td>Mobility</td>
<td>Cellphone mobility index</td>
<td>Weekly</td>
<td>Jan 13, 2020</td>
<td>1</td>
<td>Apple</td>
<td>NA</td>
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<tr>
<td></td>
<td>Retail gasoline price</td>
<td>Weekly</td>
<td>May 22, 2000</td>
<td>2</td>
<td>EIA</td>
<td>NSA</td>
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<tr>
<td></td>
<td>Vehicle miles traveled</td>
<td>Monthly</td>
<td>Dec 1970</td>
<td>2</td>
<td>FRED</td>
<td>NSA</td>
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<tr>
<td>Labor Market</td>
<td>Initial unemployment insurance claims</td>
<td>Weekly</td>
<td>Jan 7, 1967</td>
<td>1</td>
<td>FRED</td>
<td>SA</td>
</tr>
<tr>
<td></td>
<td>Continued unemployment insurance claims</td>
<td>Weekly</td>
<td>Jan 7, 1967</td>
<td>1</td>
<td>FRED</td>
<td>SA</td>
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<tr>
<td></td>
<td>Total nonfarm employment</td>
<td>Monthly</td>
<td>Jan 1939</td>
<td>2</td>
<td>FRED</td>
<td>SA</td>
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<tr>
<td></td>
<td>Unemployment rate</td>
<td>Monthly</td>
<td>Jan 1948</td>
<td>1</td>
<td>FRED</td>
<td>SA</td>
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<tr>
<td></td>
<td>Average hours worked in manufacturing</td>
<td>Monthly</td>
<td>Jan 1960</td>
<td>1</td>
<td>FRED</td>
<td>SA</td>
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<tr>
<td>Real Activity</td>
<td>Coal production</td>
<td>Weekly</td>
<td>Jan 8, 2000</td>
<td>2</td>
<td>CEIC</td>
<td>NSA</td>
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<td></td>
<td>Oil rig counts</td>
<td>Weekly</td>
<td>Jul 18, 1987</td>
<td>4</td>
<td>BH</td>
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<td></td>
<td>Oil production</td>
<td>Monthly</td>
<td>Jan 1920</td>
<td>2</td>
<td>EIA</td>
<td>NA</td>
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<tr>
<td></td>
<td>Electricity consumption</td>
<td>Monthly</td>
<td>Jan 2003</td>
<td>2</td>
<td>EIA</td>
<td>NSA</td>
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<td>Real exports of goods†</td>
<td>Monthly</td>
<td>Jan 1992</td>
<td>2</td>
<td>FRED</td>
<td>SA</td>
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<td>Industrial production</td>
<td>Monthly</td>
<td>Jan 1919</td>
<td>2</td>
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<td>Real GDP</td>
<td>Quarterly</td>
<td>Q1:1947</td>
<td>2</td>
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<td>SA</td>
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<td>Expectations</td>
<td>Business applications</td>
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<td>Jan 7, 2006</td>
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<td>FRED</td>
<td>NSA</td>
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<td>New housing permits</td>
<td>Monthly</td>
<td>Jan 1960</td>
<td>3</td>
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<td>SA</td>
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<td>University of Michigan: Consumer sentiment</td>
<td>Monthly</td>
<td>Nov 1952</td>
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<td>Business Tendency Survey for Manufacturing</td>
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<td>Jan 1960</td>
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<td>SA</td>
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<td>Financials</td>
<td>10-year Treasury yield</td>
<td>Weekly</td>
<td>Jan 5, 1962</td>
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<td>FRED</td>
<td>NA</td>
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<td>Corporate bond spread: BAA-AAA</td>
<td>Weekly</td>
<td>Jan 5, 1962</td>
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<td>FRED</td>
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<td>Real trade-weighted value of the dollar</td>
<td>Monthly</td>
<td>Jan 1973</td>
<td>2</td>
<td>FRED</td>
<td>NSA</td>
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<td>Households</td>
<td>Credit and debit card spending</td>
<td>Weekly</td>
<td>Jan 24, 2020</td>
<td>1</td>
<td>AS</td>
<td>SA</td>
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<td>Real wage and salary income†</td>
<td>Quarterly</td>
<td>Q1:1986</td>
<td>2</td>
<td>FRED</td>
<td>SA</td>
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<tr>
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<td>Real home price index†</td>
<td>Quarterly</td>
<td>Q1:1975</td>
<td>2</td>
<td>FRED</td>
<td>NSA</td>
</tr>
</tbody>
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NOTES: See Table 1.