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Tracking Weekly State-Level Economic Conditions

Abstract

In this paper, we develop a novel dataset of weekly economic conditions indices for the 50 U.S. states going back to 1987 based on mixed-frequency dynamic factor models with weekly, monthly, and quarterly variables that cover multiple dimensions of state economies. We show that there is considerable heterogeneity in the length, depth, and timing of business cycles across individual states. We assess the role of states in national recessions and propose an aggregate indicator that allows us to gauge the overall weakness of the U.S. economy. We also illustrate the usefulness of these state-level indices for quantifying the main forces contributing to the economic collapse caused by the COVID-19 pandemic and for evaluating the effectiveness of federal economic policies like the Paycheck Protection Program.

JEL-Codes: C320, C550, E320, E660.

Keywords: local economic conditions, government policies, weekly indicators, state economies, cross-state heterogeneity, mixed-frequency dynamic factor model, economic weakness index, Markov-switching, recession, probabilities.

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1 Introduction

Measuring the current state of the economy in an accurate and timely manner is challenging. Yet such measurements are critical for policymakers, government agencies, economic analysts, and business people who make decisions about policy, budget allocations, production volumes, sales strategies, plant closures, and the like. The difficulty in accurately measuring the state of the economy at high frequencies arises from the fact that most headline macroeconomic data series are measured at the monthly or quarterly frequency and are released with a considerable delay. This is even more of an issue in a fast-evolving economic environment like the one we experienced at the onset of the COVID-19 pandemic.

In an effort to facilitate an early and reliable assessment of economic conditions, the academic literature has developed composite indices of economic activity at the monthly (e.g., Stock and Watson, 1989, 1991; Mariano and Murasawa, 2003; Camacho and Pérez-Quirós, 2010; Baumeister, Korobilis, and Lee, 2020), weekly (e.g., Lewis, Mertens, Stock, and Trivedi, 2020), and daily (e.g., Aruoba, Diebold, and Scotti, 2009; Diebold, 2020) frequencies using dynamic factor models to summarize the comovement among individual economic variables. Higher-frequency indicators have become particularly popular in the wake of the COVID-19 outbreak for the purpose of keeping abreast of the rapid economic deterioration due to the public health crisis and related policy measures. While the weekly economic index of Lewis et al. (2020) relies on only one frequency common to all underlying variables, Aruoba et al. (2009) emphasize the benefits of mixing data observed at different frequencies to track continuously evolving business conditions.[1]

Most studies in this literature have focused on measures of cyclical variation in real activity at the national level. Much less attention has been devoted to corresponding measures at the state level. The only ones we are aware of are the monthly coincident indices for the 50 U.S. states of Crone and Clayton-Matthews (2005), reviewed by Chinn and LeCloux (2018) and regularly updated by the Federal Reserve Bank of Philadelphia. These indicators of state-level economic activity are based on a small set of data series which exclusively capture labor market dynamics.[2]

One of the contributions of our paper is to extend recent efforts to measure weekly economic conditions to the state level. For this purpose, we assemble a diverse state-level database that combines new high-frequency data – such as credit and debit card spending, business applications, and mobility indices – with more traditional low-frequency indicators such as employment and income. Specifically, we include weekly, monthly, and quarterly data series that cover different aspects of state economies, such as labor market indicators, household spending, real economic

[1] Aruoba et al. (2009) show that incorporating weekly data greatly improves the accuracy of their real activity factor, especially during recessionary periods, while adding daily data makes little difference.

[2] The four input series for the Philadelphia Fed state coincident indices are monthly nonfarm payroll employment, the monthly unemployment rate, monthly average hours worked in manufacturing, and quarterly wage and salary disbursements deflated by the U.S. CPI. In January 2020, a fifth series, proprietors' income, was added to capture some changes in capital movements unrelated to the labor market.

activity, mobility measures, financial indicators, and expectations measures.[3] Recently, Bokun, Jackson, Kliesen, and Owyang (2020) compiled a real-time dataset for U.S. states that contains both monthly and quarterly variables, but no weekly variables. Another feature that distinguishes our dataset from theirs is that they focus on the sectoral breakdown of employment and output data, while we include a variety of non-standard variables (e.g., electricity consumption, vehicle miles traveled, oil rig counts, coal and oil production) to capture state-specific characteristics as well as to obtain a more comprehensive measure of economic conditions for each U.S. state.

We use the resulting state-level indicators of economic conditions to study similarities and differences in the length, depth, and timing of business cycles across individual states with a particular focus on the four most recent recessionary episodes over the period 1987-2021.[4] We show that there is considerable cross-state heterogeneity along all three criteria during the early 2000s slowdown and the Great Recession, while the COVID-19 downturn was nearly perfectly synchronous across states, even though the magnitude of the economic fallout differed greatly. Given that the indicators cover multiple dimensions of state economies, we can decompose economic fluctuations into their main underlying driving forces. For example, adverse labor market developments and the abrupt decline in mobility were the key determinants of the economic collapse in the early stages of the COVID-19 pandemic for most states, whereas the sources of the subsequent recovery are more diverse, even though the labor market continues to play an important role.

We also show that the weekly frequency of our state-level indices is particularly valuable for assessing the efficacy of policy interventions. When tracing out the dynamic response to the Paycheck Protection Program, the nation's largest fiscal policy initiative to combat the pandemic crisis, we find that the effect is positive but only lasts for a few weeks. Given this rather short duration, an analysis conducted with lower-frequency data is likely to miss the beneficial consequences of this program, which according to our estimates amount to a 1.3 percent increase in state-level economic conditions indices for every $500 increment in loan volume per capita. This is but one illustration of how our state-level indices can be put to use in policy analysis. Our indices will enable researchers to study the responses of individual states to a range of macroeconomic shocks and federal economic policies including fiscal, monetary, trade, and industrial policies, as well as state-specific fiscal measures, environmental regulations, transportation policies, infrastructure programs, (de)regulation of energy markets, property tax reforms, and land-use rules.[5]

Exploiting the differential behavior of state economies to aggregate shocks can also enhance our understanding of how the aggregate economy works. For example, Carlino and DeFina (1998) use the varying strength of responses to monetary policy shocks for states with different economic structure to infer the relative importance of different transmission channels. Similarly, Owyang,

[3] The benefits of a diverse dataset to measure global economic conditions have been illustrated by Baumeister et al. (2020) in the context of forecasting oil prices and petroleum consumption.

[4] Studies that analyze state-level business cycle dynamics at the quarterly frequency for some of these and earlier recessions include Diebold and Rudebusch (1996), Carlino and Sill (2001), Crone (2005), Owyang, Piger, and Wall (2005), and Hamilton and Owyang (2012).

[5] The dataset of state-level economic conditions indicators can be downloaded here and will be regularly updated.

Piger, and Wall (2008) rely on heterogeneous state-level patterns in terms of timing and magnitude of volatility reductions to uncover the origins of macroeconomic phenomena like the Great Moderation.

To study the implications of state-level economic conditions for the U.S. economy as a whole, we explicitly model the contribution of each state to national economic weakness. Specifically, we apply a Markov-switching model to each state-level indicator in the tradition of Diebold and Rudebusch (1996), and Owyang, Piger, and Wall (2005) to obtain recession probabilities for each individual state. We then use these recession probabilities to construct an aggregate economic weakness index. We analyze various sources of weakness by grouping states according to a set of criteria, such as the industrial composition of the workforce, the degree of resource richness, and others. In the last week of February 2021, the end of our sample period, we also generate weekly forecasts of state economic conditions to project the national recovery path one-year ahead. Again, this is just one example of how weekly forecasts for each state can be used to inform policymakers. An interesting extension would be to include our high-frequency state-level indicators in mixed-frequency models to explore their promise for forecasting lower-frequency national aggregates.

The remainder of the paper is structured as follows. Section 2 develops a new set of composite measures to gauge the economic situation in each of the 50 U.S. states on a weekly basis. Section 2.1 describes our model framework to generate weekly indicators of economic conditions at the state level and Section 2.2 proposes a new state-level dataset that spans a wide range of economic variables with mixed frequencies that we consider critical to capture economic developments in each state. In Section 2.3, we illustrate how these state-level indicators can be used to track the evolution of economic performance week-by-week, to quantify the main contributors to business cycle fluctuations in state economies, and to evaluate the impact of government policies like the Paycheck Protection Program. Section 3 studies the role of state-level economic conditions for the U.S. economy by aggregating the information on state-level recession probabilities into a national weakness index. Section 3.1 introduces a regime-switching model that allows for heterogeneity across both recessionary and expansionary episodes. Section 3.2 discusses the sources of economic weakness, the evolution of risks during the pandemic, and the projected recovery path. Section 3.3 examines the economic geography of recession probabilities. Section 4 offers some concluding remarks.

2 Weekly Indicators of Economic Conditions at the State Level

2.1 A Mixed-Frequency Dynamic Factor Model

Since the important early contributions of Stock and Watson (1989, 1991), dynamic factor models have been widely used to construct indices to measure aggregate real activity in a timely fashion. We follow Mariano and Murasawa (2003), Aruoba et al. (2009), and Camacho and Pérez-Quirós (2010) and combine data sampled at different frequencies within a dynamic factor framework to generate high-frequency indicators of economic conditions at the state level. The model is estimated for each of the 50 U.S. states separately.

The base frequency of observation is weekly. Let $t = 1, ..., T$ index weeks, where T is the total number of weeks in the sample, and let $m = 1, ..., M$ index months, where M is the total number of months in the sample. Associated with any week t is a month m_t within which the Saturday for that week falls, and associated with any month m is a number of weeks, $c(m) = 4$ or 5, whose Saturday falls in month m. Let Y_m be a variable such as employment that gets reported for month m. We think of this as the sum of unobserved weekly values, Z_t, over each of the weeks in month m. Thus, if week t is the last week in month m_t,

$$Y_{m_t} = Z_t + Z_{t-1} + \cdots + Z_{t-c(m_t)+1}. \tag{1}$$

We can approximate (1) with

$$Y_{m_t} = c(m_t)(Z_t Z_{t-1} \cdots Z_{t-c(m_t)+1})^{1/c(m_t)}. \tag{2}$$

Camacho and Pérez-Quirós (2010) note that typically (2) gives an excellent approximation to (1). Taking logs of (2) yields

$$\ln Y_{m_t} = \ln(c(m_t)) + [c(m_t)]^{-1}[\ln Z_t + \ln Z_{t-1} + \cdots + \ln Z_{t-c(m_t)+1}].$$

A typical year consists of 52 weeks. The year-over-year growth rate of Y_{m_t} is given by

$$\begin{aligned}
\ln Y_{m_t} - \ln Y_{m_t-12} \quad = \quad & \ln c(m_t) - \ln c(m_t - 12) \\
& +[c(m_t)]^{-1}[\ln Z_t + \ln Z_{t-1} + \cdots + \ln Z_{t-c(m_t)+1}] \\
& -[c(m_{t-52})]^{-1}[\ln Z_{t-52} + \ln Z_{t-53} + \cdots + \ln Z_{t-c(m_{t-52})-51}].
\end{aligned}$$

If the month associated with week t has the same number of weeks as the same month in the preceding year, then

$$\ln Y_{m_t} - \ln Y_{m_t-12} = [c(m_t)]^{-1}(z_t + z_{t-1} + \cdots + z_{t-c(m_t)+1}], \tag{3}$$

for $z_t = \ln Z_t - \ln Z_{t-52}$, the weekly year-over-year growth rate. When t is the last week of a month, we observe the left-hand side of (3) from the difference between the log of, say, employment reported for that month and the log of employment for that month in the preceding year.

Similarly, let $q = 1, ..., Q$ denote quarters and $d(q)$ the number of weeks falling in quarter q. $d(q)$ can take the values of $12, 13$, or 14. Let Y_q denote the value of a variable such as real GDP in quarter q and X_t an unobserved weekly level of GDP. We can model growth rates of Y_q at a weekly frequency as

$$\ln Y_{q_t} - \ln Y_{q_t-4} = [d(q_t)]^{-1}(x_t + x_{t-1} + \cdots + x_{t-d(q_t)+1}], \tag{4}$$

where x_t denotes the year-over-year growth rate associated with week t.

We postulate that there is a single latent weekly cyclical factor, f_t, that is common to all the variables in the system. We assume it is characterized by a Gaussian $AR(p_f)$ process:

$$f_t = \phi_1 f_{t-1} + \phi_2 f_{t-2} + \cdots + \phi_{p_f} f_{t-p_f} + \epsilon_t \qquad \epsilon_t \sim N(0, \omega). \tag{5}$$

For variables that are observed weekly, such as new claims for unemployment insurance, we assume that the observed weekly value for variable i, y_{it}, is given by a loading, λ_i, times the common cyclical factor, plus an idiosyncratic component, u_{it}:

$$y_{it} = \lambda_i f_t + u_{it} \qquad\qquad \text{if } i \text{ observed weekly.} \tag{6}$$

The idiosyncratic component follows an $AR(p_w)$ process:

$$u_{it} = \psi_{i1} u_{i,t-1} + \psi_{i2} u_{i,t-2} + \cdots + \psi_{ip_w} u_{i,t-p_w} + \varepsilon_{it} \qquad \varepsilon_{it} \sim N(0, \sigma_i). \tag{7}$$

Modeling the idiosyncratic process explicitly is useful in the case of state-level data, since this allows us to distinguish between idiosyncratic experiences in specific parts of state economies, such as mining strikes in West Virginia or hurricanes hitting the U.S. Gulf Coast, and the pervasive component of state-level economic fluctuations.

The value for a monthly indicator tracks the weekly cyclical factor as in (3)

$$\begin{aligned} y_{it} &= \lambda_i [c(m_t)]^{-1} (f_t + f_{t-1} + \cdots + f_{t-c(m_t)+1}) + \\ & \quad [c(m_t)]^{-1} (u_{it} + u_{i,t-1} + \cdots + u_{i,t-c(m_t)+1}) \qquad \text{if } t \text{ is the last day of the month,} \end{aligned}$$

with u_{it} again characterized by (7).[6] For quarterly indicators we have

$$\begin{aligned} y_{it} &= \lambda_i [d(q_t)]^{-1} (f_t + f_{t-1} + \cdots + f_{t-d(q_t)+1}) + \\ & \quad [d(q_t)]^{-1} (u_{it} + u_{i,t-1} + \cdots + u_{i,t-d(q_t)+1}) \qquad \text{if } t \text{ is the last day of the quarter.} \end{aligned}$$

Let n^w, n^m, and n^q denote the number of weekly, monthly, and quarterly indicators, respectively, and $n = n^w + n^m + n^q$ the total number of indicators for each U.S. state. We can write this system in state-space form in which the state vector is given by

$$\boldsymbol{\xi}_t = (f_t, f_{t-1}, ..., f_{t-D+1}, u_{1t}, ..., u_{1,t-D+1}, ..., u_{nt}, u_{n,t-p_w+1})', \tag{8}$$

with $D \equiv \max(d(q))$ denoting the largest number of weeks that a quarter may contain. The law of motion for the state vector is

$$\boldsymbol{\xi}_t = \mathbf{F}\boldsymbol{\xi}_{t-1} + \mathbf{v}_t \qquad \mathbf{v}_t \sim N(\mathbf{0}, \mathbf{R}). \tag{9}$$

Let $\mathbf{y}_t$ be an observed vector of indicators associated with week t. Note that $\mathbf{y}_t$ is an $(n_t \times 1)$ vector where $n_t = n$ if t is the last day of a quarter, $n_t = n^w + n^m$ if t is the last week of the month but

[6] In the empirical application, we postulate that both the common factor and the idiosyncratic terms follow $AR(4)$ processes to account for the persistence associated with year-over-year growth rates.

not the last week of a quarter, and $n_t = n^w$ for all other weeks. The observation equation is given by

$$\mathbf{y}_t = \mathbf{H}_t \boldsymbol{\xi}_t, \tag{10}$$

where the number of rows of $\mathbf{H}_t$ is given by n_t. Note that the matrix $\mathbf{H}_t$ that relates the observables with the state vector varies over time in order to accommodate all the calendar irregularities concerning the different number of weeks within a given month or quarter. In addition to the missing observations that result from the presence of mixed frequencies, missing data also result from the "ragged edge" at the end of the sample because of the asynchronous timing of data releases, from occasional incomplete reporting or data-entry errors, and from data series that are only available for part of the sample period.

Equation (9) is the state equation and (10) the observation equation for a state-space system. This allows us to jointly estimate the common factor, the model parameters, and the missing observations using the Kalman filter in a Bayesian setting that is well suited to deal with the high dimensionality of the state vector. Even though the monthly and quarterly indicators are observed irregularly, the Kalman filter and smoother associated with the state equation give us an estimate of the weekly value of $\boldsymbol{\xi}_t$ for every t:

$$\boldsymbol{\xi}_{t|T} = E(\boldsymbol{\xi}_t | \mathbf{y}_T, ..., \mathbf{y}_1).$$

The first element of this vector is the weekly common factor. More details on the estimation algorithm and the choices of priors are provided in Appendix A.

2.2 A Diverse State-Level Dataset

We compile a diverse set of indicators that span a broad range of weekly, monthly, and quarterly variables covering numerous aspects of economic life at the state level. We carefully select publicly available variables from a variety of data categories sampled at different observational frequencies and available over different time periods. We group variables into six broad categories: mobility measures, labor market indicators, real economic activity, expectations measures, financial indicators, and household indicators. Table 1 summarizes the state-level data used in the construction of our weekly economic conditions indices, including information on the data frequency, data source, data transformation, seasonal adjustment, and the start date of each series.

Mobility measures. Given the shelter-in-place orders and other restrictions on the movements of people and goods put into place during the pandemic, mobility measures are an important component to track economic conditions in the recent crisis. Transportation is key for any type of economic activity and therefore variables capturing the demand for transportation are useful indicators, even prior to the pandemic. We include information on vehicle miles traveled, which is based on count data of vehicles on roads and highways, to determine overall traffic volume at the monthly frequency. Weekly retail gasoline prices are also indicative of the strength for transportation demand, even though they are only available for a subset of states. A novel measure of mobility that has gained popularity in the wake of the COVID-19 crisis tracks people's movements via their cellphones. Even though this cellphone mobility index only starts in January 2020, it is likely to provide useful information during the lockdown and reopening periods.

Labor market indicators. The richest state-level information pertains to the labor market. We include weekly jobless claims, both initial and continued. Initial claims are filed by an unemployed individual directly after separation from an employer to determine eligibility for the unemployment insurance program, while continued claims refer to people who have already been deemed eligible and claim unemployment benefits for that week. Total nonfarm employment, the unemployment rate, and average hours worked in manufacturing are standard monthly variables to characterize the state of the labor market that have been used in the construction of state-level indices before (see, e.g., Crone and Clayton-Matthews, 2005). Crone and Clayton-Matthews (2005) point out that while nonagricultural payroll employment is the most accurate among the employment series, it may be less representative of economic conditions in states where agriculture is prevalent. Average weekly hours of production employees in the manufacturing sector can be viewed as a substitute for industrial output, which does not exist at the state level.

Real economic activity. The most comprehensive measure of real economic activity is real GDP. State-level measures of real GDP were introduced only in 2005, are only available at the quarterly frequency, and become available with a considerable delay. Therefore, we supplement this classical indicator of the business cycle with monthly and weekly data. Monthly electricity consumption is a useful indicator of the overall intensity of economic activity since the production of most goods and services requires electricity (see Arora and Lieskovsky, 2014). We also include monthly exports of manufactured and non-manufactured commodities, which capture trade flows and are thus indicative of a state's economic activity. Some resource-rich states specialize in the production of primary commodities like coal and oil. For oil-producing states, we use oil rig counts as a weekly indicator of real activity starting in 1990, and the amount of oil pumped each month from 1986 onward. Coal mining is, or was, an important sector in about half of the U.S. states. While its importance has varied across states and time, weekly data on coal production go back to 1984 and thus contain valuable information for aggregate fluctuations over a long period of time.

Expectations measures. We include four forward-looking variables that should be indicative of expected economic conditions. Weekly business applications signal the intent of the establishment of new businesses, while monthly private housing building permits authorize the future construction of new homes. For a subset of states, we have survey-based indicators about firms' perceptions of broader business activity and households' assessment of their own financial situation as well as their outlook on the general economy, respectively represented by the monthly manufacturing and consumer sentiment indices.

Financial indicators. We consider three financial indicators. The municipal bond yield index is a broad, market value-weighted index that seeks to measure the performance of bonds issued within each state. We include both the yield to maturity and the total return. Given that the municipal bond market provides funding for state and local governments, it allows one to gauge a state's overall fiscal situation, which is an important determinant of future spending and thus influences economic activity (see, e.g., Bi and Marsh, 2020). The real trade-weighted value of the dollar is the inflation-adjusted value of the U.S. dollar against the currencies of countries to which a state exports. The exchange rate movements reflect trade and financial flows and are tied to economic conditions since they capture changes in demand for a state's exports.

Household indicators. We use two quarterly series on the asset side of households' balance sheets as an indicator for their spending behavior. Specifically, we include the wage and salary component of real personal income, as well as the real all-transactions house price index. As a more direct measure of spending activity, we also include weekly data on credit and debit card transactions. Galbraith and Tkacz (2018) document the usefulness of electronic payments data for monthly nowcasts of Canadian GDP and retail sales growth.

Overall, this dataset provides a suitable mix of different frequencies and kinds of variables representative of state economies, while at the same time keeping the model tractable. While the three quarterly variables (real GDP, house prices, and household income) are available for all states, there is some diversity in the number and types of variables available at the monthly and weekly frequencies, which allows us to take state-specific features such as resource richness into account. The average number of series per state is 21, with a minimum of 19 series and a maximum of 24. The sample period spans from the first week of March 1986 to the last week of February 2021. The start date is determined by the weekly series on jobless claims, which go furthest back in time and are available for all 50 states.

2.3 A Set of Weekly Indicators for all 50 U.S. States

The weekly economic conditions indicator, ECI, for state j is obtained as follows:

$$ECI_j = (\boldsymbol{\lambda}_j' \boldsymbol{\lambda}_j)^{-1} \boldsymbol{\lambda}_j' \mathbf{y}_j^P, \tag{11}$$

where $\boldsymbol{\lambda}_j$ is the median estimate of the $(n_j \times 1)$ vector of factor loadings for the weekly, monthly, and quarterly variables and $\mathbf{y}_j^P$ is the $(n_j \times T)$ dataset, with the missing observations for lower-frequency variables replaced by the projected values of the Kalman filter. Deriving the state-level indices by exploiting the cross-sectional dimension not only provides a more robust assessment of economic conditions,[7] but also allows us to study the main determinants of weekly fluctuations in the ECIs.

We next illustrate how these composite measures can be used for the purposes of analyzing developments of economic conditions in each state at the weekly frequency. Specifically, in Section 2.3.1, we compare the evolution of cyclical patterns of selected states over time; in Section 2.3.2, we focus on the severity of the COVID-19 contraction for a subset of states and decompose the

[7] Relying on a point estimate for the factor loadings along with the observed and model-implied data to obtain the indices minimizes the effect of revisions to the factor estimates when new information is added. However, generally the ECI and the common factor are rather close across all states.

weekly indices into the six broad categories defined above to determine the main forces behind the 2020 downturn at the state level; in Section 2.3.3, we track the economic performance across states during three recessionary periods; and in Section 2.3.4, we make use of our weekly state-level indices to evaluate the effectiveness of the Paycheck Protection Program.

2.3.1 Monitoring State-Level Economic Conditions

Figure 1 shows the weekly indices of economic conditions for nine selected U.S. states – New York representing the Northeast, Florida and South Carolina representing the South Atlantic region, California representing the West Coast, Idaho representing the Mountain region, Iowa and Michigan representing the Midwest, and North Dakota and Texas representing the oil-producing states. We plot indices from the first week of April 1987 through the end of February 2021.[8] To facilitate comparison across states and to put state-level economic conditions into the national context, we scale the indices to four-quarter growth rates in U.S. real GDP following the method proposed by Lewis et al. (2020).[9] We normalize the indices such that a value of zero indicates that state economic conditions are comparable to the nation's long-run average growth. The gray bars correspond to recession dates as identified by the NBER.

The broad cyclical movements of the weekly state-level indices line up well with general trends in the aggregate economy.[10] For all nine states, the recessions of 1990-1991, 2001, 2007-2009, and 2020 are clearly visible, albeit with varying depth and timing, which we will explore further in Section 2.3.3. For example, North Dakota performed significantly below average in the aftermath of the 2014 oil price slump after experiencing a boom during the shale oil revolution in 2011-13.

However, the most striking feature of the figure is the dramatic decline in the indices in the spring of 2020, with Iowa contracting by a staggering 16% below national trend growth, followed by New York and Michigan at -14%, Florida and South Carolina at -12%, California and Texas at -10%, North Dakota at -7%, and Idaho at -5%. The trough is reached in most states in the last week of April 2020. Compared to earlier recessionary episodes, the recovery has been relatively swift with economic conditions improving considerably in all states by early 2021. But there is still substantial heterogeneity in the degree of the recovery across states. As an illustration, while Idaho was back at the long-run national average by October 2020, growth in the other states was more sluggish, with the indicators still being 1% to 4% below the national trend in February 2021.

[8] Figure 1A in the appendix displays the indices for the other 41 states over the same period and Figure 2A zooms in on the cross section of economic conditions indices for all 50 states during the pandemic period.

[9] Specifically, the weekly state-level indices are normalized to match the mean and standard deviation of the four-quarter growth of real GDP from 1987Q2 to 2020Q4.

[10] For completeness, we also report the national analogue of the state-level economic conditions indicators in Figure 3A in the appendix and compare it to the Lewis et al. (2020) Weekly Economic Index (WEI). Our 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.

2.3.2 What are the Main Drivers of the 2020 Downturn Across States?

To fully appreciate the differences across states not just in terms of the depth of the 2020 contraction, but also in terms of its key drivers, it is useful to take a closer look at the contributions of each data category to the economic disruption caused by the COVID-19 crisis and to the subsequent recovery. This decomposition is presented in Figure 2, focusing on the first week of January 2020 to the last week of February 2021 for another set of selected states which are representative with regard to economic size, geographic coverage, and resource endowment. We include the three economically largest states – California, Texas, New York – which are also geographically spread out. Illinois, Pennsylvania, and North Carolina belong to the next largest tier and round out the spatial distribution of state economies that carry economic weight. Texas is the nation's top crude oil-producing state, while Oklahoma and Wyoming recently contributed about 4% and 2% to total U.S. oil production. Among the resource-rich states, Texas has the most well-diversified economy; Oklahoma also has a good industry mix with the energy sector accounting for about one fifth of the state's income, whereas Wyoming's economy is heavily concentrated in mining activities. It is also among the smallest states both in terms of value added and population. Kansas and Oklahoma are mid-sized states with distinct economic profiles and represent the center of the country.

In the early stages of the pandemic, labor market developments were the dominant driver of the steep decline in economic conditions, while real activity accounted for only a relatively small share of the slump, except for Wyoming, where the contribution of both is roughly equal. The dramatic reduction in mobility as a result of widespread lockdown measures from mid-March to May 2020 further contributed to the deterioration in economic conditions in all selected states but Oklahoma and Wyoming. Even during the reopening process, transportation measures continued to exert some downward pressure, mainly on the economies of New York, Pennsylvania, and Illinois. Expectations are the third most important contributor to the downturn in New York at the peak of the crisis; they also matter for Pennsylvania and Kansas, albeit to a lesser extent. The role of variables characterizing household behavior varies somewhat across states, but overall played a rather limited role.

There are also interesting differences in the recovery dynamics across states. After bottoming out in late April, most states started a steady path to recovery, albeit with varying speed. The breakdown of the weekly indices reveals that a strengthening of the labor market was key to the improvement of economic conditions. In North Carolina, and to a lesser extent in Illinois and New York, financial variables were positive contributors during the recovery phase. Oklahoma experienced a double-dip recession in the second quarter of 2020, but steeply rebounded thereafter, which can be almost entirely explained by a rapid improvement in the state's labor market situation. In contrast, Kansas gradually recovered until October 2020, but then made a U-turn, with economic conditions reaching a trough of 8% below national average growth in January 2021, which was the lowest level across all 50 states. A similar pattern is observed for Illinois, albeit less stark. The main factor behind this reversal in both states was a second wave of labor market weakness, which was more persistent in Illinois than in Kansas. While some of the labor market slack brought about by lockdown measures and economic dislocations was absorbed relatively quickly in the early stages of the recovery, it remained a major drag on economic conditions in the majority of states. While the recovery also stalled in Wyoming, the main force keeping economic conditions below the nation's long-run average was the sustained sluggishness in real activity. The two most buoyant states in our selection are Kansas and North Carolina. In both states the labor market situation has normalized. While Kansas is on its way to closing the gap, North Carolina was already back at trend level growth in September 2020, and has since exhibited more standard business cycle fluctuations, determined by a mix of factors similar to those in the pre-pandemic months.

2.3.3 Tracking State-Level Economic Performance during Recessions

To further explore the cross-sectional variation in the timing of state-level business cycle dynamics, we summarize the evolution of economic conditions in a heat map for all 50 U.S. states. Blue colors indicate that the state economy is performing above average with varying growth rates, while brighter colors from light green to the extreme of red indicate subpar growth with an increasing degree of economic slack.[11] We compare the pattern of state-level economic developments across three recessionary episodes.

Figure 3 focuses on the economic contraction associated with the COVID-19 pandemic and the subsequent recovery. It is based on data from the third week of January 2020 to the last week of February 2021. The period of benign economic conditions across almost all states at the beginning of 2020 ended abruptly in the third week of March, when all states switched to red. Relative to earlier recessions, this sharp deterioration in economic conditions was remarkably synchronous across states. The majority of states remained in the most contractionary phase until the end of April. The nascent recovery was more heterogeneous across states, with conditions improving faster in some states than in others. A few states underwent another, milder spell of slowdown in the summer of 2020 before continuing on their upward trajectory. The first two states to emerge permanently from the slump were Alaska and Utah in August 2020, followed by Nebraska and North Carolina in October 2020. Idaho was on a promising path toward the end of the year, but experienced a weakening in economic conditions in February 2021. In the last quarter of 2020, about two-thirds of U.S. states entered a second downturn; for most of these states, this downturn extended into 2021. While widespread, this second episode is less uniform in timing. The two states with the longest stretch of dire economic conditions are West Virginia and Wyoming, both of which have been in negative territory since the beginning of 2020.

To put the current episode into perspective, we also consider the weeks during the worst part of the Great Recession, from August 2008 to December 2009, in Figure 4. In contrast to the

[11] Specifically, we distinguish between the following 10 categories of economic performance ranging from dark blue to red: positive and increasing at an increasing rate; positive and increasing at a decreasing rate; positive turning point; positive and decreasing at a decreasing rate; positive and decreasing at an increasing rate; negative and increasing at an increasing rate; negative and increasing at a decreasing rate; negative turning point; negative and decreasing at a decreasing rate; negative and decreasing at an increasing rate.

COVID-19 pandemic, the economic consequences of the financial crisis were much less synchronized across states. In particular, the indices for several resource-rich states (e.g., Oklahoma, North Dakota, West Virginia, and Wyoming) remained above the national average for most of the fall of 2008. While the bulk of red was concentrated in early 2009, indicating that the deterioration in economic conditions was shared by a large number of states, the timing is more scattered. Signs of improvement in economic conditions started to appear in June 2009, with about one-fourth of the states having reached their turning point into the recovery phase. There were nevertheless some short but temporary reversals. Indiana, Michigan, and New Jersey are the only three states that were continuously on an upward trajectory from August 2009 to the end of the year.

Figure 5 examines more closely the economic performance across states during the 2001 recession, covering the weeks from January 2001 to June 2002. It is immediately evident that the early 2000s slowdown was not as pervasive an event as the other two recessions on which we have focused. In fact, the economic conditions indices for three states – Alaska, Maine, and Wyoming – were in positive territory throughout the entire period. While the recession was dated to have begun in March 2001, roughly half of the states were growing above national trend at that time and about one-fifth continued to do so at least until the summer. On the other hand, 12 states had already entered the contractionary phase by January 2001 and stayed there until June 2002 or later. Despite the disparate pattern of state-level economic conditions, the deceleration in growth is visibly clustered in the fall of 2001. Even after the official end of the recession in November 2001, the return to normal conditions was sluggish, with protracted periods of orange and red colors for most states. This is in line with evidence presented in Owyang et al. (2005). The state that comes closest to being the poster child of this recessionary episode is Pennsylvania, where economic conditions worsened considerably in early April 2001 and a path to recovery emerged in early December of the same year. In sum, the 2001 recession was not only the mildest one in post-WWII history, but also the most heterogeneous one at the state level.

A comparison of Figures 3, 4, and 5 highlights one of the unique aspects of the COVID-19 pandemic, in that the collapse in economic conditions was nearly perfectly synchronous across states, something that is not a feature of prior recessions.

2.3.4 An Evaluation of the Effectiveness of the Paycheck Protection Program

In addition to monitoring the high-frequency evolution of economic performance at the state level, our measures of economic conditions can also be used to assess the effectiveness of various policy interventions.

One of the major policy interventions during the early stages of the COVID-19 pandemic was the Paycheck Protection Program (PPP). The PPP was instituted as part of the CARES Act to help businesses remain afloat during the pandemic. Eligible borrowers contracted with certified private lenders to obtain loans, who were in turn funded by the Small Business Administration (SBA). Loan amounts were limited to a multiple of an applicant's payroll expenses. The first round of PPP loans were made between April 3 and April 16, 2020. The total loan amount disbursed to companies in the 50 U.S. states from this first round totaled more than \$340 billion, with an average loan volume per state of \$6.8 billion. The average individual loan was slightly more than \$200,000. Relative to the population size of each state, the average loan volume per capita was \$1,142, with a standard deviation across states of \$295, a maximum loan volume per capita of \$2,010, and a minimum loan per capita of \$641.[12]

After the first round, the program was subsequently extended, with more loans being made over the course of the spring and summer of 2020. The program was paused in August of 2020, but restarted again in January of 2021. In total, almost \$1 trillion in loans have been given out to small businesses. We focus only on the first round of PPP loans made through April 16 of 2020. These loans were arguably unexpected, whereas with extensions and later incarnations of the program there was likely an expectation that the funds would continue to flow. As one illustration of how our state-level indices of economic conditions might be used by researchers, we estimate the following regression related to PPP loans:

$$ECI_{j,t+h} = \beta_0^{(h)} + \beta_1^{(h)} x_{j,t} + \beta_2^{(h)} ECI_{j,t-k} + \beta_3^{(h)} ECI_{j,t-\ell} + \varepsilon_{j,t+h}, \tag{12}$$

where $ECI_{j,t+h}$ is the economic conditions index for state j at time $t+h$, for $h = 0, ..., H$, measured at a weekly frequency. The reference period, t, is taken to be the week ending April 18, 2020. $x_{j,t}$ is the log of the total loan volume allocated to state j through the completion of the first round of the PPP program, which ended on April 16, 2020. The loan volume is expressed relative to a state's population. $\beta_1^{(h)}$ is the coefficient of interest. By estimating separate regressions for each horizon h, we can assess the dynamic effects of PPP loans on state-level economic conditions over time. Estimating separate regressions for different horizons is a straightforward application of the Jordà (2005) local projection technique for constructing impulse response functions.

To control for the potential endogeneity of PPP loans to states, in estimating (12) we control for two different lagged values of the economic conditions index. $ECI_{j,t-k}$ is meant to control for economic conditions at the early stages of the pandemic, but prior to the disbursement of PPP loans. We take $k = 2$, using the economic conditions index for the week ending April 4, 2020, as a control. $ECI_{j,t-\ell}$ is meant to control for economic conditions prior to the onset of the pandemic. We set $\ell = 7$, using the economic conditions index for the week ending February 29, 2020, as an additional control. Our results are robust to using other reasonable values of k and ℓ.[13]

[12] We retrieve the volume of PPP loans by state from the SBA. State populations are based on estimates for 2019 made by the Census Bureau, and were downloaded here.

[13] A caveat here is that k needs to be sufficiently small so as to capture economic conditions at the state level during the early stages of the pandemic. Initial PPP loans were negatively correlated with how states fared during the initial phase of the pandemic, with a correlation between the log of PPP loans disbursed by April 16 and economic conditions dated April 4 of -0.2. If we drop $ECI_{j,t-k}$ from the regression altogether, and only control for economic conditions prior to the pandemic, our estimates of $\beta_1^{(h)}$ are significantly lower. This is consistent with our prior that loans were negatively correlated with economic performance. If the true $\beta_2^{(h)} > 0$, excluding a control for the initial severity of the pandemic will bias downward our estimates of $\beta_1^{(h)}$.

Panel A of Figure 6 shows the estimated $\widehat{\beta}_1^{(h)}$ against the time horizon h, from separately estimating (12) at successive horizons, going up to October 3 ($H = 24$). Point estimates are plotted along with 68 percent confidence intervals that are constructed using Newey-West standard errors. Our point estimates reveal that a one percentage point increase in PPP loans per capita to a state resulted in a 0.03 percentage increase in the state-level economic conditions index on impact (i.e. the week ending April 18). To put these units into perspective, a 1 percent increase in loan volume per capita amounts to about \$11 per person. So, our estimates suggest that each \$500 increment in loan volume per capita translates into a state-level index that is about 1.3 percent higher.

The positive impact effect that we estimate persists and remains statistically significant for an additional two weeks (weeks ending April 25 and May 2). The estimated effect of the initial round of PPP loans ceases to be statistically significantly positive by May 9, and dips slightly negative for several weeks in the early summer of 2020, before returning to zero by mid-summer.

The estimated responses shown in the upper panel of Figure 6 suggest a positive but short-lived economic impact of the first round of PPP loans. The figure demonstrates an important advantage of our high-frequency indicators. Given that we estimate a positive effect that persists for only a matter of weeks, a researcher using a lower frequency of the outcome variable might miss the initial, positive effects of the intervention.

Our indices are scaled to match four-quarter growth rates in U.S. real GDP, and are therefore most closely comparable to a state-level growth rate. To get a better sense of the persistent level effects on state-level economic activity, we estimate an alternative version of (12):

$$\sum_{q=0}^{h} ECI_{j,t+q} = \delta_0^{(h)} + \delta_1^{(h)} x_{j,t} + \delta_2^{(h)} ECI_{j,t-k} + \delta_3^{(h)} ECI_{j,t-\ell} + \nu_{j,t+q}, \tag{13}$$

where the left-hand-side variable is the cumulative sum of weekly economic conditions up to horizon h. Panel B of Figure 6 plots the estimated effects of a one-standard-deviation shock to PPP loan volume per capita against the time horizon h for this specification. Dashed lines denote 68 percent confidence intervals. State-level economic conditions improve on impact and continue to improve for several weeks, with a peak effect of about 2 percent in mid-May. The effect then slowly dies out, ceasing to be statistically significantly different from zero by the end of May, with point estimates very near zero by mid-June.

Our results are broadly in line with existing evidence. In particular, Bartik et al. (2020) show that states that received the least in PPP funds had the lowest trough in hours worked and slower recoveries relative to states who received more initial PPP funding. Similarly, Chetty et al. (2020) report that PPP loans stimulated employment at small businesses by about 2 percent. Hubbard and Strain (2020) conclude that PPP funding has considerably improved the employment situation, financial health, and survival chances of small businesses. Granja et al. (2020) also find a small but positive effect of PPP loan disbursement on a variety of micro-level economic indicators.

3 The Role of States in National Recessions

To establish a link between the business cycle dynamics of state economies and the national economy, we fit a regime-switching model to the weekly common component obtained with the dynamic factor model for each state.[14] Owyang, Piger, and Wall (2005) also apply a Markov-switching model to state-level coincident indices to compute monthly recession probabilities and study expansionary and recessionary phases of individual states. In contrast to their approach, we allow the depth of recessions and expansions to vary over time, which is a particularly useful feature given the severity of the two most recent contractionary episodes. Moreover, we provide state-level recession probabilities at the weekly frequency based on indices that cover additional dimensions of state economies. We also propose an aggregate indicator that allows us to gauge the overall weakness of the U.S. economy.

3.1 A Markov-Switching Model with Heterogeneous Recessions and Expansions

This section describes the model framework that we use to construct the Economic Weakness Index for the U.S. economy as a whole. The procedure follows Leiva-León, Pérez-Quirós, and Rots (2021) and consists of two steps that provide a simple-to-compute and easy-to-interpret index that measures the state of the aggregate economy in a timely fashion along with its underlying sources. In the first step, the common component of the estimated weekly state-level economic conditions indices are used to compute the time-varying recession probabilities associated with each U.S. state. In the second step, the estimated recession probabilities for each state are aggregated based on the relative economic size of each state. This composite time-varying probability constitutes our proposed Economic Weakness Index (EWI). In what follows, we provide a detailed description of the two steps employed to compute the EWI.

Step 1: Computing recession probabilities

Let f_t be the common factor associated with a given U.S. state. The aim is to decompose f_t into two components, the mean, μ_t, and a noise term, ε_t. In doing so, it is assumed that there are two states of the economy, defined by the binary latent variable $s_t = \{0, 1\}$. If the economy is in its τ_1-th expansionary regime at time t, then $s_t = 1$ and $E(f_t) = \mu_{1,\tau_1}$, for $t \in \tau_1$. Instead, if the economy is in its τ_0-th recessionary regime at time t, then $s_t = 0$ and $E(f_t) = \mu_{0,\tau_0}$, for $t \in \tau_0$. This implies that we allow each expansion and recession to be of unique magnitude and account for the evolving heterogeneity of both regimes over time. Accordingly, the dynamics of f_t can be

[14] This two-step approach was first proposed by Diebold and Rudebusch (1996), where the first step relies on a linear factor model to construct a coincident indicator that is then used in a second step to compute Markov-switching probabilities to determine business cycle turning points. Estimating a Markov-switching dynamic factor model in one step is a useful alternative for identifying turning points, but not so much for deriving composite indices of economic activity, especially when working with annual growth rates. However, Camacho et al. (2015) show that when the economic indicators are carefully selected, the two methods do not differ much in their ability to track business cycles.

described as follows:

$$f_t = \mu_{0,\tau_0}(1 - s_t) + \mu_{1,\tau_1} s_t + \varepsilon_t \qquad \varepsilon_t \sim \mathcal{N}(0, \sigma_\varepsilon^2) \tag{14}$$

where the mean component is defined by the regime-dependent means and the latent variable indicating the state of the economy, $\mu_t = \mu_{0,\tau_0}(1 - s_t) + \mu_{1,\tau_1} s_t$. Our modelling approach for f_t builds on the time-varying regime-dependent means model of Eo and Kim (2016). In their setting, they constrain μ_{0,τ_0} and μ_{1,τ_1} to exhibit time dependence through random walks. This assumption could be highly restrictive when applying the model to a rapidly, and substantially, changing economic environment, as is the case for measuring weekly economic conditions during the COVID-19 period. Therefore, we relax this assumption by letting the magnitudes associated with all recessions and expansions be independent, that is, $cov(\mu_{\iota,\tau_\iota}, \mu_{\iota,\tau_\iota - j}) = 0$, $\forall j$, for $\iota = 0, 1$.[15] This feature allows the model to fit business cycle dynamics involving any sequence of expansions and recessions of either small or extreme magnitudes.

The variable governing the business cycle, s_t, is assumed to follow a two-state Markov chain defined by transition probabilities:

$$\Pr(s_t = i \mid s_{t-1} = j) = p_{ij}. \tag{15}$$

Since there are only two states, these probabilities can be summarized by the chance of remaining in expansion, p, and the chance of remaining in recession, q.

The model is estimated with Bayesian methods, assuming as priors Normal distributions for μ_{0,τ_0} and μ_{1,τ_1}, Beta distributions for p and q, and a Gamma distribution for σ_ε^2. Inference on s_t is performed by relying on the algorithm implemented in Kim and Nelson (1999), which is an adaptation of the Carter and Kohn (1994) algorithm.[16]

Step 2: Aggregating recession probabilities

The EWI is constructed as a weighted average of the recession probabilities of all individual states. Since the models are estimated in a Bayesian fashion, we can generate many replications associated with the realization of recessionary episodes for each state, that is, $s_{\kappa,t}^{(l)}$ for $\kappa = 1, ..., K$, and $l = 1, ..., L$, where $K = 50$ is the number of U.S. states and $L = 10,000$ is the number of retained draws. Consequently, the l^{th} replication of the EWI is given by:

$$EWI_t^{(l)} = \sum_{\kappa=1}^{K} \omega_{\kappa,t} s_{\kappa,t}^{(l)}, \tag{16}$$

where $\omega_{\kappa,t}$ denotes the time-varying weight for each U.S. state. These weights are based on the evolving economic size of each state relative to national real GDP. The collection of all the replications $\{EWI_t^{(l)}\}_{l=1}^{l=L}$ constitutes the simulated density of the weakness index at time t. Based on this posterior density, we can compute point estimates along with any percentiles for risk assessment.

[15] For identification purposes, μ_{0,τ_0} (μ_{1,τ_1}) is truncated so that it can only take negative (positive) values (see, e.g., Hamilton and Owyang, 2012).

[16] For additional details on the sampling algorithm, see Leiva-León et al. (2021).

3.2 Economic Weakness Index

Panel A of Figure 7 shows the median estimate of the Economic Weakness Index. The EWI can be interpreted as the share of states that are facing a recession in any given week over the period April 4, 1987 to present. The gray shaded areas represent periods of national recessions designated by the NBER. Given that recession start and end dates are usually determined many months after the fact, we also include the dates when recessions were called by the NBER. The black dashed lines indicate the week of the announcement of the peak month, and the blue dotted lines indicate the week of the announcement of the trough month. Note that the NBER announcement dates are always well after the beginning and the end of the four recessionary episodes in our sample.[17]

The EWI generally lines up well with official NBER-dated recessions. Furthermore, its magnitude accurately reflects the severity of the different recessionary episodes, with the 1990/91 and 2001 recessions being milder and less pervasive compared to the Great Recession and the COVID-19 recession; these results are in line with the earlier evidence presented in the heatmaps.[18] While the EWI tends to rise steeply before the official start dates for all four recessions in the sample, it remains elevated for some time after the NBER dates these recessions to have ended, indicating that a considerable fraction of the country is still experiencing slow growth.

It is also interesting to explore to what extent our probability-based weakness indicator can be used for dating business cycles. This requires some formal rule that involves a threshold for when to call and date a turning point. If we were to apply the decision rule proposed by Chauvet and Hamilton (2006) to our EWI,[19] we would always call the beginning of a recession earlier than the NBER. We would also be fairly accurate in dating the start of three out of four recessions, falling short of the NBER peak month only by a few weeks. The exception is the Financial Crisis, where the EWI lagged the start date of the Great Recession by eight months. While we would have called the end of two out of three recessions around the same time as the NBER, the EWI misses the turning point and thus is not useful for determining the end date of recessionary periods, at least not based on this particular rule.[20] The fact that the EWI would date recessions as lasting substantially longer than the NBER is a feature that we share with Hamilton and Owyang (2012), whose framework relies on monthly state employment growth. While some of this sluggishness is inherent in the fact that we are using annual growth rates, the likely economic reason for the protracted nature of recovery periods is the phenomenon of jobless recoveries (see, e.g., Koenders and Rogerson, 2005; Jaimovich and Siu, 2020) given that labor market variables form an important part of our state-level economic conditions indicators.

[17] At the time of this writing, the NBER has not yet declared the COVID-19 recession to be over.

[18] See also the depth and severity measures for U.S. recessions reported in Diebold (2020).

[19] Chauvet and Hamilton's (2006) decision rule to call and date recessions works as follows: when their index exceeds 0.66, they call a recession and date it to have started when the index first exceeded 0.5; the end of the recession is called when their index drops below 0.33 and dated when the index fell below 0.5 for the first time. One important difference is that their analysis is fully real time, while ours is based on full-sample estimates.

[20] Designing an appropriate rule inevitably involves some judgement and is best based on the past performance of the indicator itself. We leave such an analysis for future research.

Prolonged weakness was expected at the end of February 2021 according to the 52-week-ahead projection of the EWI shown as the red dotted line in Figure 7, panel A. This seems to confirm the role of jobless recoveries given that the labor market was at the core of the recent crisis. In fact, Chetty et al. (2020) anticipate another jobless recovery from the pandemic-induced recession because job losses in sectors that have been hit hard by the health crisis, such as leisure and hospitality, might persist for a long time. Applying the same decision rule as above to the projected path suggests that we would still be in recession in February 2022. Given the new information that has arrived since, the economy remaining in recession until 2022 seems highly unlikely, but was not unexpected at the time considering the past performance of the EWI.

The picture changes dramatically when we include more recent data. Panel B of Figure 7 provides real-time updates of the EWI at the end of March (blue line), April (green line), and May (black line). While the evolution of the EWI in the first two weeks of March is closely aligned with the expected path as of February 27, 2021, the situation improves much faster thereafter with the EWI falling to 0.62 by the end of April relative to the forecasted 0.77. In the first week of May, we observe a steep decline in economic weakness, which would lead us to declare that the COVID-19 recession ended on May 8, 2021.[21] This acceleration of growth is consistent with rising vaccination rates which considerably lower the risk of infections, which enables firms to resume normal operations and consumers to make up for subdued spending. Contrary to earlier assessements, this seems to suggest that we are not in a situation of structural reallocation, but rather a year of pent-up demand which is likely to benefit service sectors like travel, leisure, and hospitality. The predicted trajectory at the end of May signals a stable environment of low economic weakness over the next year. This once again illustrates the benefits of using high-frequency data to obtain a timely assessment of the current state of the national economy.

3.2.1 Drivers of National Weakness

To get a better sense of the role of the labor market in contributing to national weakness relative to other factors, Figure 8 presents a decomposition of the weekly EWI into its main driving forces. Panel A displays the relative importance of each data category for periods of economic weakness for the entire sample period, while panel B focuses on the COVID-19 episode.[22]

The decomposition shows that the labor market accounts for only a modest share in the build-up of economic weakness in most recessions, with the COVID-19 recession being a notable exception, where the labor market was the major contributor from the beginning. In the early stages of the

[21] This time the signal of our weakness indicator would precede the NBER announcement of the trough month. The Chauvet-Hamilton algorithm already called the end of the recession on January 28, 2021 and dated it to have ended in the second quarter of 2020 (see here). See Figure 4A in the appendix for the updated EWI in historical context.

[22] While it might seem surprising that we report the contribution of data categories for which data are not available for the entire sample period (e.g. mobility), we take advantage of the Kalman smoother which replaces missing observations with optimal estimates. Thus, one can interpret this exercise as a counterfactual that shows what the contribution of these categories would have been had those data existed.

1990 downturn as well as the Great Recession, expectations and household indicators were the most important drivers of national weakness, whereas real activity and household indicators were the key contributors during the early 2000s slowdown. During these three episodes, the relative contribution of the labor market gradually increased and typically plateaus toward the end of a recession. When real activity, household spending, and expectations start improving, it tends to be the labor market that keeps economic weakness elevated well after the turning point, which is in line with the idea of jobless recoveries. Compared to the other categories of variables, financials play a relatively modest role in all of these recessions. Measures of mobility make a fairly constant contribution over time. Interestingly, in spite of widespread lockdown orders, mobility variables do not seem to play an outsized role in the COVID downturn, even though they are temporarily more relevant than in earlier episodes. Together with labor market variables they drive almost all of the initial uptick in the EWI at the beginning of the pandemic in the spring of 2020. Expectations were relatively unimportant throughout this episode. The relative contribution of real activity and household indicators increases slightly as the pandemic drags on. Most of the reduction in the EWI since the fall of 2020 comes from improving labor market conditions.

3.2.2 Other Sources of Weakness

Figure 9 considers a set of non-model-based criteria for classifying the sources of national economic weakness. Panel A provides a geographical breakdown based on the nine census divisions. Not surprisingly, the Pacific, East North Central, Mid- and South Atlantic divisions are the main contributors to the national cycle, which makes sense given that they carry a lot of economic weight. Although the Mountain, West North Central, and East South Central divisions account for about half of the contiguous area of the US, they do not make much of a difference for economic weakness. Overall, the contributions of the different geographic regions to the EWI are fairly stable across recessionary episodes.

Panel B decomposes the EWI according to the degree of economic diversification across states. We measure diversification using the Hachman Index. The Hachman Index measures the employment diversity of a given state relative to the US as a whole. The index takes values between 0 and 1, with values closer to 0 indicating greater industrial specialization and values closer to 1 a more diverse industrial composition similar to the US.[23] We group states into three different categories based on the time-varying distribution of diversification across states – low diversification (lower

[23] The monthly Hachman Index (HI) is computed as follows:

$$HI_t = \left(\sum_{i=1}^{N} \left[\left(\frac{E_{i,t}^S}{E_{i,t}^{US}} \right) * E_{i,t}^S \right] \right)^{-1}$$

where $E_{i,t}^S$ is the employment share in industry i of state S at time t, $E_{i,t}^{US}$ is the employment share in industry i for the U.S. economy at time t, and N is the number of industries. The index is based on the following eight industry classifications for which employment data are available from FRED at both the state and national levels from January 1990 onward: construction, financial activities, information, manufacturing, mining and logging, private services, real estate, and total government (see also Bokun et al., 2020).

third), intermediate diversification (middle third), and high diversification (upper third). While a low level of diversification should make states more vulnerable to cyclical fluctuations, their contribution to the total EWI is limited because more specialized states tend to be economically small. In contrast, the more diversified states are also larger in economic size and thus drive economic weakness at the national level. In the four recessions in our sample, high and intermediate diversification states contribute about equally to the overall EWI.

Panel C sorts states by their resource richness. We classify states as "No Resources" if their monthly mining plus logging share of nonfarm employment is lower than 0.25 percent and as "Resource Intensive" if this share exceeds 1 percent. States with a mining share between 0.25 and 0.5 percent belong to "Low Resources," and between 0.5 and 1 percent to "Intermediate Resources." In all recessions, the contributions of different states to the EWI is roughly inversely related to their resource intensity. In particular, states categorized as "No Resources" account for the bulk of the movements in the EWI in the early stages of a recessionary phase, typically followed by "Low Resources" states. "Resource Intensive" states seem more resilient when economic weakness is building up, but account for a larger share of the EWI later in a recession. "Intermediate Resource" states play only a minor role.

Panel D shows the contributions of states depending on how they voted in each presidential election. Switches in political positions across states are recorded during inauguration week. The contributions to the EWI reflect a combination of voting shares and economic importance of states. For example, the EWI during and immediately after the 1990-1991 recession was primarily driven by states that had voted for the Republican party. Instead, the Great Recession appears to have been dominated by Democratic-voting states. There is a roughly equal split between Republican- and Democratic-voting states in contributing to the early 2000s and COVID-19 recessions.

3.2.3 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 10 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.

3.3 The Economic Geography of Recession Probabilities

To get a better sense of the geographic dimension in the relationship between state and national business cycles, we explore the spatial distribution of weekly recession probabilities of individual states for three selected episodes. We consider the Great Recession, the oil price decline of 2014-16, and the COVID-19 recession. Figure 11 presents maps for the 48 contiguous states where shades of green indicate low recession probabilities and shades of red indicate high recession probabilities.[24]

3.3.1 The Great Recession

The period in the run-up to the Great Recession was characterized by a sharp reversal of the house price boom in 2006 and ensuing trouble in the banking sector. In June 2008, the U.S. stock market plunged but oil was still trading at a historic high of $140 a barrel. The snapshot for the last week of June reported in Panel A of Figure 11 shows that 16 states, among which many were oil-producing states, were still in expansion with recession probabilities smaller than 0.3. Even though the NBER later deemed the recession to have begun in December 2007, only 13 states were in recession in June 2008 and another eight were on the brink of recession. The states with the weakest economies at the time include Florida, California, and Arizona, three states hit particularly hard by the housing market bust.

Between the second and fourth quarter of 2008, we observe a gradual increase in recession probabilities across states, first spreading along both coasts before gravitating inland. After months of holding the interest rate steady at 2%, the Federal Reserve lowered the policy rate to 1.5% at its October meeting and the IMF warned of a systemic meltdown of the global financial system. These events coincided with a few more states falling into recession, for a total of 27 in the last week of October 2008. The states that were still withstanding the downturn were mainly oil producers, even though oil prices had started to decline. The deterioration of economic conditions accelerated thereafter, with 40 states being in recession by the time that the NBER called the recession in early December 2008.

The first half of 2009 was the most contractionary phase of the Great Recession, with almost all states being in recession throughout this period. What is noteworthy is that, according to our model, all states still had a recession probability of 1 until August 2009, despite the fact that the end of the national recession was dated June 2009 by the NBER. However, this seems to be in line with an assessment made by the FOMC committee that described the situation at the end of June 2009 as one where "(h)ousehold spending has shown further signs of stabilizing but remains constrained by ongoing job losses, lower housing wealth, and tight credit [and] (b)usinesses are cutting back on fixed investment and staffing."[25]

[24] A movie showing the week-by-week evolution of recession probabilities for the entirety of the three episodes is available here. Figure 11 is showing frames from this movie for selected weeks.

[25] See here for the press release of the FOMC statement.

The snapshot in mid-May 2010 illustrates that the recovery took hold in the second quarter of 2010, with 21 states in expansion and 5 more with a recession probability of less than 40%. The lingering effects of the housing crisis were concentrated on the West Coast and in Florida, with those states still performing poorly. Despite the rebound in energy prices, some oil-producing states were sluggish to recover.

Overall, Panel A shows that the Great Recession, while severe at the aggregate level, was not as synchronous across states as one might expect.

3.3.2 The 2014-16 Oil Price Slump

Another interesting episode is the prolonged decline in oil prices that started in the second half of 2014 and persisted until early 2016. Given the increased importance of the U.S. shale oil sector, oil-producing states were likely to be negatively affected, whereas others might have benefitted from lower energy prices. However, there is also the possibility that lower investment by oil states could spill over to other states that produce machinery and other equipment for the oil industry, slowing growth nationwide. While many observers expected lower oil prices to boost aggregate growth, Baumeister and Kilian (2016) show that the net stimulus for the U.S. economy as a whole was close to zero. We explore the spatial pattern of this finding.

In the last week of July 2014, oil prices stood at \$104 before starting their descent to the first trough of \$45; this trough was reached in the last week of January 2015. Panel B of Figure 11 shows that in July 2014 the majority of U.S. states were in the dark green territory with recession probabilities below 0.1, except for Minnesota, which had been contracting since the beginning of the year. While Minnesota's economy is relatively diversified, its energy-intensive agricultural sector is a major part of its value added, in particular as it relates to the production of ethanol biofuels. One possible factor in Minnesota's poor performance during this period is the fact that ethanol prices plunged in early 2014 while oil prices were at record levels.

When oil prices bottomed out at the end of January 2015, Wyoming – which is heavily reliant on fracking and whose economic performance had been deteriorating from week to week since November 2014 – entered into recession alongside Minnesota. The only other state showing incipient signs of weakness was Nebraska. Like Minnesota, Nebraska is an important producer of fuel ethanol. Over the course of the year, more and more oil-producing states started experiencing difficulties. By early February 2016, when oil prices fell below \$30, Panel B shows that states like Louisiana, North Dakota, New Mexico, and West Virginia – all of whom had initially weathered the oil price slump – were now in contraction. Other oil-producing states such as Texas, Oklahoma, Colorado, and Montana were, however, resilient throughout this entire episode.

There is little evidence for spillovers across states – states adjacent to oil-producing states did just as well as states without geographic contiguity over this time period. Taken together, the oil price decline caused some heterogeneity in state-level business cycles with energy-dependent states in the Great Plains and along the Gulf Coast performing rather poorly while the rest of the country was in expansion.

3.3.3 The COVID-19 Recession

The outbreak of the global pandemic was a cataclysmic event that pushed the U.S. economy into collapse in the second half of March 2020, all within a matter of a few weeks. Panel C of Figure 11 tracks the evolution of state-level recession probabilities in three consecutive weeks starting with the week ending on March 14, 2020. In mid-March, many states were performing quite well, with 18 states having recession probabilities of less than 40%, even though there were scattered initial signs of weakness with 11 states already in recession. In the following week, as the public health crisis unfolded, the deterioration of economic conditions ran rampant with a widespread jump in recession probabilities, more than tripling the number of states in recession. The economic shutdown took hold in the last week of March, when another 10 states switched into recession. By the end of the first week of April 2020, all states were in recession. What stands out most from this sequence of maps is the extreme degree of synchronization across states in the pandemic recession. This synchronization of state-level business cycles, particularly in the early stages of a downturn, is not a feature of earlier episodes.

In sum, the analysis of these three episodes underscores the heterogeneity in geographic patterns across events and the value of a high-frequency assessment of economic developments at the state level.

4 Conclusions

Economic conditions at the state level are a key determinant for the national business cycle. In this paper we developed a novel dataset of weekly economic conditions indices for the 50 U.S. states going back to 1987. Our indices are based on mixed-frequency dynamic factor models with weekly, monthly, and quarterly variables that cover multiple features of state economies going beyond traditional indicators. We illustrated the usefulness of these indices by studying the weekly evolution of economic conditions across states for several recessionary episodes and by quantifying the contribution of each data category to the economic disruption caused by the COVID-19 crisis and the subsequent recovery. We showed that there is considerable heterogeneity across space and time of state-level business cycle dynamics, except for the economic collapse associated with the COVID-19 pandemic, which was an unusually uniform event. We also studied the geographic distribution of state-specific expansionary and recessionary phases and proposed an economic weakness index that connects state economies to the national economy by aggregating the state-level information about recession probabilities.

Being able to track economic developments at the state level and knowing the probability of entering a recession on a week-by-week basis should be valuable for state policymakers to take targeted actions earlier in an effort to counteract contractionary tendencies, especially in turbulent economic times. Particularly useful for this purpose is the decomposition to identify which segment of the state economy is the main source of economic weakness to tailor policy measures accordingly. Understanding cross-state differences in economic performance within one country is also useful for understanding aggregate dynamics and for informing federal policymaking.

Our dataset offers many promising avenues for applications in a variety of areas. One interesting question for future research is to what extent the forecasting performance of macroeconomic variables at the national level can be improved by augmenting standard forecasting models with our high-frequency state-level information. Studying differences in cross-state dynamics in response to macroeconomic shocks such as energy price shocks, technological innovation, the diffusion of news shocks, changes in economic policy uncertainty, and exchange rate shocks could help uncover economic mechanisms at work in shock transmission. Exploiting the cross-sectional and/or time-series variation of our state-level indices should also improve our understanding of the effectiveness of various nationwide policy interventions. Given the weekly frequency of our dataset, it is also possible to study the responses of state economies to high-frequency surprises using instruments or proxies derived from policy or macroeconomic announcements or narrative sources. This is particularly useful if the effects are short-lived and aggregation to lower frequencies might result in masking potentially significant effects.

A A Dynamic Factor Model with Three Mixed Frequencies

Let $\boldsymbol{\theta} = (\boldsymbol{\psi}^q, \boldsymbol{\psi}^m, \boldsymbol{\psi}^w, \boldsymbol{\sigma}^q, \boldsymbol{\sigma}^m, \boldsymbol{\sigma}^w, \boldsymbol{\lambda}^q, \boldsymbol{\lambda}^m, \boldsymbol{\lambda}^w, \boldsymbol{\phi})'$ 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, $\boldsymbol{\psi}_i^q = (\psi_{i,1}^q, ..., \psi_{i,p_q}^q)'$, $\boldsymbol{\psi}_j^m = (\psi_{j,1}^m, ..., \psi_{j,p_m}^m)'$ and $\boldsymbol{\psi}_k^w = (\psi_{k,1}^w, ..., \psi_{k,p_w}^w)'$ contain the autoregressive coefficients of the idiosyncratic terms associated with i^{th} quarterly, j^{th} monthly and k^{th} weekly variables, respectively, and σ_i^q, σ_j^m, and σ_k^w denote the corresponding innovation variances. Accordingly, we have that $\boldsymbol{\psi}^q = (\boldsymbol{\psi}_1^q, ..., \boldsymbol{\psi}_i^q, ..., \boldsymbol{\psi}_{n^q}^q)'$, $\boldsymbol{\psi}^m = (\boldsymbol{\psi}_1^m, ..., \boldsymbol{\psi}_j^m, ..., \boldsymbol{\psi}_{n^m}^m)'$ and $\boldsymbol{\psi}^w = (\boldsymbol{\psi}_1^w, ..., \boldsymbol{\psi}_k^w, ..., \boldsymbol{\psi}_{n^w}^w)'$ for the autoregressive coefficients, and $\boldsymbol{\sigma}^q = (\sigma_1^q, ..., \sigma_i^q, ..., \sigma_{n^q}^q)'$, $\boldsymbol{\sigma}^m = (\sigma_1^m, ..., \sigma_j^m, ..., \sigma_{n^m}^m)'$ and $\boldsymbol{\sigma}^w = (\sigma_1^w, ..., \sigma_k^w, ..., \sigma_{n^w}^w)'$ for the innovation variances. Similarly, the factor loadings linking the quarterly, monthly, and weekly variables with the common factor f_t are collected in $\boldsymbol{\lambda}^q = (\lambda_1^q, ..., \lambda_i^q, ..., \lambda_{n^q}^q)'$, $\boldsymbol{\lambda}^m = (\lambda_1^m, ..., \lambda_j^m, ..., \lambda_{n^m}^m)'$, $\boldsymbol{\lambda}^w = (\lambda_1^w, ..., \lambda_k^w, ..., \lambda_{n^w}^w)'$, respectively. The autoregressive coefficients of the common factor are collected in $\boldsymbol{\phi} = (\phi_1, ..., \phi_{p_f})'$.

Let $\mathbf{Y} = [\mathbf{y}_1, \mathbf{y}_2, ..., \mathbf{y}_T]$ denote the entire set of information on the data of economic variables at the quarterly, monthly, and weekly frequencies, in that order. $\boldsymbol{\xi}_t$ 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 into two broad steps. First, generate a draw of $\boldsymbol{\xi}_t$, conditional on $\boldsymbol{\theta}$ and $\mathbf{Y}$. Second, generate a draw of $\boldsymbol{\theta}$, conditional on $\boldsymbol{\xi}_t$ and $\mathbf{Y}$. These two steps are sequentially repeated for a large number of iterations.[26] 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 steps of the estimation algorithm and the chosen priors.

1. **Sample latent variables**

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

$$\mathbf{H}_t = \begin{bmatrix} \mathbf{H}_t^q \\ \mathbf{H}_t^m \\ \mathbf{H}_t^w \end{bmatrix},$$

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

$$\mathbf{H}_t^q = \begin{bmatrix} \frac{\lambda_1^q}{d(q_t)}\mathbf{1}'_{[d(q_t)]} & \mathbf{0}'_{[D-d(q_t)]} & \frac{\mathbf{1}'_{[d(q_t)]}}{d(q_t)} & \mathbf{0}'_{[D-d(q_t)]} & \cdots & \mathbf{0}'_{[d(q_t)]} & \mathbf{0}'_{[D-d(q_t)]} & \mathbf{0}'_{[Cn^m+p_w n^w]} \\ \frac{\lambda_2^q}{d(q_t)}\mathbf{1}'_{[d(q_t)]} & \mathbf{0}'_{[D-d(q_t)]} & \mathbf{0}'_{[d(q_t)]} & \mathbf{0}'_{[D-d(q_t)]} & \cdots & \mathbf{0}'_{[d(q_t)]} & \mathbf{0}'_{[D-d(q_t)]} & \mathbf{0}'_{[Cn^m+p_w n^w]} \\ \vdots & & \vdots & & \ddots & & \vdots & \\ \frac{\lambda_{n^q}^q}{d(q_t)}\mathbf{1}'_{[d(q_t)]} & \mathbf{0}'_{[D-d(q_t)]} & \mathbf{0}'_{[d(q_t)]} & \mathbf{0}'_{[D-d(q_t)]} & \cdots & \frac{\mathbf{1}'_{[d(q_t)]}}{d(q_t)} & \mathbf{0}'_{[D-d(q_t)]} & \mathbf{0}'_{[Cn^m+p_w n^w]} \end{bmatrix}.$$

[26] In the empirical application, we use 12,000 iterations and discard the first 2,000 to ensure convergence.

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.[27]

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

$$\mathbf{H}_t^m = \begin{bmatrix} \frac{\lambda_1^m}{c(m_t)}\mathbf{1}'_{[c(m_t)]} & \mathbf{0}'_{[D(1+n^q)-c(m_t)]} & \frac{\mathbf{1}'_{[c(m_t)]}}{c(m_t)} & \mathbf{0}'_{[C-c(m_t)]} & \cdots & \mathbf{0}'_{[c(m_t)]} & \mathbf{0}'_{[C-c(m_t)]} & \mathbf{0}'_{[p_w n^w]} \\ \frac{\lambda_2^m}{c(m_t)}\mathbf{1}'_{[c(m_t)]} & \mathbf{0}'_{[D(1+n^q)-c(m_t)]} & \mathbf{0}'_{[c(m_t)]} & \mathbf{0}'_{[C-c(m_t)]} & \cdots & \mathbf{0}'_{[c(m_t)]} & \mathbf{0}'_{[C-c(m_t)]} & \mathbf{0}'_{[p_w n^w]} \\ \vdots & & \vdots & & \ddots & & \vdots & \\ \frac{\lambda_{n^m}^m}{c(m_t)}\mathbf{1}'_{[c(m_t)]} & \mathbf{0}'_{[D(1+n^q)-c(m_t)]} & \mathbf{0}'_{[c(m_t)]} & \mathbf{0}'_{[C-c(m_t)]} & \cdots & \frac{\mathbf{1}'_{[c(m_t)]}}{c(m_t)} & \mathbf{0}'_{[C-c(m_t)]} & \mathbf{0}'_{[p_w n^w]} \end{bmatrix},$$

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

$$\mathbf{H}_t^w = \begin{bmatrix} \lambda_1^w & \mathbf{0}'_{[D(n^q+1)+Cn^m+p_w n^w-1]} \\ \lambda_2^w & \mathbf{0}'_{[D(n^q+1)+Cn^m+p_w n^w-1]} \\ \vdots & \\ \lambda_{n^w}^w & \mathbf{0}'_{[D(n^q+1)+Cn^m+p_w n^w-1]} \end{bmatrix}.$$

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

$$\mathbf{F} = \begin{bmatrix} \mathbf{F}^f & & & & & & & & & \\ & \mathbf{F}_1^q & & & & & & & & \\ & & \ddots & & & & & & & \\ & & & \mathbf{F}_{n^q}^q & & & [\mathbf{0}] & & & \\ & & & & \mathbf{F}_1^m & & & & & \\ & & & & & \ddots & & & & \\ & & & & & & \mathbf{F}_{n^m}^m & & & \\ & & & [\mathbf{0}] & & & & \mathbf{F}_1^w & & \\ & & & & & & & & \ddots & \\ & & & & & & & & & \mathbf{F}_{n^w}^w \end{bmatrix},$$

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

$$\mathbf{F}^f = \left[\begin{array}{ccccccccc} \phi_1 & \phi_2 & \cdots & \phi_{p_f} & & & & & \mathbf{0}'_{[D-p_q]} \\ 1 & 0 & \cdots & 0 & & & & & \mathbf{0}'_{[D-p_q]} \\ \vdots & \vdots & \ddots & \vdots & & & & & \vdots \\ 0 & 0 & \cdots & 1 & & & & & \mathbf{0}'_{[D-p_q]} \\ \multicolumn{4}{c}{\mathbf{0}'_{[p_q]}} & 1 & & & & \mathbf{0}'_{[D-p_q-1]} \\ \multicolumn{5}{c}{\mathbf{0}'_{[p_q+1]}} & 1 & & & \mathbf{0}'_{[D-p_q-2]} \\ \multicolumn{6}{c}{\vdots} & \ddots & & \vdots \\ \multicolumn{7}{c}{\mathbf{0}'_{[p_q+(D-p_q-2)]}} & 1 & 0 \end{array}\right].$$

[27]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

$$\mathbf{F}_i^q = \left[\begin{array}{cccccccc}
\psi_{i,1}^q & \psi_{i,2}^q & \cdots & \psi_{i,p_q}^q & & & & \mathbf{0}'_{[D-p_q]} \\
1 & 0 & \cdots & 0 & & & & \mathbf{0}'_{[D-p_q]} \\
\vdots & \vdots & \ddots & \vdots & & & & \vdots \\
0 & 0 & \cdots & 1 & & & & \mathbf{0}'_{[D-p_q]} \\
 & \mathbf{0}'_{[p_q]} & & & 1 & & & \mathbf{0}'_{[D-p_q-1]} \\
 & \mathbf{0}'_{[p_q+1]} & & & & 1 & & \mathbf{0}'_{[D-p_q-2]} \\
 & \vdots & & & & & \ddots & \vdots \\
 & \mathbf{0}'_{[p_q+(D-p_q-2)]} & & & & & 1 & 0
\end{array}\right],$$

for the i^{th} quarterly indicator, by

$$\mathbf{F}_j^m = \left[\begin{array}{ccccc}
\psi_{j,1}^m & \psi_{j,2}^m & \cdots & \psi_{j,p_m}^m & \mathbf{0}'_{[C-p_m]} \\
1 & 0 & \cdots & 0 & \mathbf{0}'_{[C-p_m]} \\
\vdots & \vdots & \ddots & \vdots & \vdots \\
0 & 0 & \cdots & 1 & \mathbf{0}'_{[C-p_m]}
\end{array}\right],$$

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

$$\mathbf{F}_k^w = \left[\begin{array}{cccc}
\psi_{k,1}^w & \psi_{k,2}^w & \cdots & \psi_{k,p_w}^w \\
1 & 0 & \cdots & 0 \\
\vdots & \vdots & \ddots & \vdots \\
0 & 0 & \cdots & 0
\end{array}\right]$$

for the k^{th} weekly indicator.[28]

2. **Sample parameters**

   Conditional on the state variable $\boldsymbol{\xi}_t$ and the data $\mathbf{Y}$, draws for each set of parameters are generated as follows.

   2.1 **Sample idiosyncratic autoregressive coefficients**

   To sample $\boldsymbol{\psi}_k^w$ we use a Normal prior distribution, $N(\underline{\boldsymbol{\alpha}}_\psi, \underline{\boldsymbol{\Sigma}}_\psi)$, with $\underline{\boldsymbol{\alpha}}_\psi = \mathbf{0}_{p_w}$ and $\underline{\boldsymbol{\Sigma}}_\psi = \mathbf{I}_{p_w}$, and generate draws from the posterior density

$$\boldsymbol{\psi}_k^w | \sigma_k^w, u_{k,t}^w, \mathbf{Y} \sim N(\overline{\boldsymbol{\alpha}}_\psi, \overline{\boldsymbol{\Sigma}}_\psi),$$

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

$$\begin{aligned}
\overline{\boldsymbol{\alpha}}_\psi &= (\underline{\boldsymbol{\Sigma}}_\psi^{-1} + X^{*\prime} X^*)^{-1} (\underline{\boldsymbol{\Sigma}}_\psi^{-1} \underline{\boldsymbol{\alpha}}_\psi + X^{*\prime} Y^*) \\
\overline{\boldsymbol{\Sigma}}_\psi &= (\underline{\boldsymbol{\Sigma}}_\psi^{-1} + X^{*\prime} X^*)^{-1},
\end{aligned}$$

[28] The term $[\mathbf{0}]$ makes reference to all the zero entries required to make the matrix conformable.

with $Y^* = \{y_t^*\}_{t=p_w+1}^T$, $X^* = \{x_t^*\}_{t=1}^{T-p_w}$, and $y_t^* = \frac{u_{k,t}^w}{\sqrt{\sigma_k^w}}$, $x_t^* = \left(\frac{u_{k,t-1}^w}{\sqrt{\sigma_k^w}}, ..., \frac{u_{k,t-p_w}^w}{\sqrt{\sigma_k^w}}\right)'$. 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 $\boldsymbol{\psi}_k^m$ and $\boldsymbol{\psi}_k^q$.[29] We use the same prior distribution to sample $\boldsymbol{\psi}_j^m$ and $\boldsymbol{\psi}_i^q$, that is, $N(\underline{\boldsymbol{\alpha}}_\psi, \underline{\boldsymbol{\Sigma}}_\psi)$, with $\underline{\boldsymbol{\alpha}}_\psi = \mathbf{0}_{p_m}$, $\underline{\boldsymbol{\Sigma}}_\psi = \mathbf{I}_{p_m}$ and $\underline{\boldsymbol{\alpha}}_\psi = \mathbf{0}_{p_q}$, $\underline{\boldsymbol{\Sigma}}_\psi = \mathbf{I}_{p_q}$, respectively.

2.2 **Sample idiosyncratic innovation variances**

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

$$\sigma_k^w | \boldsymbol{\psi}_k^w, u_{k,t}^w, \mathbf{Y} \sim IG(\overline{\tau}, \overline{\eta}),$$

where the corresponding shape and scale parameters are given by

$$\begin{aligned} \overline{\tau} &= \underline{\tau} + \frac{T}{2} \\ \overline{\eta} &= \left(\underline{\eta} + \frac{e_{k,t}^{w\prime} e_{k,t}^w}{2}\right)^{-1} \end{aligned}$$

with $e_{k,t}^w = u_{k,t}^w - \psi_{k,1}^w u_{k,t-1}^w - ... - \psi_{k,p_W}^w u_{k,t-p_w}^w$ and where T denotes the sample size.[30] Similar to Step 2.1, the same procedure used to generate σ_k^w is employed to sample draws of σ_j^m and σ_i^q, using the same prior distribution.

2.3 **Sample factor loadings**

Conditional on the common factor and idiosyncratic terms, the factor loadings contained in $\boldsymbol{\lambda}^w$ are sampled independently for each weekly variable using a Normal prior distribution $N(\underline{\alpha}_\lambda, \underline{\Sigma}_\lambda)$ with $\underline{\alpha}_\lambda = 0$ and $\underline{\Sigma}_\lambda = 1$. The draws are generated from the posterior density

$$\lambda_k^w | f_t, u_{k,t}^w, \boldsymbol{\psi}_k^w, \sigma_k^w, \mathbf{Y} \sim N(\overline{\alpha}_\lambda, \overline{\Sigma}_\lambda)$$

where the posterior mean and variance are given by

$$\begin{aligned} \overline{\alpha}_\lambda &= (\underline{\Sigma}_\lambda^{-1} + X^{\dagger\prime} X^\dagger)^{-1} (\underline{\Sigma}_\lambda^{-1} \underline{\alpha}_\lambda + X^{\dagger\prime} Y^\dagger) \\ \overline{\Sigma}_\lambda &= (\underline{\Sigma}_\lambda^{-1} + X^{\dagger\prime} X^\dagger)^{-1} \end{aligned}$$

with $Y^\dagger = \{y_t^\dagger\}_{t=p_w+1}^T$, $X^\dagger = \{x_t^\dagger\}_{t=p_w+1}^T$, and $y_t^\dagger = \frac{y_{k,t}^w - \psi_{k,1}^w y_{k,t-1}^w - ... - \psi_{k,p_W}^w y_{k,t-p_w}^w}{\sqrt{\sigma_k^w}}$, $x_t^\dagger = \frac{f_t - \psi_{k,1}^w f_{t-1} - ... - \psi_{k,p_w}^w f_{t-p_w}}{\sqrt{\sigma_k^w}}$. Following Antolín-Díaz et al. (2017), draws for $\boldsymbol{\lambda}^m$ and $\boldsymbol{\lambda}^q$ are generated using GLS, and relying on the same prior distribution as for the case of $\boldsymbol{\lambda}^w$.

[29] A similar approach is pursued by Antolín-Díaz et al. (2017) when estimating a factor model that includes variables at the quarterly and monthly frequencies.

[30] In the empirical application, we choose slightly different values for $\underline{\tau}$ and $\underline{\eta}$ for a few U.S. states to accommodate state-specific idiosyncracies.

2.4 Sample factor autoregressive coefficients

To generate draws of $\boldsymbol{\phi}$, we use the Normal prior distribution $N(\underline{\boldsymbol{\alpha}}_{\phi}, \underline{\boldsymbol{\Sigma}}_{\phi})$ where $\underline{\boldsymbol{\alpha}}_{\phi} = \mathbf{0}_{p_f}$ and $\underline{\boldsymbol{\Sigma}}_{\phi} = \mathbf{I}_{p_f}$. Accordingly, draws are sampled from

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

where the moments of the posterior distribution are given by

$$\begin{aligned}\overline{\boldsymbol{\alpha}}_{\phi} &= (\underline{\boldsymbol{\Sigma}}_{\phi}^{-1} + X^{\ddagger\prime}X^{\ddagger})^{-1}(\underline{\boldsymbol{\Sigma}}_{\phi}^{-1}\underline{\boldsymbol{\alpha}}_{\phi} + X^{\ddagger\prime}Y^{\ddagger}) \\ \overline{\boldsymbol{\Sigma}}_{\phi} &= (\underline{\boldsymbol{\Sigma}}_{\phi}^{-1} + X^{\ddagger\prime}X^{\ddagger})^{-1}\end{aligned}$$

with $Y^{\ddagger} = \left\{f_t^{\ddagger}\right\}_{t=p_f+1}^{T}$, $X^{\ddagger} = \left\{x_t^{\ddagger}\right\}_{t=1}^{T-p_f}$, and $x_t^{\ddagger} = \left(f_{t-1}, ..., f_{t-p_f}\right)'$.[31]

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

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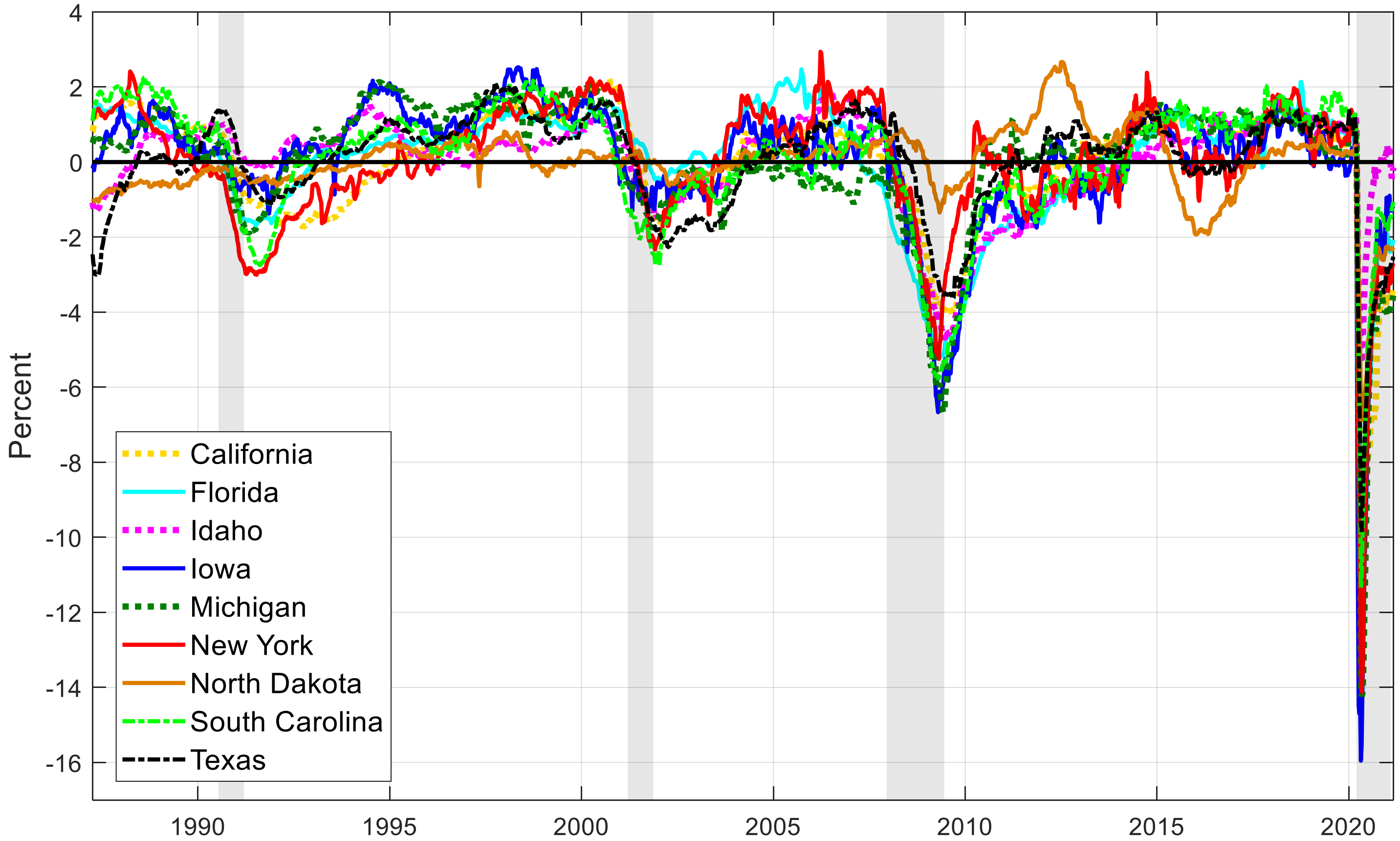
Figure 1. Weekly Economic Conditions Indices for Selected States
1987.4-2021.2



NOTES: The gray shaded areas indicate NBER recessions.

Figure 2. Decomposition of Weekly Economic Conditions Indices for Selected States 2020.1-2021.2

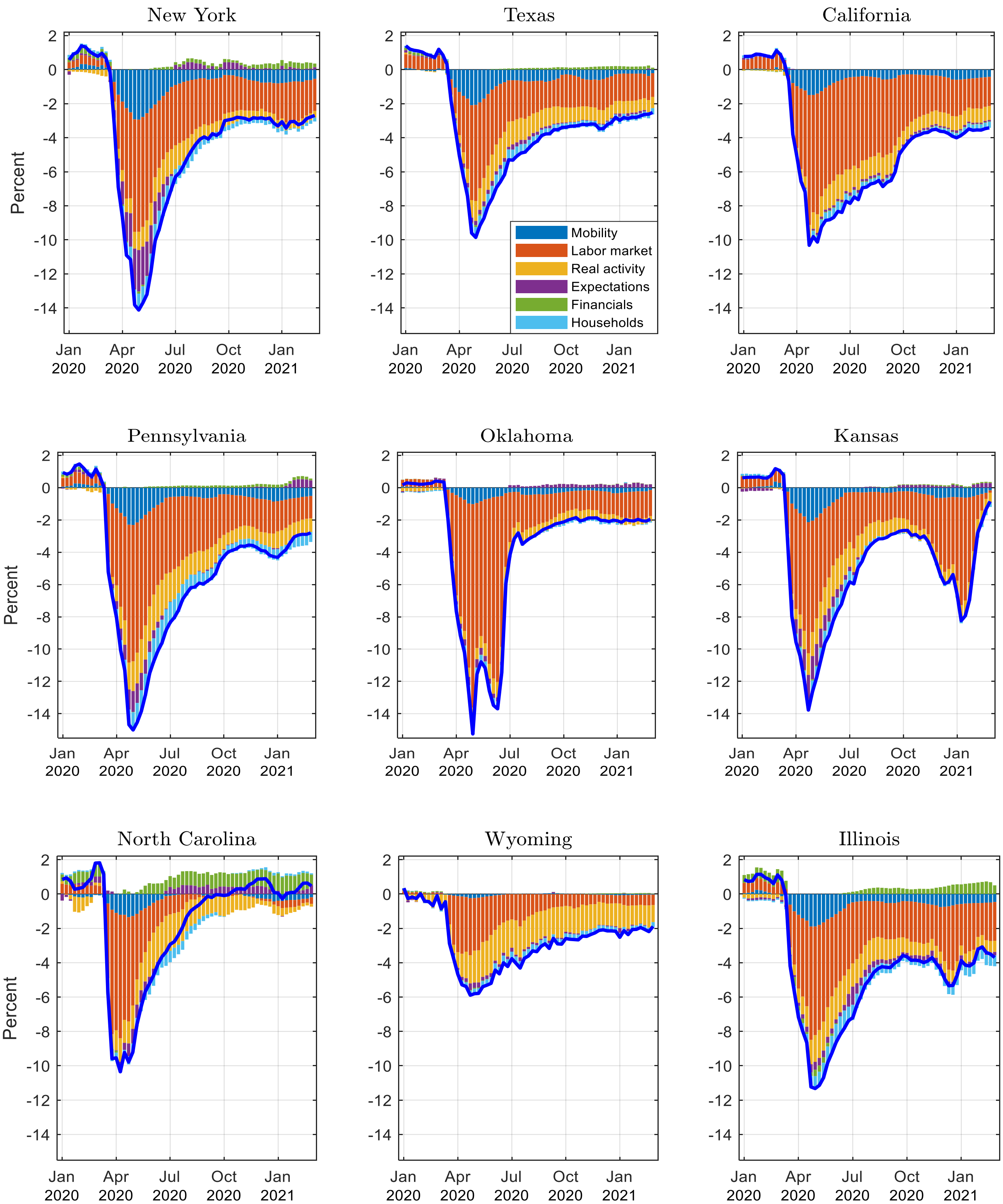
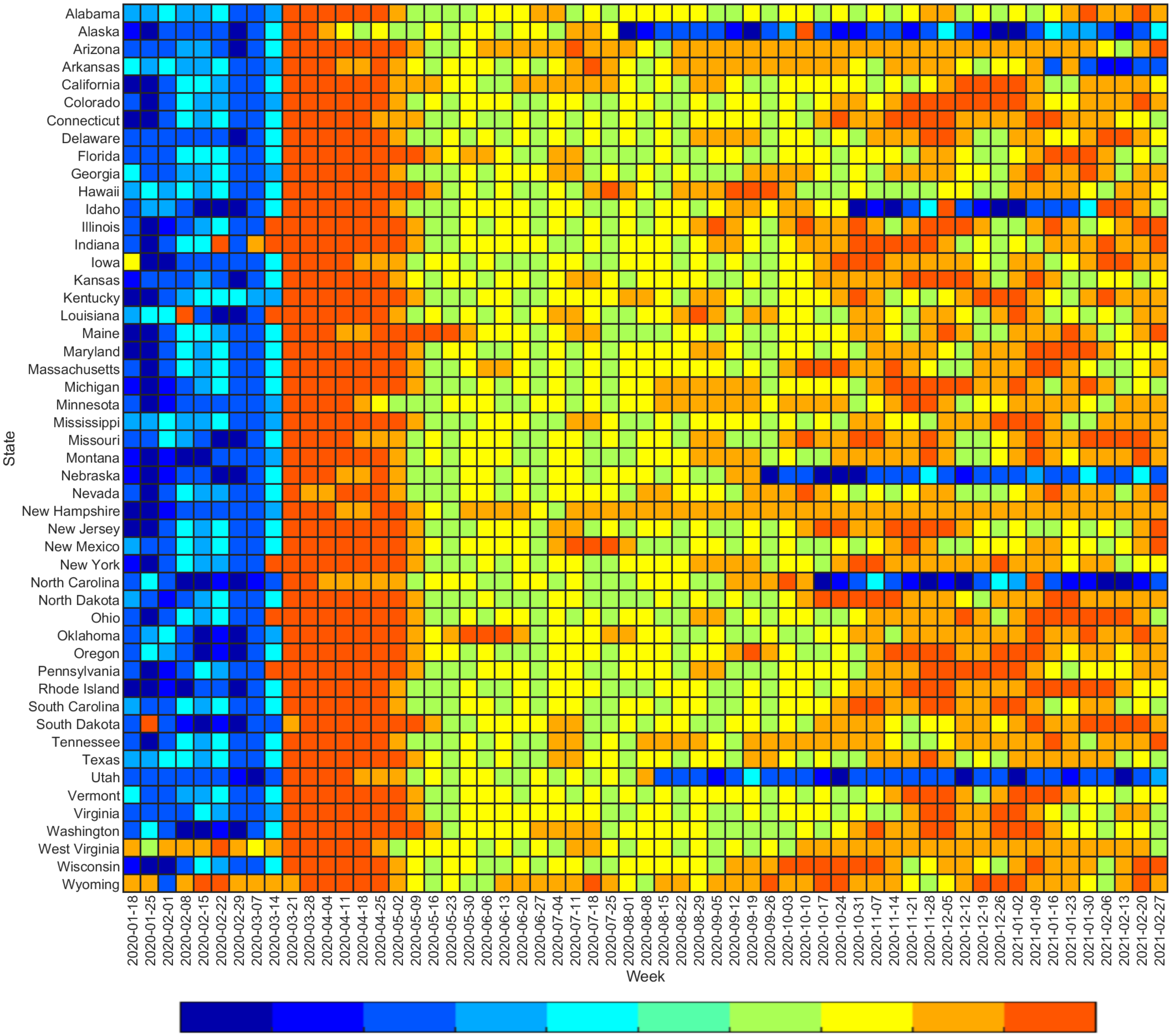
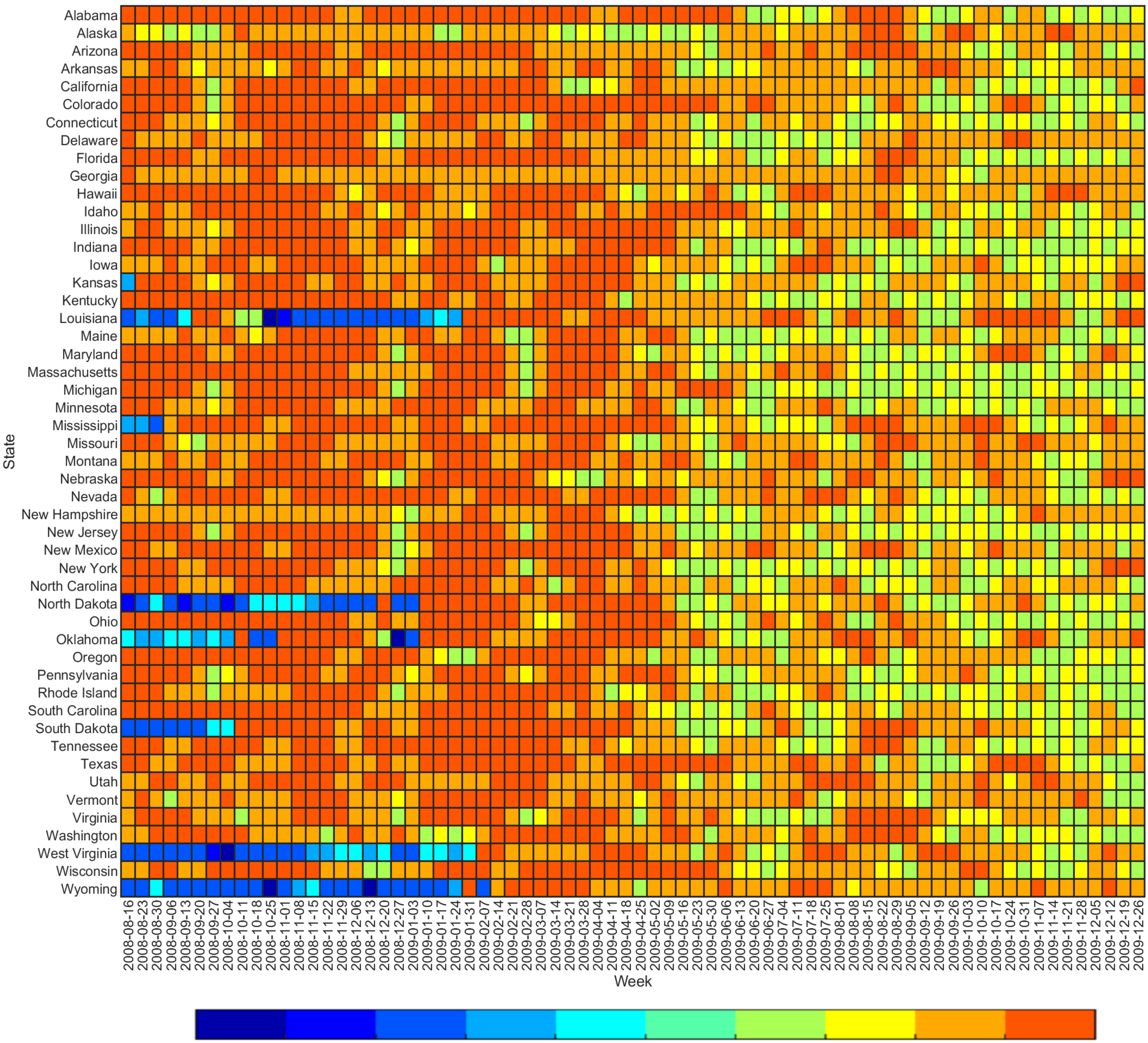


Figure 3. Weekly Developments of State-Level Economic Conditions during the COVID-19 Pandemic 2020.1-2021.2



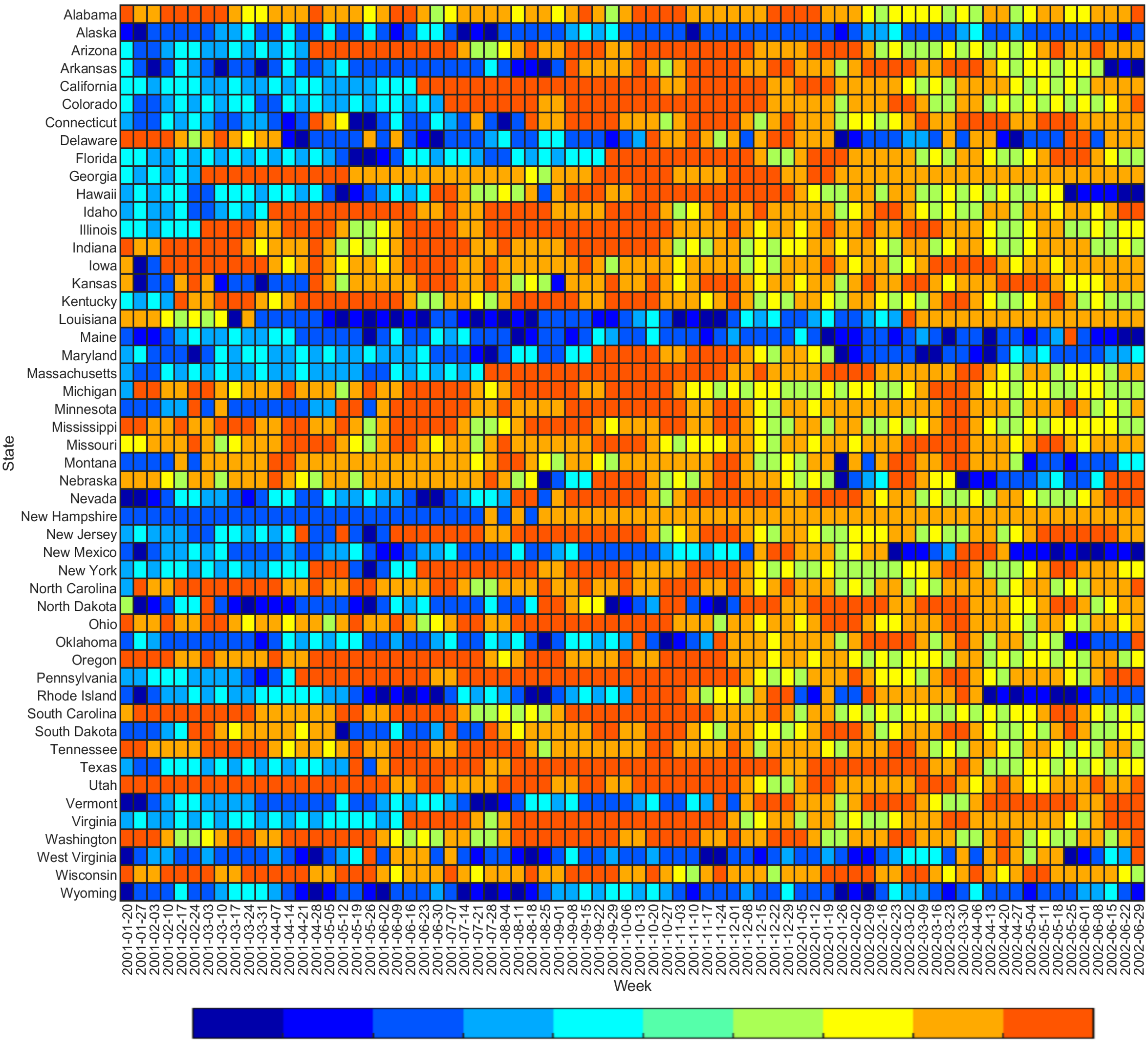
NOTES: The 10 categories of economic performance from dark blue to red are defined as follows: positive, increasing at increasing rate; positive, increasing at decreasing rate; positive, turning point; positive, decreasing at decreasing rate; positive, decreasing at increasing rate; negative, increasing at increasing rate; negative, increasing at decreasing rate; negative, turning point; negative, decreasing at decreasing rate; negative, decreasing at increasing rate.

Figure 4. Weekly Developments of State-Level Economic Conditions during the Great Recession 2008.8-2009.12



NOTES: See Figure 3.

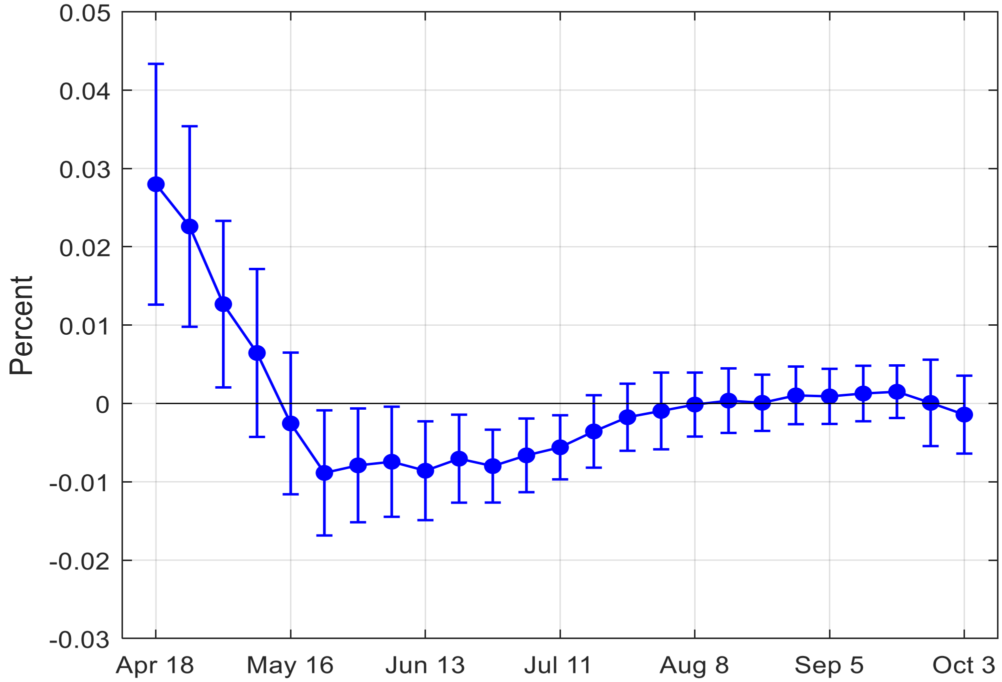
Figure 5. Weekly Developments of State-Level Economic Conditions during the 2001 Recession 2001.1-2002.6



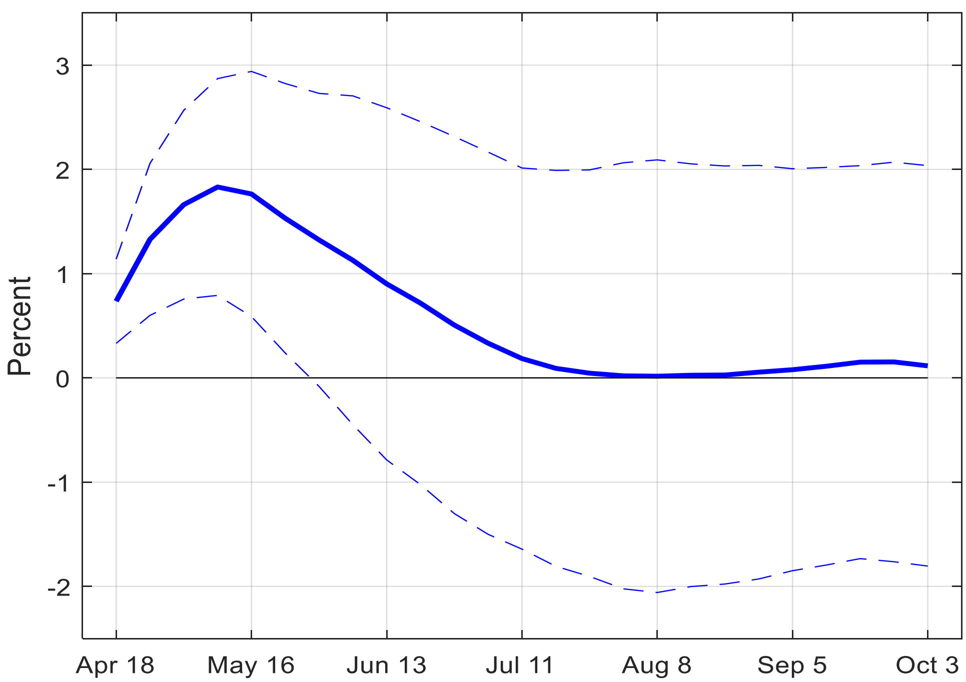
NOTES: See Figure 3.

Figure 6. Weekly Assessment of the Effectiveness of the PPP Program

Panel A: Effect of a 1% increase in loan amounts per capita on economic conditions



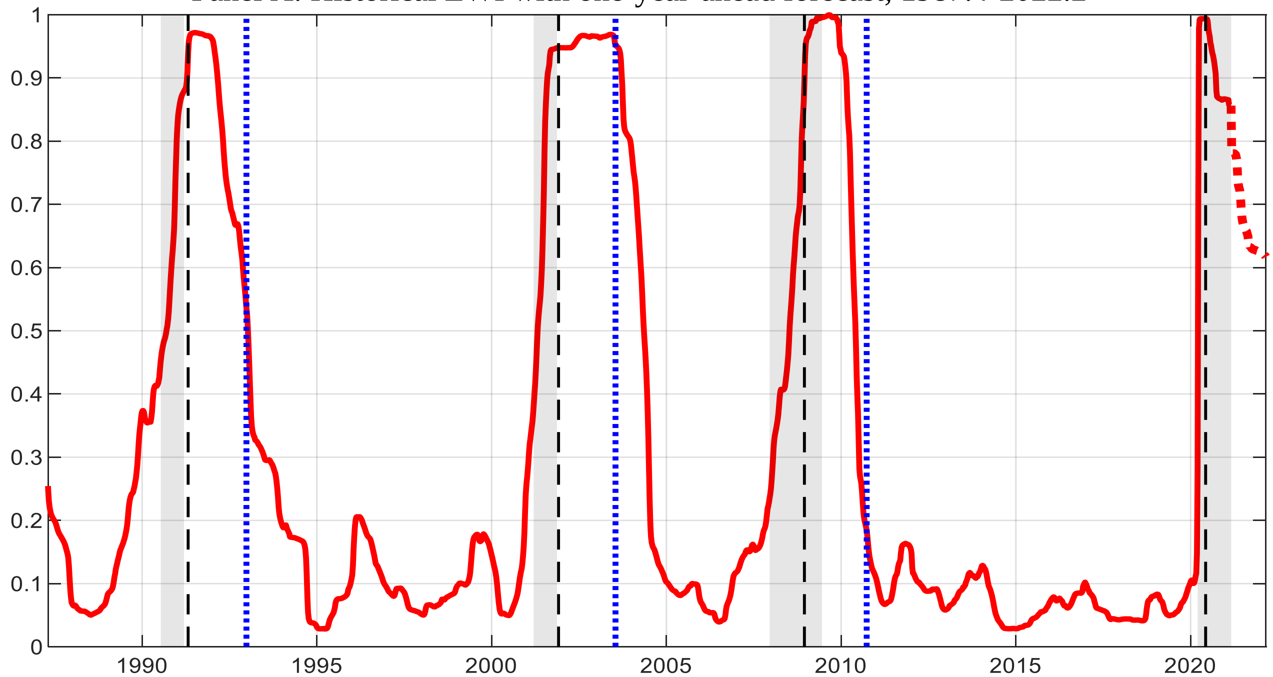
Panel B: Cumulative effect of a one-standard-deviation shock to loan amounts per capita on economic conditions



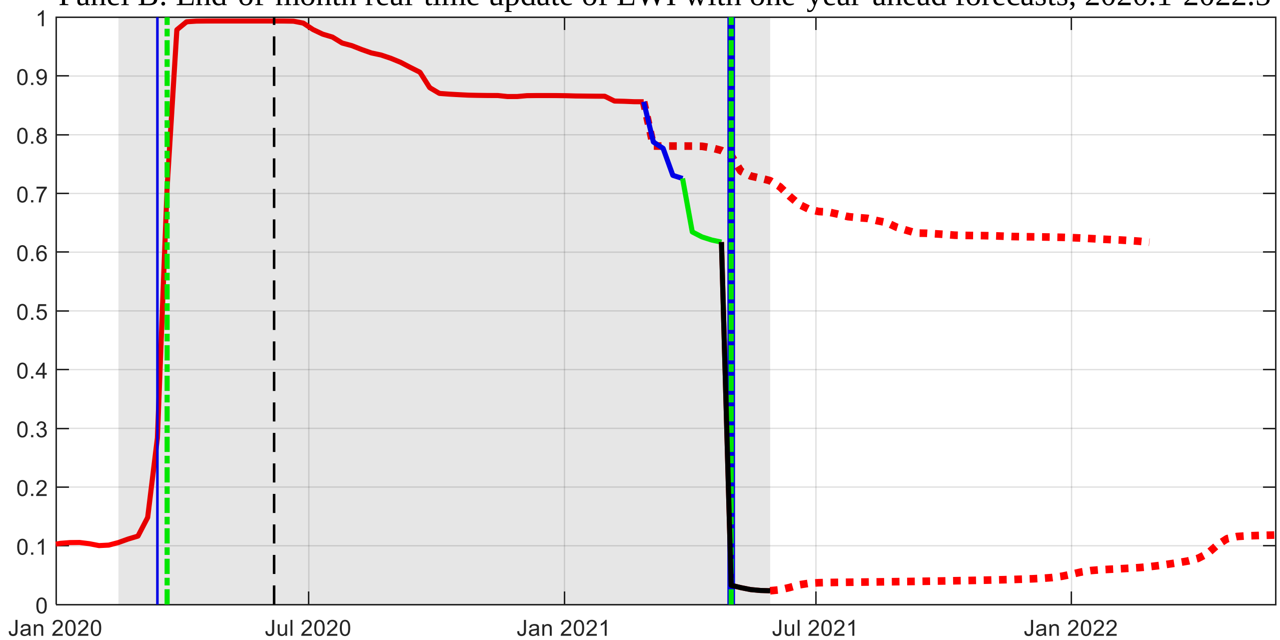
NOTES: The regression coefficients are based on local projections of the PPP intervention on April 16, 2020 on economic conditions for the weeks from April 18, 2020 to October 3, 2020. The error bands are 68% confidence intervals based on Newey-West standard errors to account for serial correlation.

Figure 7. Weekly Economic Weakness Index (EWI)

Panel A: Historical EWI with one-year-ahead forecast, 1987.4-2022.2

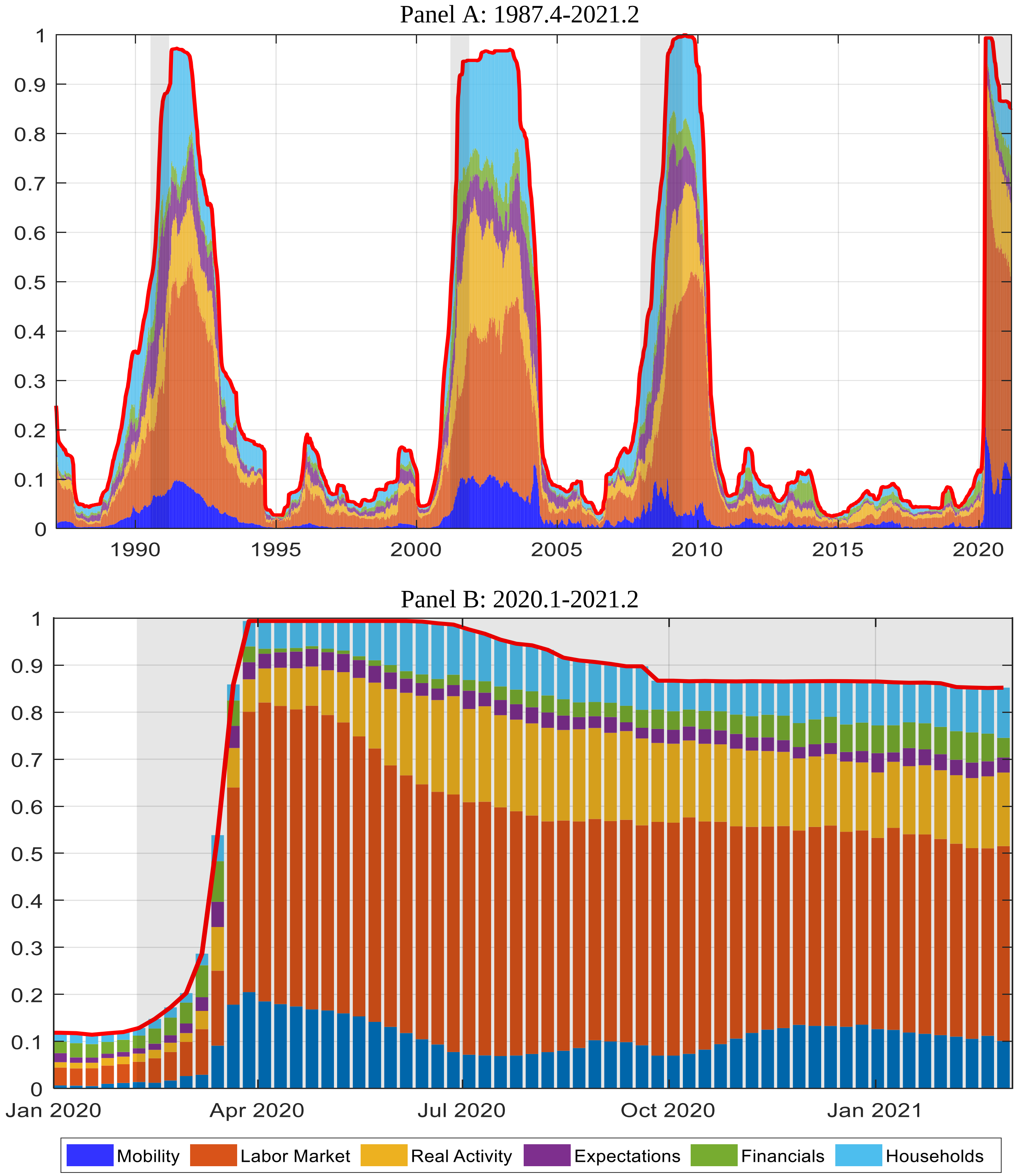


Panel B: End-of-month real-time update of EWI with one-year-ahead forecasts, 2020.1-2022.5



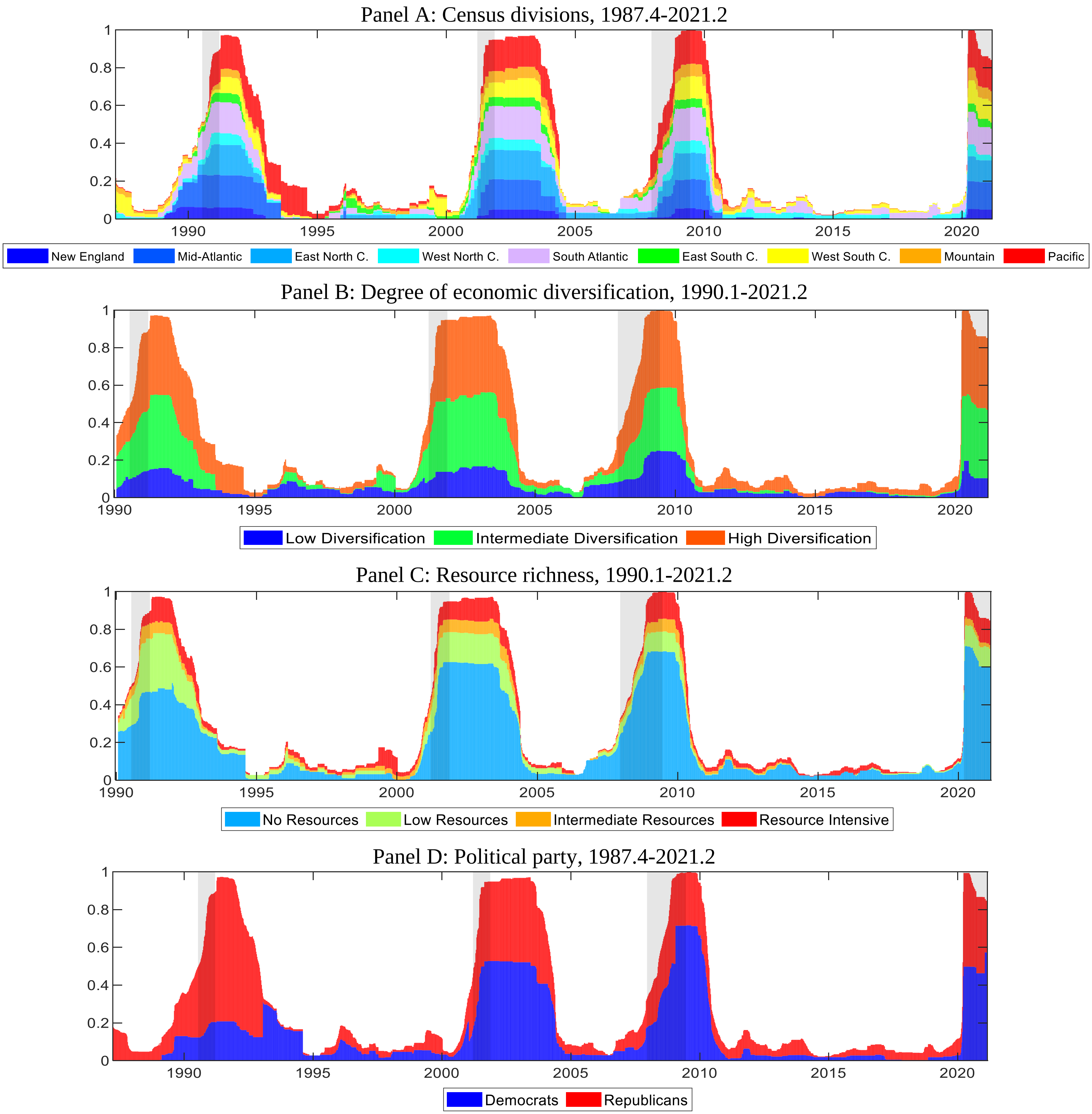
NOTES: The gray shaded areas indicate NBER recessions. The black dashed lines indicate the week of the announcement date of the peak month and the blue dotted lines indicate the week of the announcement date of the trough month. The NBER trough month for the COVID-19 recession has not yet been announced. The red dotted lines are 52-week-ahead forecasts of the EWI as of February 27 and May 29, 2021. The blue, green, and black lines of the EWI in panel B are end-of-month real-time updates based on real-time recession probabilities similar to Chauvet and Hamilton (2006). The blue vertical lines in panel B indicate the start and end dates of the COVID-19 recession applying the Chauvet-Hamilton rule to the EWI and the green dashed-dotted lines indicate the call dates.

Figure 8. Historical Decomposition of the Weekly Economic Weakness Index into its Main Driving Forces



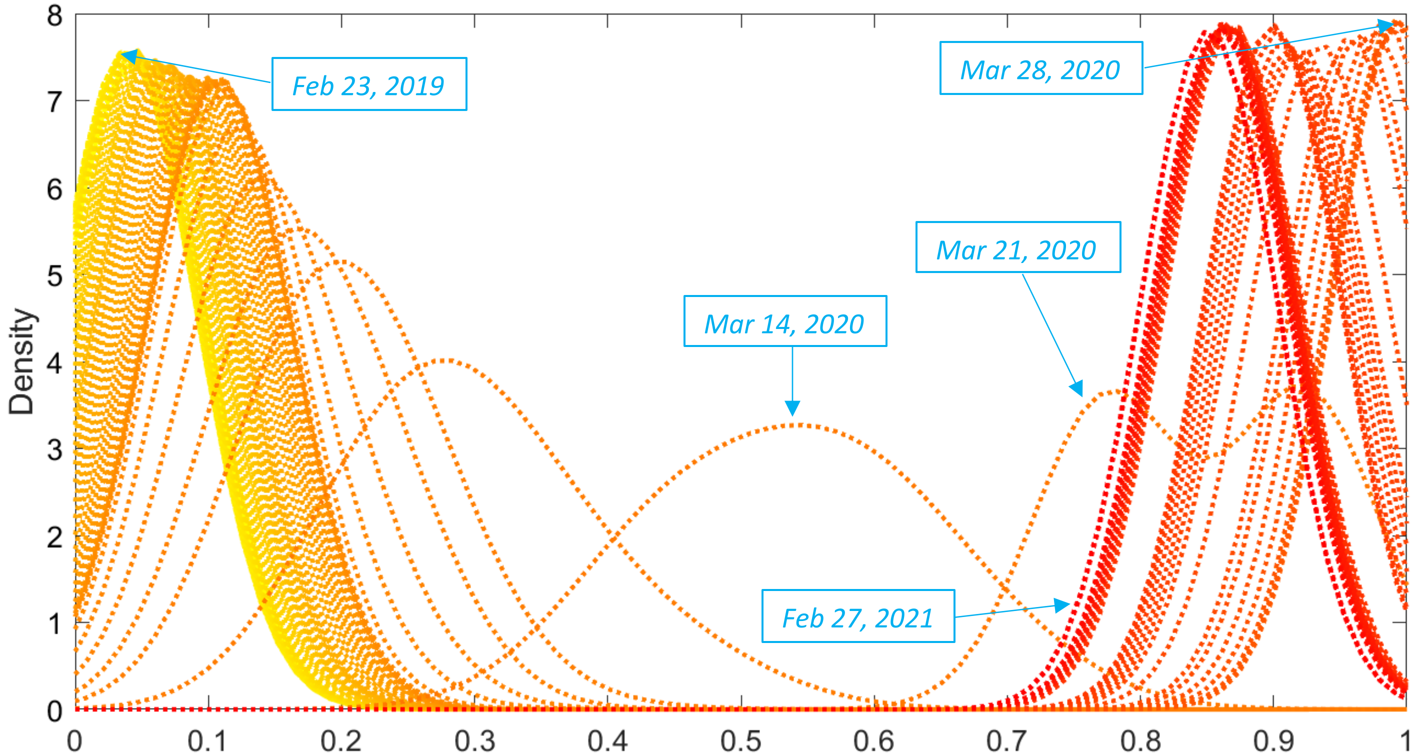
NOTES: This decomposition is obtained by summing the contributions associated with a given category of indicators across all U.S. states. The gray shaded areas indicate NBER recessions.

Figure 9. The Role of Additional Criteria in Determining Weekly Economic Weakness



NOTES: The definition of the various categories is provided in the text. The gray shaded areas indicate NBER recessions.

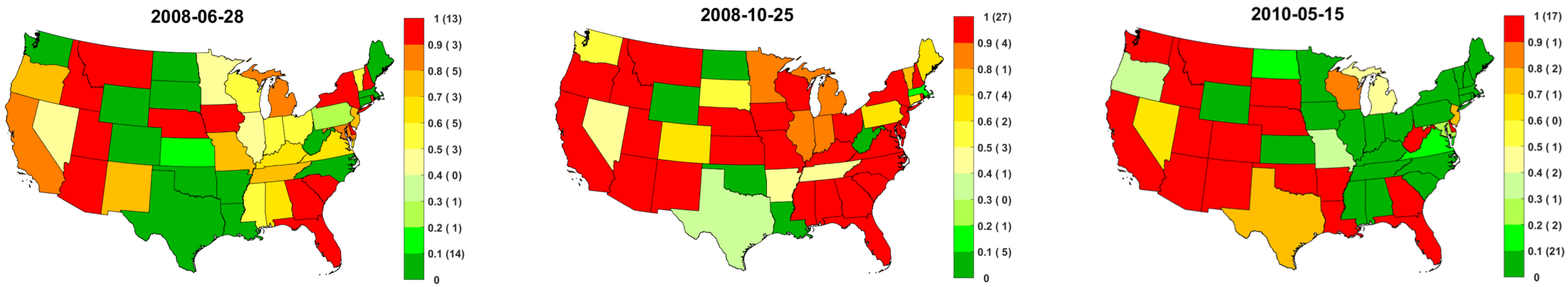
Figure 10. Time-varying Densities of the Weekly Economic Weakness Index 2019.2-2021.2



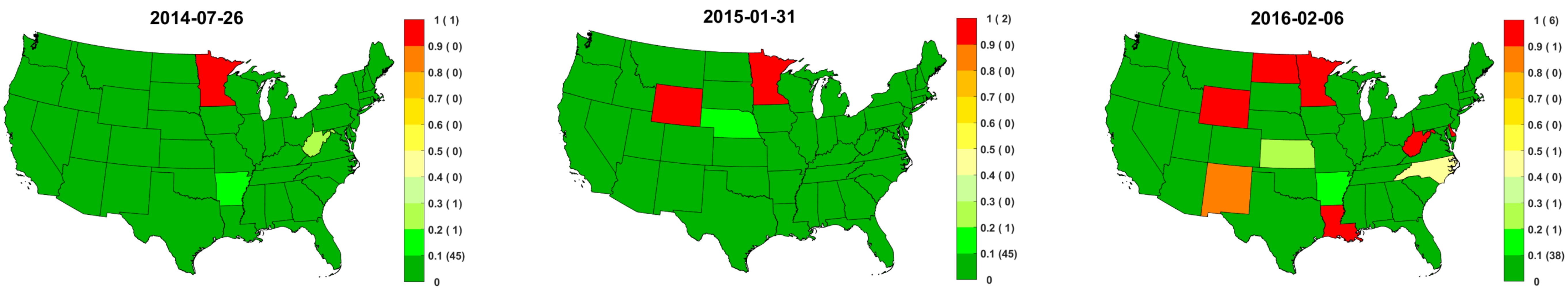
NOTES: The figure shows the evolution of the posterior density of the Weekly Economic Weakness Index over time. Distributions with darker colors are associated with more recent time periods.

Figure 11. Weekly Recession Probabilities across U.S. States for Selected Episodes

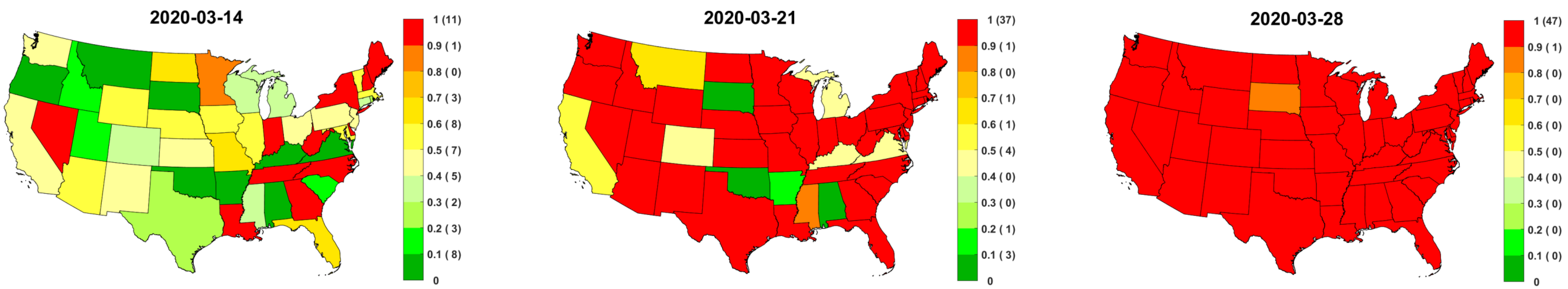
Panel A: Great Recession



Panel B: 2014-16 Oil Price Slump



Panel C: COVID-19 Recession



NOTES: The entries in parenthesis on the color bar for the recessions probabilities indicate the number of U.S. states in the corresponding bin. The entries sum to 48 since we exclude Alaska and Hawaii which are not shown in the maps.

Table 1. State-Level Dataset

Data category	Variables	Frequency	Geographic coverage	First observation	Tcode	Data source	Seasonal adjustment
Mobility	Cellphone mobility index	Weekly	All States	Jan 13, 2020	1	Apple	NA
	Retail gasoline price	Weekly	Subset**	May 22, 2000	2	EIA	NSA
	Vehicle miles traveled	Monthly	All States	Jan 2003	2	FHWA	NSA
Labor Market	Initial unemployment insurance claims	Weekly	All States	Mar 1, 1986	1	FRED	NSA*
	Continued unemployment insurance claims	Weekly	All States	Mar 1, 1986	1	FRED	NSA*
	Total nonfarm employment	Monthly	All States	Jan 1960	2	BLS	NSA*
	Unemployment rate	Monthly	All States	Jan 1976	1	FRED	SA
	Average hours worked in manufacturing	Monthly	All States	Jan 2001	1	FRED	SA
Real Activity	Coal production	Weekly	Subset**	Jan 7, 1984	2	CEIC	NSA
	Oil rig counts	Weekly	Subset**	Jan 5, 1990	4	BH	NA
	Oil production	Monthly	Subset**	Jan 1981	2	EIA	NA
	Electricity consumption	Monthly	All States	Jan 2003	2	EIA	NSA
	Real exports of goods†	Monthly	All States	Aug 1995	2	FRED	NSA*
	Real GDP	Quarterly	All States	Q1:2005	2	BEA	SA
Expectations	Business applications	Weekly	All States	Jan 7, 2006	2	FRED	NSA
	New housing permits	Monthly	All States	Jan 1988	3	FRED	SA
	Consumer sentiment index	Monthly	All States	Mar 1978	1	UMS	NA
	Manufacturing sentiment index	Monthly	Subset**	varying	1	FED	NA
Financials	Municipal bonds: yield to maturity	Weekly	All States	Dec 3, 2011	1	SPG	NA
	Municipal bonds: performance	Weekly	All States	Jun 11, 2010	2	SPG	NA
	Real trade-weighted value of the dollar	Monthly	All States	Jan 1988	2	FRED	NSA*
Households	Credit and debit card spending	Weekly	All States	Jan 24, 2020	1	AS	SA
	Real wage and salary income†	Quarterly	All States	Q1:1980	2	BEA	SA
	Real home price index†	Quarterly	All States	Q1:1975	2	FRED	NSA*

NOTES: Tcode indicates the transformation of the variable where 1 indicates the variable is included in its original units, 2 stands for year-over-year growth rates, 3 refers to taking logs, and 4 to taking annual differences. To accurately measure the large fluctuations during the COVID-19 period, we switch from logs to percent when computing growth rates. However, the results are similar when using log differences throughout the sample period. The codes for the data sources are as follows: Apple

(https://covid19.apple.com/mobility), AS – Affinity Solutions via Opportunity Insights (https://github.com/OpportunityInsights/EconomicTracker), BEA – Bureau of Economic Analysis, BH – Baker & Hughes (https://rigcount.bakerhughes.com/), BLS – Bureau of Labor Statistics, CEIC (https://www.ceicdata.com), EIA – U.S. Energy Information Administration, FED – data collected from the following regional Federal Reserve Banks: Chicago, Dallas, Kansas City, New York, Philadelphia, Richmond, FHWA – Federal Highway Administration, FRED – Federal Reserve Bank of St. Louis Economic Database, SPG – S&P Global (https://www.spglobal.com/spdji/en/index-family/fixed-income/us-municipal/#overview), UMS – Survey of Consumers, University of Michigan, broken down by 4 regions with each state getting assigned its regional value (http://www.sca.isr.umich.edu/). If data are available at a frequency higher than weekly, we obtain weekly data by averaging. NSA indicates that the series has not been seasonally adjusted, SA indicates that the series is available in seasonally-adjusted form, an asterisk indicates that the series has been seasonally adjusted using the X13-ARIMA procedure for monthly and quarterly data and the BLS MoveReg procedure for weekly data, and NA indicates that seasonal adjustment does not apply. We only seasonally adjust the weekly series that enter the model in levels; for weekly series that enter in annual growth rates, this transformation takes care of the seasonal component (see Lewis et al., 2020). A dagger indicates that the nominal series has been deflated with the national personal consumption expenditure price index obtained from FRED.
**Retail Gasoline Price: CA, CO, FL, MA, MN, NY, OH, TX, WA
**Coal Production: AL, AR, CO, IL, IN, LA, MD, MT, NM, ND, OH, OK, PA, TN, TX, UT, VT, VA, WV, WY
**Oil Rig Counts: CO, LA, NM, ND, OK, PA, TX, WY
**Oil Production: AL, AK, CA, CO, IL, KS, LA, MS, MT, NM, ND, OK, TX, UT, WY
**Manufacturing Sentiment Index: CO, DE, IL, IN, IA, KS, MD, MI, NE, NJ, NC, OK, PA, SC, TX, VA, WV, WI, WY

Figure 1A. Weekly Economic Conditions Indices for all 50 U.S. States, 1987.4-2021.2

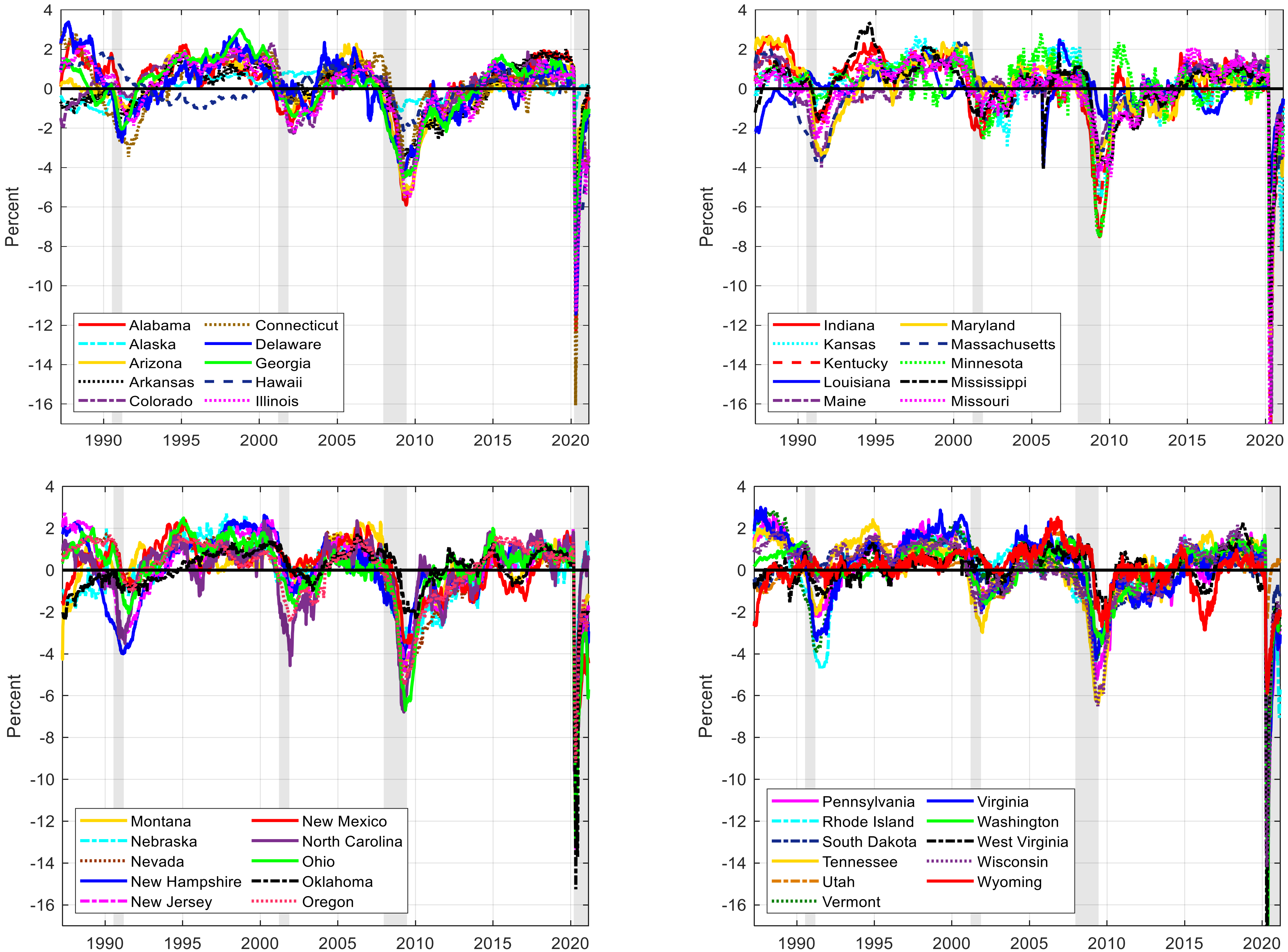


Figure 2A. Weekly Economic Conditions Indices for all 50 U.S. States 2020.1-2021.2

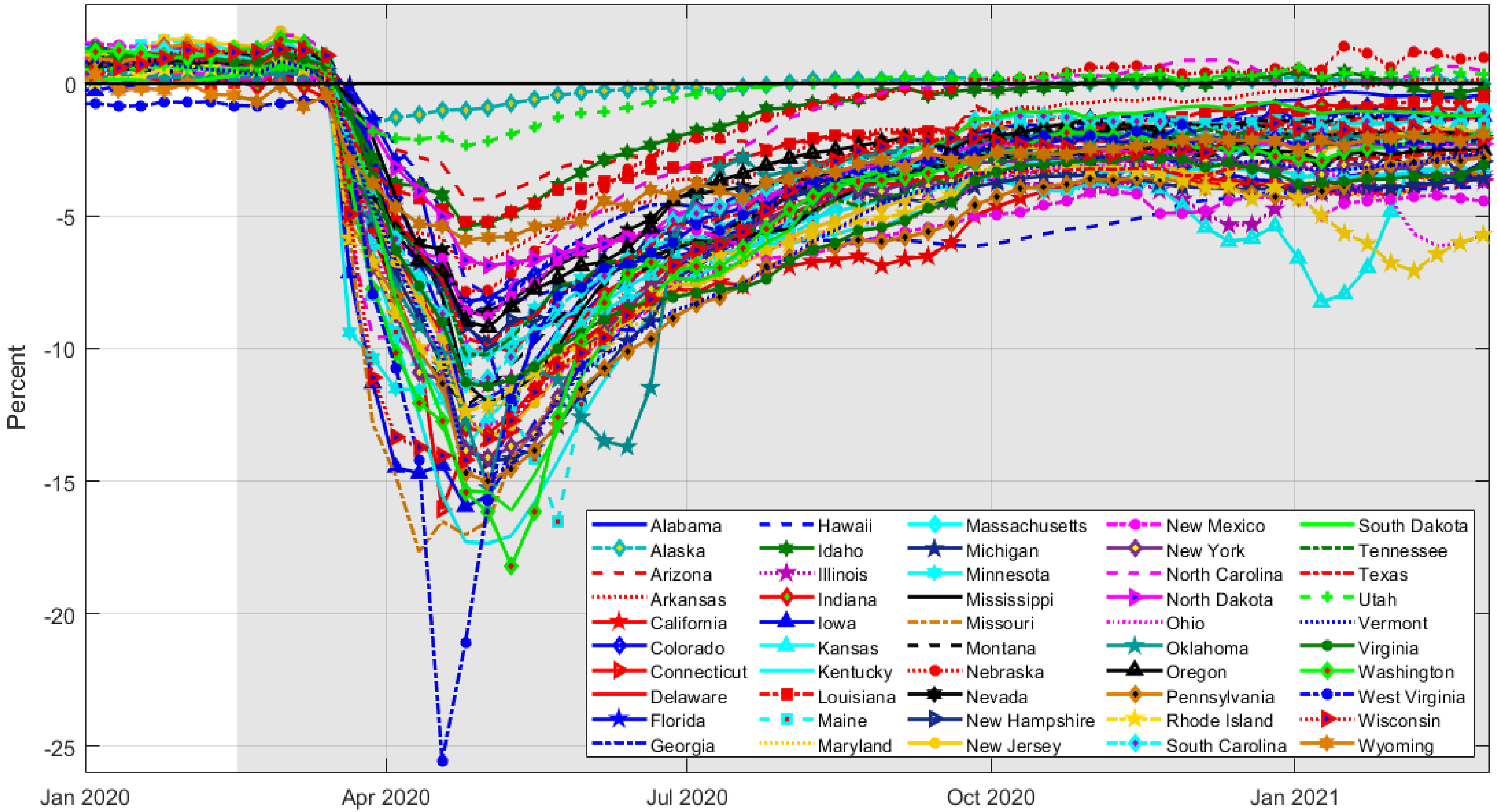
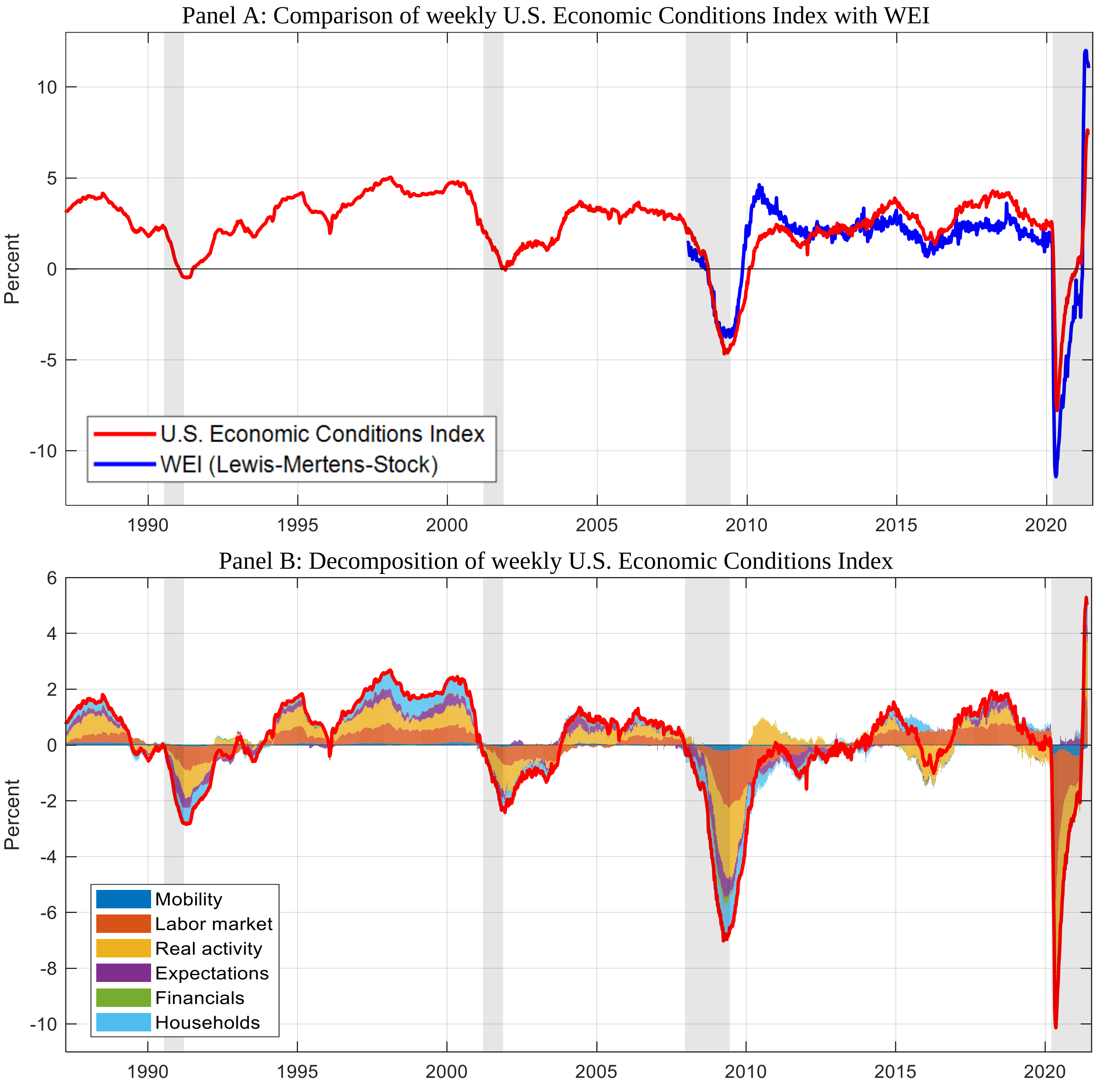
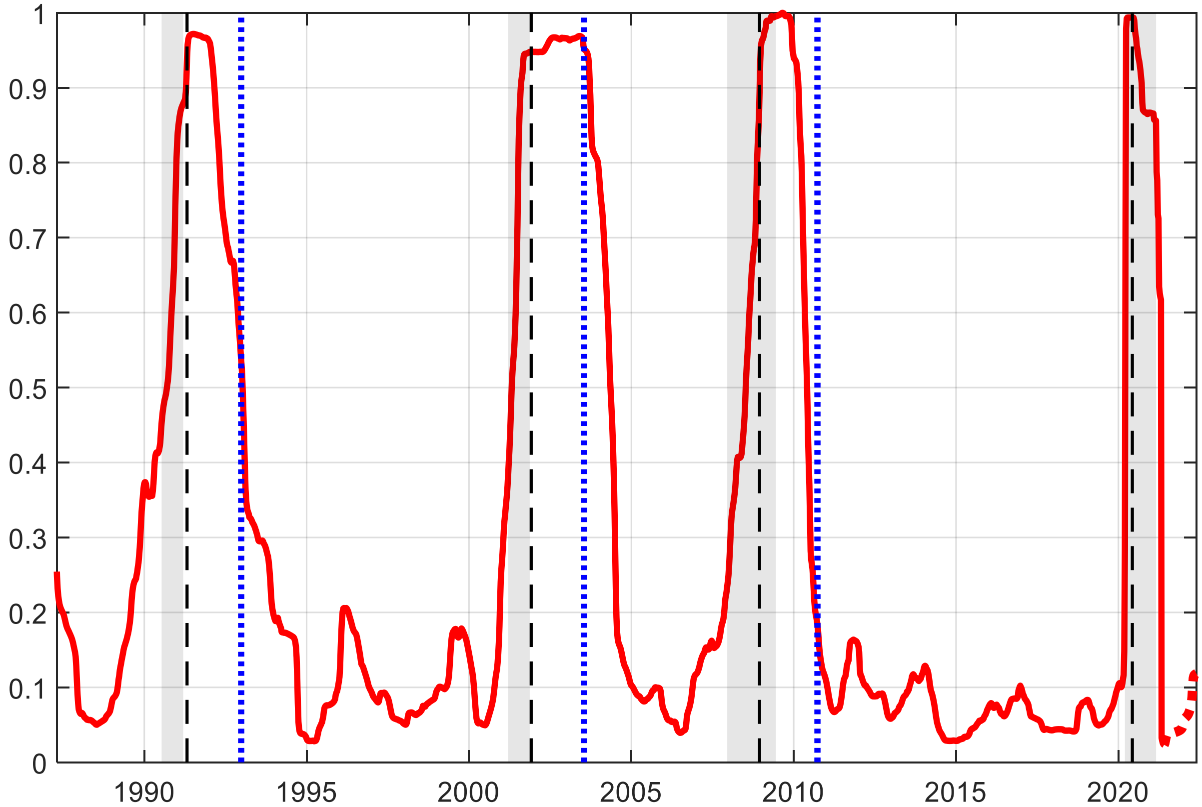


Figure 3A. Weekly Economic Conditions Index for the U.S. Economy 1987.4-2021.5



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.

Figure 4A. Updated Weekly Economic Weakness Index as of May 29, 2021
1987.4-2022.5



NOTES: See Table 7. The red dotted line is a 52-week-ahead forecast of the expected path of the Economic Weakness Index as of May 29, 2021.

Table 1A. Dataset for Weekly U.S. Economic Conditions Index

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

NOTES: See Table 1.