U.S. State-Level Business Cycles Since the Civil War*

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Abstract

We introduce a novel state-level dataset for the United States covering 65 macroeconomic time series since the 1860s, and use them to estimate an annual index of state-level economic activity spanning 150 years. Our index closely tracks existing state-level economic indicators such as GDP and unemployment rate. The expanded coverage of our index offers novel insights into state-level business cycles from a long-run perspective. Our findings indicate that: (1) both national and state-level recessions have become shorter with faster recoveries in the post-WWII period; (2) business cycle dynamics vary significantly across states; and (3) state business cycles have exhibited greater synchronization since WWII. We provide evidence suggesting that the policy changes leading to a stronger fiscal union enhanced risk sharing across states.

Keywords: state-level business cycle; mixed-frequency dynamic factor model; fiscal union

JEL classification: C38, N91, N92, O47

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1 Introduction

Reliable data on the state of the macroeconomy is the currency for research in empirical macroeconomics, economic history, and economic development. Even for an advanced economy like the United States, such currency is not always easy to find, especially when going back in time. In the case one stumbles upon a treasure trove, such as long-run estimates on real GDP (Williamson, 2025) or industrial production (Davis, 2004), it contains a single time series for the United States as a whole. However, individual states differ considerably in the rate at which they grow (e.g., Barro and Sala-i-Martin, 1991, 1992; Blanchard and Katz, 1992), their composition of economic activity, and their resilience to shocks.

Perhaps surprisingly, there is relatively limited historical state-level data for the United States. The Bureau of Economic Analysis (BEA) publishes annual estimates of GDP by state only from 1963. Before that, there was no consistent annual measure of economic activity at the state-level, except for a few related indicators that capture only part of the state economy such as personal income (going back to 1929), agricultural output (going back to 1924) and value added of the manufacturing sector (decennial from 1870 and annual from 1949). As such, there are many open questions about state-level growth, in particular, their business cycle fluctuations: How do states differ in their business cycles in terms of volatility and the timing of downturns? To what extent do they associate with or detach from the nationwide cycle? Which underlying economic forces drive these differences? How do state-level business cycles today compare to the past? Have they become more or less synchronized over time?

This paper aims to address these questions by constructing a novel dataset containing a variety of state-level economic indicators which are used to estimate a new state-level annual economic index spanning from 1871 to today. Based on an extensive effort in digitizing historical publications by U.S. federal and state government agencies and building on the work of other economic historians, we construct a harmonized dataset covering 65 variables for the period 1863-2022. In this dataset, only around 22% of the observations we assemble are available from existing official statistics; the remainder are newly digitized or assembled from various official or private sources. We document how we build these time series from 109 sources in a dedicated data appendix that also details the adjustments and imputations required to ensure data consistency. Overall, we believe this new dataset has many potential applications in fields such as macroeconomics, development economics, or economic history.

Equipped with our dataset covering over 150 years of U.S. economic history, we estimate an annual index of state-level economic activity covering 1871-2021, which, to the best of our knowledge, is the first attempt to estimate state-level economic activity for such a long span of time. We build on the existing literature following the spirit of Burns and Mitchell (1946) and view business cycles as common fluctuations in many underlying indicators which calls for a factor model. We use a mixed-frequency dynamic factor model similar to Baumeister, Leiva-León and Sims (2024), adapted to our dataset with mixed frequency both within and across variables, to estimate an index from a set of 16 core indicators for each state. For our baseline estimation, these indicators include real activity measures such as output in the agriculture, mining, and manufacturing sectors, as well as data on local labor markets, wealth, government statistics, price level, and proxies for mobility.

We confirm the validity of our index by comparing it with existing statistics such as GDP, personal income, unemployment rate, and State Coincident Indexes, and find that it has strong correlations with them for the time periods when these other measures are available. Moreover, our index is also a highly statistically significant and economically meaningful predictor of economic variables *not* used in the construction of the index, such as the number of business failures and bankruptcies and the number of patents. These findings lend credence to the reliability of the economic activity index in properly capturing state business cycle fluctuations.

Our estimated state-level economic activities index with a very long horizon allows us to provide novel insights into the difference in local business cycles as well as their changes over time. Three observations stand out. First, the structure of both nationwide and state-level business cycles has changed over time. Before 1950, recessions were longer and recoveries slower, often concentrated in specific regions. After WWII, economic downturns became shorter and recoveries faster, possibly mitigated by monetary policy, government stimulus, and broader economic diversification.

Second, there is enormous variation in business cycle fluctuations across states in terms their phases and volatilities. We construct a new NBER-type chronology of state-level recessions and provide narrative evidence that the identified local recessions indeed capture state-specific economic downturns linked to events such as crop failures in the late 1800s, natural disasters and civil unrest in the early 1900s. With this definition of state business cycles, we proceed to show that the variation in the length of these local recessions is considerable, although the most severe recession episodes, such as the Great Depression, coincide with nationwide turning points as identified by the NBER. As a result, the co-movement of state-level economic activity with the nationwide business cycle differs considerably across states, similar to the finding in Owyang, Piger and Wall (2005), but using much longer data.

States also differ significantly in economic volatility, i.e., the magnitude of economic downturns and upswings, as well as the frequency of boom-bust cycles. For example, during the Long Depression (1873-1896) and the Panic of 1893, significant economic declines showed particularly in railroad-dependent and farming states, while in more recent recessions, such as the 2008 Great Recession and the COVID-19 downturn of 2020, financial hubs (New York) and real estate-heavy states (Florida, Arizona, Nevada) suffered more severe contractions. A comparison across states of the frequency of boom-bust cycles shows that energy-dependent states such as North Dakota, Wyoming, and West Virginia exhibit high volatility, likely due to the highly volatile resource prices, whereas states like California, Texas, and New York demonstrate relatively consistent growth due to their diversified economies.

Third, despite the heterogeneity, state-level business cycles exhibit co-movement that has intensified in the post-war era. We focus on two statistics to assess the time variation in business cycle co-movement. Our primary measure is to calculate the dispersion of the index across states, which directly measures the variation in economic conditions across states in a given year. Second, we follow Kalemli-Özcan, Papaioannou and Peydró (2013) and calculate a synchronization measure for each state as the sum of negative absolute differences between the state's economic activity index and those of all other states in a given year. Intuitively, this measures how each state is different from every other state. We report this second measure in the Appendix. For both measures, we observe a dramatic shift from less to more synchronization starting since WWII, indicating that state business cycles tend to converge over time.

In ongoing work, we propose the fiscal union hypothesis to explain the significant changes in business cycle co-movement across states. This hypothesis is motivated by early 20th-century policy shifts that strengthened the fiscal union, including the introduction of federal income taxes, the New Deal, the expansion of federal spending, and various interstate fiscal transfer programs. These developments have played a crucial role in enhancing automatic fiscal stabilizers, improving cross-state risk sharing, and reducing regional economic disparities, a mechanism emphasized in Liu (2021).

Literature. The primary contribution of this paper is to study state-level business cycle fluctuations dating back to 1860s based on a newly-constructed dataset that covers a variety of state-level indicators. Our work builds upon the following three strands of literature.

First, we contribute to the literature on historical U.S. business cycle fluctuations. Davis (2004) constructs a measure of U.S. industrial production for 1790-1915, which in turn builds on previous efforts including, among others, Frickey (1947), Romer (1989) and Miron and Romer (1990). While our focus is on constructing regional time series, our work is close to the spirit of this literature in attempting to overcome the limitations of existing data through a large-scale effort to digitize and harmonize information from many sources. Our work is also related to a voluminous literature investigating the properties of the U.S. business cycle (e.g., Long and Plosser, 1983; DeLong and Summers, 1986; Hodrick and Prescott, 1997; Stock and Watson, 1999; McConnell and Perez-Quiros, 2000; Stock and Watson, 2002). Different from them, our study examines a much longer sample period and utilizes disaggregated data.

Second, we extend existing work that constructs regional measures of economic activity for the United States and studies regional business cycles. Crone and Clayton-Matthews (2005), Aruoba, Diebold and Scotti (2009), Arias, Gascon and Rapach (2016), and Baumeister, Leiva-León and Sims (2024) construct economic activity indices for states (or MSAs), but their time series do not start until after the beginning of BEA's GDP by state. Bokun et al. (2023) introduce a real-time database with 28 indicators per state for recent decades. We contribute to this literature by constructing new time series pre-dating the official statistics that have annual frequency, providing data on 65 indicators, and estimating an annual economic activity index that covers a much longer time span. Our analysis of state-level business cycles is related to existing work on state-level business cycles including, among others, Owyang, Piger and Wall (2005), Owyang, Rapach and Wall (2009) and Hamilton and Owyang (2012). Our contribution is to extend such efforts by taking a historical perspective.

Third, our empirical analysis using cross-state variations builds on a growing strand of literature that study macro questions using regional identification (see a review of this literature by Nakamura and Steinsson, 2018). For example, our analysis of the sentiment-driven business cycle is particularly related to Benhabib and Spiegel (2019), Lagerborg, Pappa and Ravn (2023) and Van Binsbergen et al. (2024) who estimate the impact of sentiments on economic fluctuations using regional-level data.

2 Data

In this section, we introduce our new state-level historical dataset that covers the 48 contiguous states (excluding Alaska, Hawaii, and Washington D.C.) for the period 1863-2021. Section 2.1 describes the data sources. Section 2.2 summarizes the variables included in our dataset. Section 2.3 provides details on how we construct the time series. Section 2.4 compares our dataset with those used in existing work. A companion data paper Hoon et al. (2025) documents further details on the dataset used in this paper.

2.1 Data Sources

Our data collection starts with two major publications compiled by the Census Bureau: The Statistical Abstract of the United States (henceforth referred to as SA) and the official decennial publications by the United States Census Bureau (henceforth referred to as Census). The SA is published on an annual basis starting from 1878, while the Census is published decennially starting from 1790. Drawn from various state and federal government reports, these two publications contain a wealth of state-level economic indicators.

However, much of the data contained in these publications has not been previously digitized, which is particularly true for the SA.[1] We utilize Optical Character Recognition (OCR) technology using Amazon Textract to process the scanned documents in the first round, and proceed to minimize transcription errors with manual verification. Note that past data is frequently revised in later issues of the SA, as it is revised by the agencies from whom the data is obtained. To account for this, we always use the data from the latest issue of the SA for which a given year's data is reported.

In some cases, data recorded by the SA or Census are presented in less detail than in their original publications, or they do not span the length of our sample period. In an effort to construct a dataset that is as complete as possible, we draw upon a broader spectrum of historical data sources, physical and digital, including government reports, books, private industry surveys, as well as previous works in the economic history literature. Much of this data is difficult to obtain—consequently, we digitize whenever necessary.

The total number of sources we use is 109, of which 80 are newly digitized, while the remainder is compiled from scattered but already digitized sources. Section I in our supplementary data paper

[1] It is often the case that aggregate US-level data are available for a particular variable but state-level data is not.

provides a full list of all the variables together with their sources and coverage across states and time.[2]

2.2 Main Variables

We focus on variables for which there are both modern-day equivalents and sufficient historical data. For example, since we are unable to identify a sufficient number of data points for retail sales (reported in SA) for the period before World War II, we do not include it in our dataset. That said, given our extensive research into historical publications and government reports containing state-level economic statistics, to the best of our knowledge, this is the most comprehensive state-level dataset that has ever been constructed for such a long time span. In fact, most variables have close to universal coverage, spanning from 1860s or 1870s until today. Some others, such as the number of motor vehicle registrations, are available starting from the early 1900s.

Our dataset contains a total of 65 individual variables, which can be grouped into seven broad categories: Real Activity, Government Finances, Labor Market, Transportation, Wealth, Housing, and Miscellaneous.

Real Activity. To begin with, our dataset covers real economic activity across three major sectors that are especially important in the earlier years in our sample: agriculture, mining and manufacturing. Variables in these sectors include value of agricultural products sold, value of minerals, value added by manufacturing. Within the agriculture and mining sectors, we collect data on major products[3] which are usually reported annually, and use them them to estimate total values in these sectors whenever they are not reported on an annual basis in the early years. We provide details on this process in Section 2.3.

In addition to sectoral output, we also report data on alternative cyclical indicators such as the number and liabilities of business failures, and total number of business concerns, which have been recognized as important indicators of economic crises (Simpson and Anderson, 1957). The fact that they have been consistently reported since the late 19th century makes them especially suitable for long-run studies of the business cycle. Moreover, we report the value of imports and exports of merchandise, matched to states from the customs district level. Given that only some states have

[2] For additional information on these data sources, we refer interested readers to this data paper, where we also include several examples of the tables in their original formats to highlight the challenge of extracting these data from many disparate sources that come in different formats.

[3] Examples of these major products include: the value of sheep, sweet potato crop and lumber produced, and the value of petroleum at mines respectively.

ports, we would expect these measures to drive growth in certain states more than others.

Local-level consumption data has been notoriously difficult to obtain even for the post-war period. Nonetheless, our dataset attempts to construct some measure of expenditure in the historical context. In the US, expenditure on motor vehicles is known to be very sensitive to aggregate demand. For example, Orchard, Ramey and Wieland (2024) find that the marginal propensity to consume is 0.3 on motor vehicles and 0 on other consumption, suggesting that motor vehicle expenditure can be a key indicator for business cycles. While direct expenditure data is not available throughout our sample period, we include motor vehicle registration which is available since 1900 and automobile tax revenues available from 1913.

Transportation. Given the importance of transportation networks in facilitating the flow of goods and people—and therefore, economic growth (e.g., Donaldson and Hornbeck, 2016)—, our dataset includes measures of transportation such as mileage of the railway track, rural road and state highway mileages.

Government Finances. Our dataset reports state-level fiscal variables on revenue, expenditure and debt. In particular, we include state government revenue, federal government internal revenue (as well as personal and corporate income tax revenues), state government total expenditure, and state government gross, net, and long-term debt. Wallis (2000) expounds upon the changing importance of the different levels of governments, moving from the era of state, local and then federal, across time. Building upon his seminal work with Richard Sylla and John Legler in Sylla, Legler and Wallis (1993), our dataset digs into two of these levels (state and federal), with detailed personal and corporate income tax data which heralds the transition into "The Era of Income Finance and the Federal Government.". More broadly, this data allows us to explore the effects that state and national-level policies have on the local economy.

Labor Market, Wealth, Housing, Miscellaneous. We cover measures of the labor market, including total non-farm employment, manufacturing employment and manufacturing payroll, which allow us to track the local economic dynamics via labor market fluctuations. Within Wealth, we report measures of personal income, the value of farmland and buildings, and the number of bankruptcies commenced and terminated. We extend the BEA official data on personal income that starts in 1929 back to 1880 at decennial intervals, and from 1919 to 1921 and in 1927-1928 annually. The Number of bankruptcies includes both corporate and personal bankruptcies, with the former used to supplement number of business failures and the latter as an indicator for personal wealth. Our banking sector data include bank assets, deposits, capital, liabilities and loans of national and state banks that stretch back to 1863. We report annual data on population starting from 1870, estimating the intercensal years by following the Census Bureau's technical reports. Finally, we report measures of patents, sentiments, newspaper circulation, as well as house and rental prices, the bulk of which draws upon existing work.

Our Data Appendix Table 1 tabulates a full list of variables, including their coverage across states and time, data sources, and frequency in the raw and imputed data.

2.3 Constructing Coherent Time Series

We describe our approaches in constructing consistent and coherent state-level time series data. Given the time span of our sample, many variables stretch back to before states were admitted to the Union in their current form. In order to ensure the data is comparable over time, we either combine or split state-level data. For example, data on the Oklahoma and the Indian Territory was reported separately in the raw data before they were jointly admitted to the Union in 1907. Accordingly, from 1870-1906, we report in our dataset the sum of both territories under "Oklahoma."

We also pay attention to the consistency of variable definitions across time and data sources, considering the length of the sample period and the breadth of the sources we draw on. To preserve comparability across time whenever definition changes occur, we take the following two approaches. First, we harmonize across different sources and across time while preserving the same definition of variables. For example, from 1921 onwards, the Annual Survey of Manufactures (ASM) stops collecting data on establishments with products valued between \$500 to \$5000. Since the Census of Manufacturing (CM) reports establishments by product value bin from 1905-1919, we are able to exclude establishments with products valued between \$500 to \$5000 before this change, such that the series remains comparable. Similarly, since CM does not report data on the number of manufacturing establishments between 1947 to 1950, while the County Business Patterns (CBP) do, we impute the CM data using the CBP data using the same variable definitions.

Second, we linearly transform data to ensure the overlapping year's are the same across different sources, i.e., ratio splicing, in cases where multiple data sources need to be combined. As in any dataset spanning long time series, the raw data sometimes exhibits breaks arising from changes in statistical classifications.[4] As an example, our coverage of the number of business failures series

[4] Note that the main objects of our study are year-on-year growth rates, which are preserved by ratio-splicing.

from Dun and Bradstreet ends in 1998. To extend the series to 2021, we ratio-splice the Dun and Bradstreet data with data on business bankruptcies, collected from Hansen, Davis and Fasules (2016) from 1998-2007, and the US Bankruptcy Court reports from 2008-2021. We ratio-splice using the overlapping year 1998.

After these changes, our raw data still include both randomly and regularly missing data points. For sporadically missing data, if only a single year is missing, we apply simple averages as a rule-of-thumb imputation method. For other cases, which typically occur at five- or ten-year intervals in the earlier years of our sample, we incorporate them into a mixed-frequency estimation framework which gives us the missing years as a by-product of the factor estimates.

An exception is the total value of the agricultural and mining sectors, where we estimate the low-frequency aggregate values using their annually-available underlying components. In particular, the value of agricultural products is only reported every ten years in the Census between 1870 to 1924, after which it is reported annually by the United States Department of Agriculture (USDA). Meanwhile, we also construct annual time series data on 16 individual major crops, livestock, and forestry that also cover 1870-1924. These higher-frequency time series contain useful information regarding the fluctuations of the total value of agricultural products, which needs to be precisely measured given its importance in the earlier years.

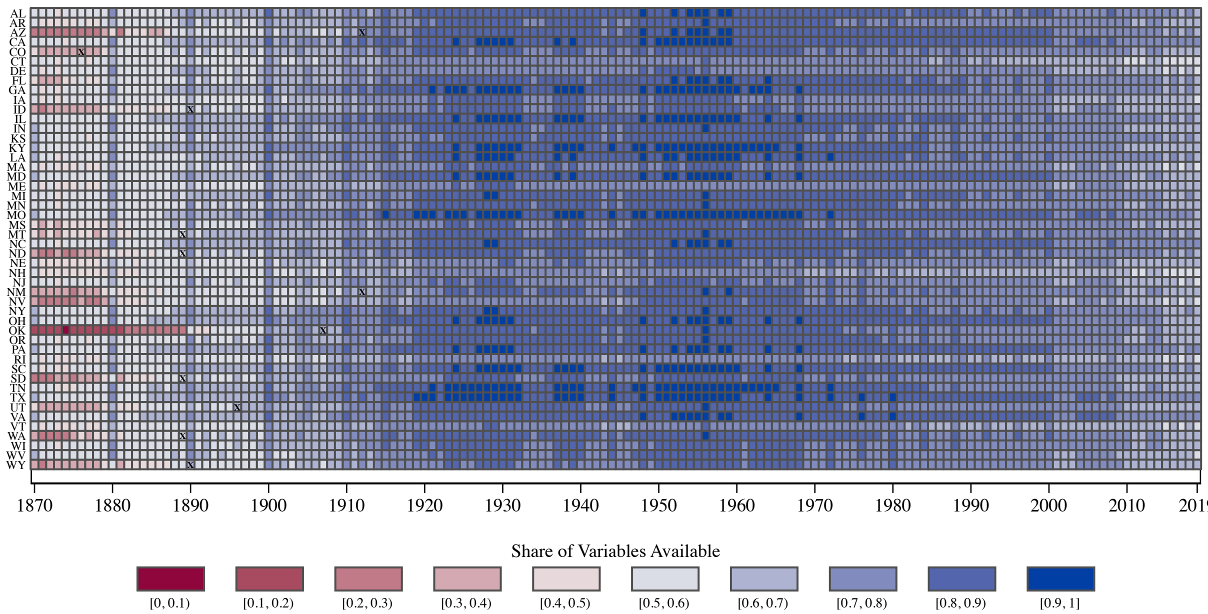
As a baseline, we temporally disaggregate low-frequency series using the Denton (1971) method. For robustness, we use the Chow-Lin method (Chow and Lin, 1971). In order to accommodate mixed frequencies within series and use all the available information, we modify the disaggregation matrices. We describe these modifications in detail in Data Appendix 2.2. Another alternative is to construct growth rates of aggregate agricultural output based on the value-weighted growth of the individual crops. As we show in Data Appendix 2.2.6, one would arrive at similar time series with either approach.

In total, we report 65 time series. Figure 1 plots the fraction of variables available in each year by state. In the early years, there is more missing data; nonetheless, by construction, our dataset has good coverage of agriculture, mining and manufacturing, which were the main sectors then.

2.4 Comparison with Existing Datasets

Table 1 compares our new dataset with existing state-level datasets and U.S.-wide historical datasets that measure economic activities. For the former, our data provide an entirely new historical perspective, adding around 100 years' data that could be useful in studying state-level economic

Figure 1: Variable Coverage by State



Notes: This figure shows the share of variables in the dataset that are available in a given year for the 48 contiguous states. We plot black crosses to indicate the year of a state's admission to the Union.

dynamics from a long-run perspective. Additionally, the dataset we construct are much more comprehensive in terms of the number of indicators. For example, the economic activity index of Baumeister, Leiva-León and Sims (2024) are based on a small number of variables, while we provide a total of 65 indicators. In sum, we believe the dataset we construct is a significant addition to the existing literature in terms of length and breadth. To the best of our knowledge, there is no other data effort incorporating historical time series in a comparable manner.

Our data effort echoes with works that attempt to build nationwide historical datasets. While we cannot directly compare our work to estimates of U.S. economic activity, it may be useful to compare their coverages. For example, Romer (1989) estimates Gross National Product (GNP) between 1869 and 1908. Davis (2004) estimates industrial production for the 1790-1915 period, just before the Federal Reserve's G.17 index of industrial production starts in 1919. Different from these efforts, our dataset emphasizes a regional dimension as well as a "big data" approach by covering a large number of individual economic indicators.

Table 1: Comparison with Existing Datasets

	Frequency	Coverage
A. State-Level		
This paper	Annually	1871–2019
BEA personal income	Annually	1929–2024
BEA GDP	Annually	1963–2024
Crone and Clayton-Matthews (2005) coincident index	Monthly	1978–2003
Baumeister, Leiva-León and Sims (2024) economic conditions index	Weekly	1987–2023
B. National-Level Historical Data		
Davis (2004) industrial production index	Annually	1790–1915
Williamson (2025) GDP	Annually	1790–2023
Balke and Gordon (1989) GNP	Annually	1869–1929
Miron and Romer (1990) industrial production index	Monthly	1884–1940

3 Estimating a State-Level Index of Economic Activity

In our dataset, variables are observed at varying frequencies — every ten, five, or two years, or every year. This mixture of frequencies occur both across and within variables. For example, state-level manufacturing value added is available every ten years before 1910, every four to five years from 1910 through the 1920s, every two years till 1949, and then annually. Thus, an estimation framework that accommodates frequency variation across both the cross-section and time is necessary to take full advantage of the data. We adopt the dynamic factor model framework of Baumeister, Leiva-León and Sims (2024) and modify it to accommodate the varying frequencies pertinent to our state-level dataset.[5]

3.1 Estimation Framework

Following Baumeister, Leiva-León and Sims (2024), we postulate that there is a latent stationary factor, $f_{i,t}$, that is common to N_i observable indicators for state i.[6] We model the common factor as an annual series, with $t = 1, 2, \ldots, T$ indexing individual years over our sample period. For each state i, let N_i represent the total number of indicators used in the estimation. Of these indicators, let N_i^y denote those that report only at annual frequency, and let $N_i - N_i^y$ denote those that report

[5]In Baumeister, Leiva-León and Sims (2024), the authors construct state-level economic conditions indices based on indicators with weekly, monthly, and quarterly reporting frequencies. Similar to Baumeister, Leiva-León and Sims (2024), earlier studies by Crone and Clayton-Matthews (2005), Aruoba, Diebold and Scotti (2009), and more recently, Lewis et al. (2022), consider time series sampled at different frequencies to construct economic coincidence indices within a dynamic factor model framework. Earlier studies, including works by Stock and Watson (1989, 1991), consider indicators with one frequency.

[6]Due to the data availability, we only consider estimating the 48 contiguous states in our application.

at mixed frequencies. We let the corresponding sets of indicators be represented by $\gamma(N_i)$, $\gamma(N_i^y)$, and $\gamma(N_i - N_i^y)$, respectively. For each indicator $j \in \gamma(N_i)$, let $Y_{i,j,t}$ denote its value for year t. If $j \in \gamma(N_i^y)$ and $Y_{i,j,t}$ is reported in levels, we compute j's annual growth rates using log-differences such that $y_{i,j,t} = \ln Y_{i,j,t} - \ln Y_{i,j,t-1}$; if $Y_{i,j,t}$ is reported in growth rates, we simply set $y_{i,j,t} = Y_{i,j,t}$. We assume that $y_{i,j,t}$ is associated with $f_{i,t}$ through the following structure:

$$y_{i,j,t} = \lambda_{i,j} f_{i,t} + u_{i,j,t}, \tag{1}$$

where $\lambda_{i,j}$ denotes the factor loading of indicator j to $f_{i,t}$. $u_{i,j,t}$ is an idiosyncratic factor, capturing idiosyncratic variations of indicator j. We assume $f_{i,t}$ follows a Gaussian AR($l_{i,f}$) process and $u_{i,j,t}$ follows a Gaussian AR($l_{i,u}$) process given by:

$$f_{i,t} = \phi_{i,1} f_{i,t-1} + \phi_{i,2} f_{i,t-2} + \cdots + \phi_{i,l_{i,f}} f_{i,t-l_{i,f}} + \epsilon_{i,t}, \qquad \epsilon_{i,t} \sim N(0, \sigma^2_{i,f}), \tag{2}$$

$$u_{i,j,t} = \psi_{i,j,1} u_{i,j,t-1} + \psi_{i,j,2} u_{i,j,t-2} + \cdots + \psi_{i,j,l_{i,u}} u_{i,j,t-l_{i,u}} + \varepsilon_{i,j,t}, \qquad \varepsilon_{i,j,t} \sim N(0, \sigma^2_{i,j}). \tag{3}$$

Following standard practice in dynamic factor model estimation, we fix the scale of the autoregressive coefficients in equation (2) by setting $\sigma_{i,f} = 1$ for all i. Moreover, we normalize $y_{i,j,t}$ to have zero mean and unit variance before estimation. The former removes the need for a constant term in equation (1). While unit-variance is not necessary for identification, it can be convenient for interpretation; see p. 594 of Crone and Clayton-Matthews (2005) for a discussion.

Suppose indicator $j \in \gamma(N_i - N_i^y)$. Then, the indicator has mixed reporting frequencies over the sample period. Let $\mathcal{T}_{i,j,t} \geq 1$ denote the number of years since indicator j was last reported in year t. For instance, if indicator j is observed in 1880 and 1890 for state i, then $\mathcal{T}_{i,j,1890} = 10$. Note that $\mathcal{T}_{i,j,t}$ varies over time for $j \in \gamma(N_i - N_i^y)$ to account for its mixed reporting frequencies. Now, let $z_{i,j,t}$ be an auxiliary variable denoting the annual growth rates of indicator j. If $\mathcal{T}_{i,j,t} = 1$, then $z_{i,j,t} = y_{i,j,t}$; otherwise, $z_{i,j,t}$ is unobserved if $\mathcal{T}_{i,j,t} > 1$. Using $z_{i,j,t}$ allows us to express indicator j's annualized growth rates between years t and $t - T_t^j$ in terms of $f_{i,t}$ as follows:

$$\begin{aligned}
&\frac{1}{\mathcal{T}_{i,j,t}} \left(\ln Y_{i,j,t} - \ln Y_{i,j,(t-\mathcal{T}_{i,j,t})} \right) \\
&\quad = \frac{1}{\mathcal{T}_{i,j,t}} \left(\ln \frac{Z_{i,j,t}}{Z_{i,j,t-1}} + \ln \frac{Z_{i,j,t-1}}{Z_{i,j,t-2}} + \cdots + \ln \frac{Z_{i,j,(t-\mathcal{T}_{i,j,t}+1)}}{Z_{i,j,(t-\mathcal{T}_{i,j,t})}} \right) \\
&\quad = \frac{1}{\mathcal{T}_{i,j,t}} \left(z_{i,j,t} + z_{i,j,t-1} + \cdots + z_{i,j,(t-\mathcal{T}_{i,j,t}+1)} \right)
\end{aligned}$$

$$= \frac{1}{\mathcal{T}_{i,j,t}} \lambda_{i,j} \left(f_{i,t} + f_{i,t-1} + \cdots + f_{i,(t-\mathcal{T}_{i,j,t}+1)} \right) + \frac{1}{\mathcal{T}_{i,j,t}} \left(u_{i,j,t} + u_{i,j,t-1} + \cdots + u_{i,j,(t-\mathcal{T}_{i,j,t}+1)} \right), \tag{4}$$

where the final equality follows from equation (1). The above derivation effectively expresses the (annualized) growth rates of all indicators in $\gamma(N_i - N_i^y)$ as lag polynomials of the common factor and idiosyncratic factor. Equations (1) and (4) together constitute the observation equation in the state-space representation of the following section.

State-Space Representation. We can express equations (1) and (4), along with equations (2) and (3), in a Gaussian state-space structure:

$$\mathbf{y}_{i,t} = \mathbf{H}_{i,t} \boldsymbol{\alpha}_{i,t}, \tag{5}$$

$$\boldsymbol{\alpha}_{i,t} = \mathbf{T}_i \boldsymbol{\alpha}_{i,t-1} + \boldsymbol{\eta}_{i,t}, \qquad \boldsymbol{\eta}_{i,t} \sim N(\mathbf{0}, \mathbf{Q}_i), \tag{6}$$

for $t = 1, \ldots, T$. In equation (5), $\mathbf{y}_{i,t}$ is a column vector of length $n_{i,t}$ that collects the observed growth rates in year t for state i. We note that $n_{i,t} \leq N_i$, and the inequality is strict when there are missing values in year t. $\boldsymbol{\alpha}_{i,t}$ is the state vector, given by:

$$\boldsymbol{\alpha}_{i,t} = \Big[\Upsilon_{c_{i,1}}(L) f_{i,t},\ \underbrace{\Upsilon_{c_{i,1}}(L) u_{i,1,t},\ \ldots,\ \Upsilon_{c_{i,N_i-N_i^y}}(L) u_{i,N_i-N_i^y,t}}_{N_i - N_i^y \text{ terms with indicator } j \in \gamma(N_i - N_i^y)},\ \underbrace{\Upsilon_{l_{i,u}}(L) u_{N_i-N_i^y+1,t},\ \ldots,\ \Upsilon_{l_{i,u}}(L) u_{N_i,t}}_{N_i^y \text{ terms with indicator } j \in \gamma(N_i^y)} \Big]^\top, \tag{7}$$

where $\Upsilon_{c_{i,j}}(L)$ defines a vector of lag operators given by:

$$\Upsilon_{c_{i,j}}(L) = \left(L^0,\ L^1,\ L^2,\ \ldots,\ L^{\max_t(\mathcal{T}_{i,j,t})-1} \right), \quad \text{for all } t = 1, \ldots, T.$$

We order the indicators in $\mathbf{y}_{i,t}$ such that:

$$\Upsilon_{c_{i,1}}(L) = \left(L^0,\ L^1,\ L^2,\ \ldots,\ L^{\max_{j,t}(\mathcal{T}_{i,j,t})-1} \right), \quad \text{for all } t = 1, \ldots, T \text{ and } j \in \gamma(N_i).$$

Likewise, we define:

$$\Upsilon_{l_{i,u}}(L) = \left(L^0,\ L^1,\ L^2, \ldots,\ L^{l_{i,u}-1} \right),$$

where $l_{i,u}$ denotes the number of autoregressive lags in equation (3). The symbol L denotes the lag operator, such that $L^k x_t = x_{t-k}$ for a variable x_t. We note in passing that the length of $\boldsymbol{\alpha}_{i,t}$ can be computed as $\max_{j,t}(\mathcal{T}_{i,j,t}) + \sum_{j=1}^{N_i - N_i^y} \max_i(\mathcal{T}_{i,j,t}) + N_i^y \times l_{i,u}$, for $t = 1, \ldots, T$ and $j \in \gamma(N_i)$. Now, matrix $\mathbf{H}_{i,t}$ has $n_{i,t}$ rows by construction. The j-th row of $\mathbf{H}_{i,t}$ consist of $\lambda_{i,j}$, $\mathcal{T}_{i,j,t} \geq 1$, and possibly zeros, so that equation (4) holds in the j-th row of equation (5). Likewise, matrix $\mathbf{T}_i$ and vector $\boldsymbol{\eta}_{i,t}$ are parameterized such that equation (6) stacks the autoregressive processes in (1) over all indicators in $\gamma(N_i)$. Unlike $\mathbf{H}_{i,t}$, $\mathbf{T}_i$ is not time-varying since the autoregressive orders $l_{i,f}$ and $l_{i,u}$ are fixed in our estimation.[7]

Estimation Strategy. For brevity, we omit the notation i from equations (5) and (6) here. We assume that the initial state vector is distributed by $\boldsymbol{\alpha}_1 \sim N(\mathbf{a}_1, \boldsymbol{\Sigma}_1)$, where $\mathbf{a}_1 = \mathbf{0}$ is a zero vector and $\boldsymbol{\Sigma}_1 = \mathbf{I}$ is an identity matrix. Building on this initial assumption, and recognizing that the conditional distributions of $\boldsymbol{\alpha}_t$ are Gaussian, we use the Kalman filter to estimate $E(\boldsymbol{\alpha}_{t+1}|\mathcal{F}_t)$ and $Var(\boldsymbol{\alpha}_{t+1}|\mathcal{F}_t)$, given a history of past observations, denoted by $\mathcal{F}_t \equiv (\mathbf{y}_1^\top,\ \mathbf{y}_2^\top,\ \ldots,\ \mathbf{y}_t^\top)^\top$, for $t = 1,\ \ldots,\ T$. Then, by using the Kalman smoother, we estimate $E(\boldsymbol{\alpha}_t|\mathcal{F}_T)$ and $Var(\boldsymbol{\alpha}_t|\mathcal{F}_T)$ for all $t = 1, \ldots, T$. Let $\hat{\boldsymbol{\alpha}}_t = E(\boldsymbol{\alpha}_t|\mathcal{F}_T)$, then equation (5) allows us to impute the missing values in year t. Specifically, given $\hat{\boldsymbol{\alpha}}$ and $\overline{\mathbf{H}}_t$, we impute $\hat{\mathbf{y}}_t = \overline{\mathbf{H}}_t \hat{\boldsymbol{\alpha}}_t$. We note that the j-th row of $\overline{\mathbf{H}}_t$ contains a value of $\mathcal{T}_{j,t}$ such that $\mathcal{T}_{j,t} = \mathcal{T}_{j,t'}$ with $t' \in \mathcal{T}$ and $t < t' \leq t''$ for all $t'' \in \mathcal{T}$. This definition of $\overline{\mathbf{H}}_t$ renders a sensible imputation by ensuring that the definition of $\hat{\mathbf{y}}_t$ is consistent across time.[8] Column vector $\hat{\mathbf{y}}_t$ has a length of N, for which n_t elements are from $\mathbf{y}_t$ whenever they are observed. Further details on the estimation algorithm, the assumed priors, and the specifications of matrices $\mathbf{H}_t$, $\mathbf{T}$, and $\mathbf{Q}$ are described in Appendix B.

Backing out the Economic Activity Index. For state i, we follow Baumeister, Leiva-León and Sims (2024) to approximate the index of economic activity using the following equation:

$$\tilde{f}_i = (\boldsymbol{\lambda}_i^\top \boldsymbol{\lambda}_i)^{-1} \boldsymbol{\lambda}_i^\top \mathbf{y}_i^P, \tag{8}$$

[7] In our baseline estimation, we choose $l_{i,f} = l_{i,u} = 4$ for all i to align the autoregressive lag length with the average peak-to-peak business cycle duration (3.9 years), as measured by the NBER since the early 1880s. We consider $l_{i,f} = l_{i,u} = 5$ in our sensitivity analysis so as to match the median peak-to-peak business cycle duration (4.9 years).

[8] To fix idea, suppose the jth indicator of $\mathbf{y}_{i,t}$ is reported at decennial intervals for some $t \leq \bar{t}$ and annually after year $\bar{t}$. To impute the indicator's missing values for $\bar{t} - 10 < t < \bar{t}$, we set the jth row of $\overline{\mathbf{H}}_{i,t}$ such that it contains $\mathcal{T}_{i,j,t} = 10$. Therefore, the jth indicator is imputed as an annualized 10-year growth rate, which is consistent to its measure for year $\bar{t}$. If $\mathcal{T}_{i,j,t} = 1$ is selected instead, then the imputed values over the period $\bar{t} - 10 < t < \bar{t}$ are year-on-year growth rates, which are not consistent to the measure for year $\bar{t}$.

with $\tilde{f}_i \equiv [\tilde{f}_{i,1}, \tilde{f}_{i,2}, \ldots, \tilde{f}_{i,T}]^\top$. $\boldsymbol{\lambda}_i$ is an $(N_i \times 1)$ vector containing the median estimates of the factor loadings. Moreover, $\mathbf{y}_i^P \equiv [\mathbf{y}_{i,1}^P, \mathbf{y}_{i,2}^P, \ldots, \mathbf{y}_{i,T}^P]$ is the $(N_i \times T)$ input data with missing observations replaced by the projected values of the Kalman filter. According to Baumeister, Leiva-León and Sims (2024) (see p. 488 therein), using $\tilde{f}_i$ in place of $\tilde{f}_i$ provides two advantages: (i) while the two measures are typically close across time, the former minimizes the effect of revisions to the factor estimates when new information is added. (ii) The contribution of the jth input series to $\tilde{f}_{i,t}$ can be computed conveniently as $(\boldsymbol{\lambda}_i^\top \boldsymbol{\lambda}_i)^{-1} \lambda_{i,j} y_{i,j,t}^P$.

Because of the identification assumptions in the estimation, as well as the normalization of the input indicators in $\mathbf{y}_i^P$, $\tilde{f}_i$ needs to be recalibrated in some ways to ensure that it is interpretable as an index for the state's economic activity. We follow Clayton-Matthews and Stock (1998) to scale $\tilde{f}_i$ so that the resulting index, from time period 1964 to 2021, has an average growth and variance matching those of the state's real GDP growth rates during the same period. More specifically, the scaled index of economic activity for state i is obtained by the following affine transformation:

$$s_{i,t} = \beta_{1,i} + \beta_{2,i} \tilde{f}_{i,t}, \qquad \text{for} \quad t = 1, 2, \ldots, T, \tag{9}$$

with $\beta_{1,i} = -\frac{\sigma_i}{\sigma_{\tilde{f}_i}} \times \mu_{\tilde{f}_i} + \mu_i$ and $\beta_{2,i} = \frac{\sigma_i}{\sigma_{\tilde{f}_i}}$. μ_i represents the average growth rates of state i's real GDP (in 2012 dollars) from 1964 to 2021. $\mu_{\tilde{f}_i}$ denotes the average value of $f_{i,t}$ from 1964 to 2021. σ_i and $\sigma_{\tilde{f}_i}$ are the standard deviations of state i's real GDP growth rates and $\tilde{f}_{i,t}$ over 1964–2021.

3.2 Estimation Results

Estimation Inputs. Our model is estimated for each of the 48 contiguous U.S. states separately. We select the state-level indicators as inputs in our baseline estimation based on two criteria. First, we select the ones that are economically relevant and tend to comove with state-level business cycles. Second, we include the raw or imputed data that are available since relatively early years. Despite the flexibility of our method to accommodate missing data in particular in the early years, the estimation accuracy can be harmed when there are many missing values.

In Table 2, we present the variables that together form the baseline inputs, together with their available period, frequency and geographic coverage. Our selected dataset covers series of varying frequencies —annual, 5-yearly and 10-yearly, sometimes varying within each variable. As detailed in Section 3.1, the flexibility of our model allows us to accommodate these variations in frequency.

Figure 2 shows our factor estimates against BEA GDP growth rates (available post-1963) for se-

Table 2: Input series used in the baseline estimation

	Indicators	Geographic and temporal coverage	
		No. of states	Years covered
Real activity	Nonfarm employment	48	1880, 1890, 1900, 1910, 1920, 1929–2021
	Liabilities of failed firms	48	1886–1983
	Value of mining production	48	1881–2021
	Value of agri. products sold	48	1871–2021
	Value of exported merchandise	27	1872–1948, 1951-1952, 1955–1981, 1984–2021
	Value of imported merchandise	33	1872–1948, 1951-1952, 1955–1981, 1984–2021
	Value added of mfg. production	48	1880, 1890, 1900, 1905, 1910, 1915, 1920–2021
Wealth	Personal income	48	1890, 1900, 1910, 1920, 1928–2021
	Value of farmland and buildings	48	1911–2021
Govt.	State govt. gross debt	48	1871–2021
	State govt. general revenue	46	1871–2021
	Federal govt. internal revenue	48	1871–2021
Others	Housing sales price index	21	1891–2021
	Housing rental price index	21	1891–2006
	Railroad operating mileage	48	1871–1973
	No. of motor vehicle registration	48	1901–2021

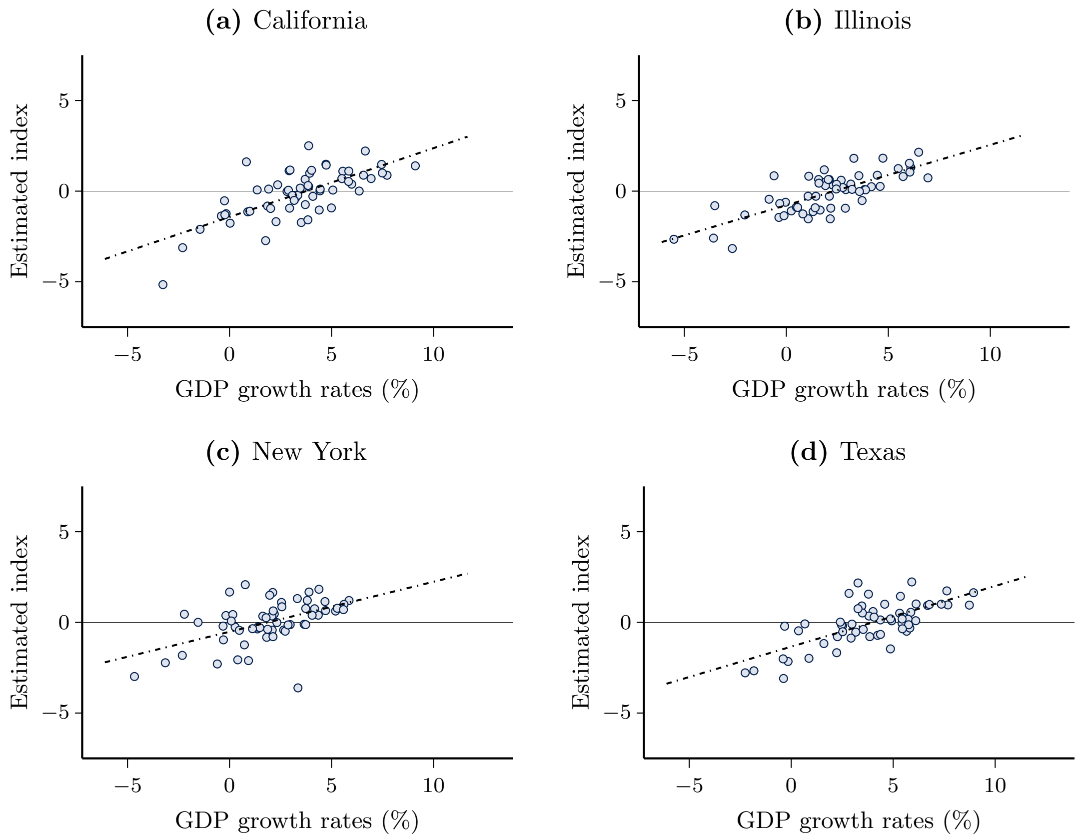
Notes: This table lists the inputs included in the baseline estimation, with all inputs expressed as annual or annualized growth rates calculated using log-differences. Liabilities of failed firms and values of imports and exports are smoothed with a three-year moving average. Farmland and building values are reported per acre. The final column presents the years in which the inputs are available for at least one state.

lected states. We observe a strong linear relationship between factor estimates and economic growth, suggesting that our estimated factor, though generally hard to interpret, successfully captures the overall economic activity at the state level. This observation validates the linear transformation in Equation (9) in generating an index that is comparable to the familiar GDP growth.

The State Economic Activity Index. Using the baseline input variables in Table 2, we estimate a state-level economic activities index (SEAI) for each state at the annual frequency. Figure 3 shows our results in a heat plot that reveals distinct patterns of economic growth and contraction across different time periods and regions.

Several major downturns stand out, particularly the Great Depression of the 1930s, which was the most severe and widespread economic collapse in US history. States reliant on manufacturing, such as Michigan, Pennsylvania, and Ohio, experienced deep recessions, while agricultural states like Oklahoma, Kansas, and Nebraska suffered due to the Dust Bowl. Thanks to the wide coverage of historical data, we also capture earlier recessions, including the Long Depression (1873-1896) and the Panic of 1893, that show significant declines particularly in railroad-dependent and farming

Figure 2: Factor estimates v.s. GDP growth rates



Notes: This figure displays the association between the factor estimates and annual GDP growth rates (in percentages) for selected states from 1964 to 2021. GDP data are from the BEA.

states. More recent recessions, such as the 2008 Great Recession and the COVID-19 downturn of 2020, also display nationwide impacts, with financial hubs (New York) and real estate-heavy states (Florida, Arizona, Nevada) suffering severe contractions.

Periods of strong economic growth are equally evident. The post-WWII boom from the 1940s to the 1960s saw widespread economic expansion across most states, likely driven by industrial production, infrastructure development, and demographic growth. The 1990s also mark a period of significant economic expansion, largely due to the rise of the technology sector, benefiting states like California, Washington, and Massachusetts.

Our heat map also delivers clear messages on cross-state variations, with some states experiencing frequent boom-bust cycles while others show long-term stability. Energy-dependent states such as North Dakota, Wyoming, and West Virginia exhibit high volatility, likely due to the highly volatile resource prices. Similarly, states with large tourism and real estate sectors, such as Nevada and Florida, show sharp declines during financial crises but rapid recoveries during periods of expansion. In contrast, states like California, Texas, and New York demonstrate relatively consistent growth due to their diversified economies. The Rust Belt states, including Ohio, Michigan, and Pennsylvania, show prolonged periods of economic decline in the late 20th century due to the decline of manufacturing industries.

Over time, the structure of economic cycles has changed. Before 1950, recessions were longer and recoveries slower, often concentrated in specific regions. After WWII, economic downturns became shorter and recoveries faster, potentially mitigated by monetary policy, government stimulus, and broader economic diversification. Overall, this heat map illustrates the evolving nature of the U.S. economy, highlighting how national economic cycles, industrial shifts, and policy changes shape state-level growth patterns.

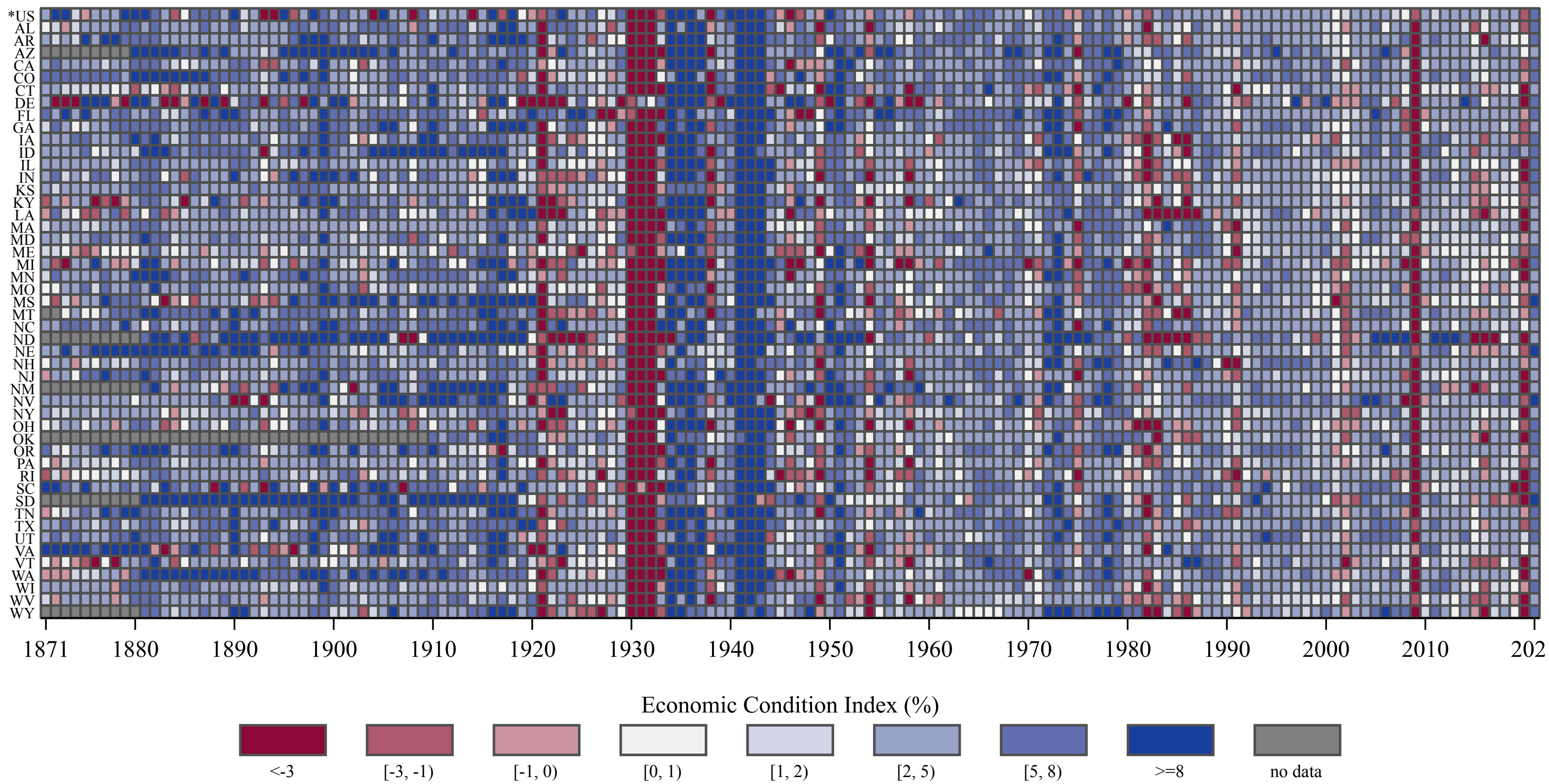
Comparison with Existing State-Level Data. In order to validate our estimates in properly capturing the state-level business cycles, we compare ours with existing data on state-level business cycles that are available with a shorter period of time in a binscatter plot Figure 4. These data include: (i) state GDP from BEA; (ii) State Coincident Index from Philadelphia Fed[9]; (iii) State unemployment rate from BLS Local Area Unemployment Statistics; and (iv) State personal income from BEA. As shown before, our factor estimates line up well with GDP, so it's not surprising that a linearly-transformed version also strongly correlates with GDP, displayed in Panel (a) of Figure 4. Similarly, the SEAI exhibits a strong correlation with established economic indicators, including personal income, State Coincident Indexes, and the unemployment rate. This consistency supports the validity of our index in capturing economic fluctuations over an extended period.

3.3 Alternative Specifications

We have done a number of robustness tests to test the sensitivity of our index to alternative input variables, different model specifications including number of lags and factors, as well as alternative estimation algorithm such as the Hamiltonian Monte Carlo algorithm. Results of these tests are presented in Appendix C.1. In general, our results are fairly robust to these changes.

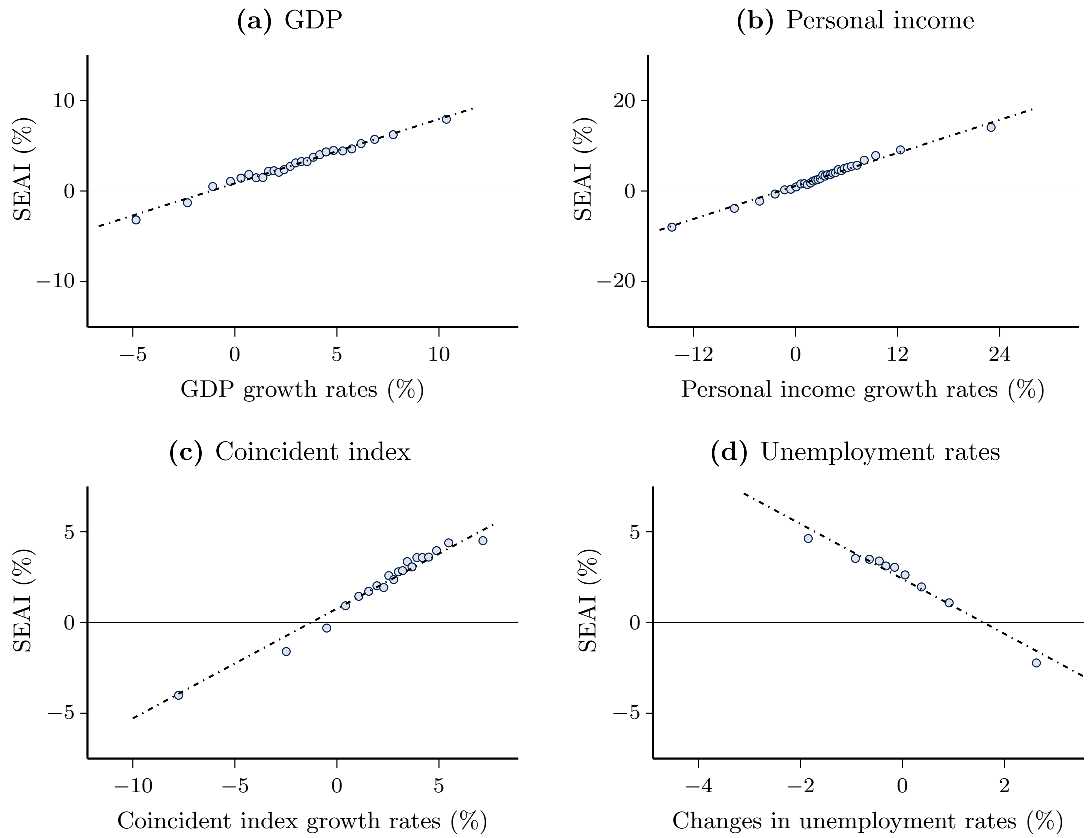
[9]https://www.philadelphiafed.org/surveys-and-data/regional-economic-analysis/state-coincident-indexes

Figure 3: State Economic Activities Index



Notes: Each cell corresponds to the binned value of our State Economic Activities Index, which details the annual change in economic activity for that particular state and year. We divide the changes across states and years into deciles. Gray cells represent years for the state for which we do not currently estimate the index. Many of these are due to less data availability before entry into the union. For reference, we include US GDP data from Williamson (2025) in growth rates, labeled as "*US".

Figure 4: SEAI and other measures of economic conditions



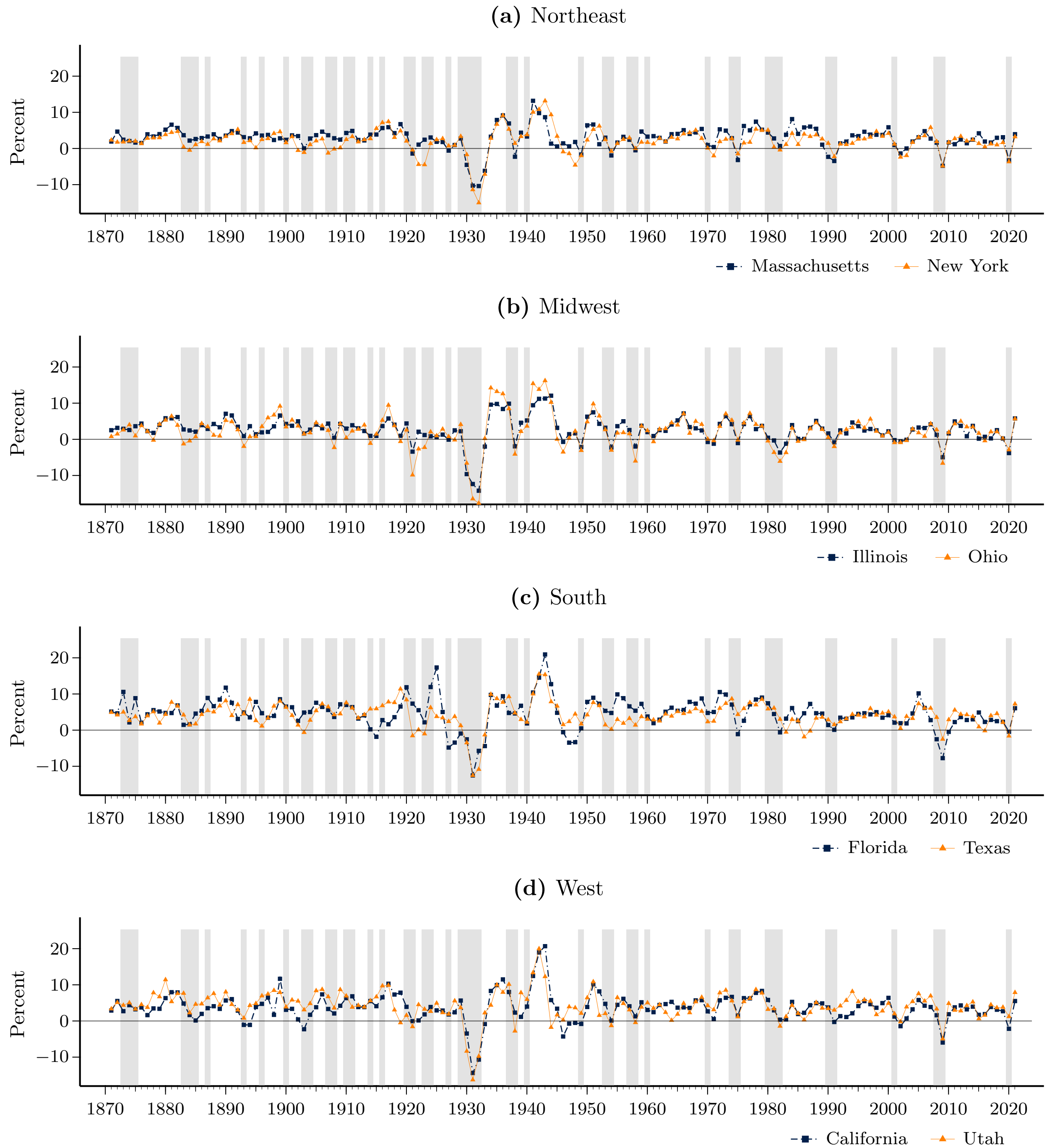
Notes: This figure presents binscatter plots of the estimated economic activity indices against alternative measures of state-level economic conditions. The number of bins is chosen using the rule-of-thumb bin selector of Cattaneo et al. (2024). Annual growth rates of state-level GDP (1964–2019), personal income (1929–2019), and the coincident index (1980–2019) are calculated as log differences, while changes in unemployment rates (1977–2019) are computed as first differences. GDP and personal income data are from the BEA, coincident indices are from the Philadelphia Fed, and unemployment rates are from the BLS.

4 150 Years of State-Level Business Cycles

4.1 Descriptive facts

In Figure 5, we present graphs of the estimated annual economic activity indices for selected states from 1871 to 2019, overlaid by recession bars shaded in gray. This figure reveals some important similarities, but also key differences in the state-level business cycles, both within the same region and across different regions. For one, all of the presented states show substantial annual growth rates from 1940 to 1943, followed by a sharp decline to negative growth rates in 1945–46 (except for Idaho). Moreover, state-level business cycles appear to be less dispersed after 1950s, compared to both the WWII period and the years prior to the 1940s.

Figure 5: Annual index of economic activity for selected states



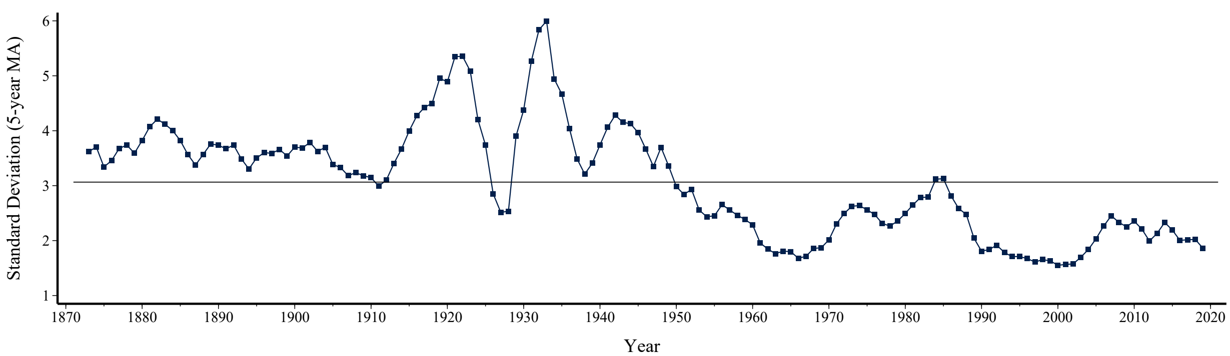
Notes: This figure displays the annual economic activity indices for selected states from 1871 to 2021. The shaded bars indicate recession years. Recession years from 1887 to 1991 are defined based on Table 3 of Romer (1999), with a year counted as a recession year if it reports at least one quarter within the peak-to-trough phase. Recession years prior to 1887 are defined according to Table 1 of Davis (2006), with a year counted as a recession year if it falls within the peak-to-trough phase. For years after 1991, the NBER chronology is used.

Table 3: Dispersion of state-level economic activity index before and after WWII

	Pre-WWII		Post-WWII	
	1871–1905	1906–1940	1945–1980	1981–2019
All years	3.72	4.21	2.61	2.19
Recession years	3.69	4.40	2.71	2.61
Recession years, except the Great Depression	3.69	3.99	2.71	2.61
Non-recession years	3.74	4.01	2.57	2.09

Notes: This table shows the average dispersion of economic activity indices across states before and after WWII. Annual dispersion of economic activity is measured by standard deviations. For the definition of recession years, refer to the notes in Figure 5.

Figure 6: Dispersion of State-Level Economic Activity Over Time



Notes: This figure shows the standard deviation of our estimated economic activity indices across states, averaged over a five-year moving window. The horizontal line represents the average value over time, which is about 3.2.

To assess the dispersion of the estimated economic activity indices, Figure 6 presents their standard deviation over time. The volatility of growth rates is notably higher in the pre-WWII period as compared to the post-WWII period, providing evidence that there are greater differences in annual growth experiences across states before WWII. Table 3 further illustrates this pattern by summarizing the average dispersion of economic activity indices across four periods: 1871—1905, 1906—1940, 1945—1980, and 1981—2019. The table shows a steady decline in business cycle dispersion after WWII. Interestingly, dispersion appears greatest, on average, during the 1906—1940 period, even after excluding the Great Depression years (1929—1932).

4.2 Decomposition of the Estimated State Economic Activity

An obvious question our estimated index of economic activity poses is which factors have historically driven business cycle fluctuations on the state-level. We can answer this question by decomposing the variation in changes in the index based on the variation in the underlying indicators. Figure 7 plots changes in economic activity for a selection of states including changes in the underlying indicators. For this exercise, we group the underlying indicators into five buckets to allow for an easier readability.

The decomposition figure for the displayed states reveals several interesting patterns. First, real activity variables are the primary negative contributors to the estimated index in most cases. However, during the 1903 recession, variables in the 'government finance' category are the main drivers of the index downturn in California, Massachusetts, and Texas. Second, government finance variables play a substantially larger role in shaping California's pre-1920 index dynamics compared to the other three states. In Massachusetts and Wisconsin, fluctuations in the real activity variables appear to be the primary drivers of the pre-1920 index dynamics, while in Texas, the dynamics are mainly accredited to wealth variables (in particular, bank assets).

4.3 State and National Business Cycles

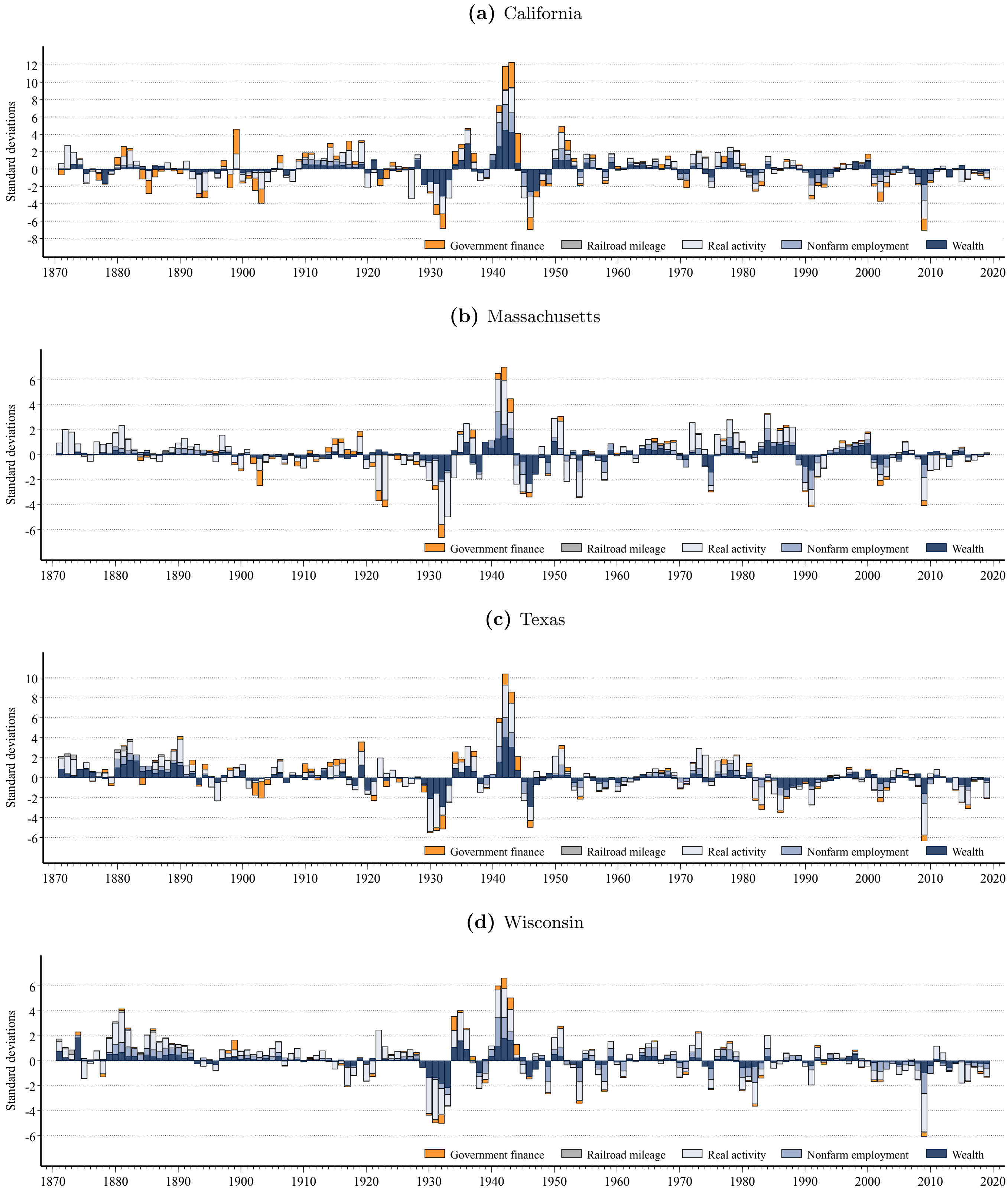
Does a national recession necessarily mean a recession happens in all states at the same time? Are some states experiencing meaningful upswings or downturns in the absence of major U.S.-wide business cycle events? We provide some new systematic evidence on these questions based on our large historical sample.

As discussed earlier, Figure 3 highlights that state-level business cycles are far from perfectly coinciding, although they seem to become more so during national downturns. The NBER recessions in 1873, 1929, and 2007 in particular stand out for how widespread the regional economic downturns were. In contrast, the 1991 and 2001 recessions were much more concentrated in certain states. Additionally, Figure 9 plots the change in our economic activity index across states during three major U.S. recessions as identified by the NBER: 1873, 1929, and 2007. For each event, we calculate the mean change in the index for the years the NBER classifies as a recession. These maps highlight that economic downturns are highly unequal in space. While most states experienced a downturn, the extent to which they did varies dramatically.

To get a sense of how closely each state's economy is aligned with the U.S. business cycle, we take an approach similar to Arias, Gascon and Rapach (2016). In particular, we calculate how often a state-level recession coincides with a national one, which allows us to assess the degree of overlap between local and aggregate cycles. We measure the U.S. business cycle turning points using the NBER dates.

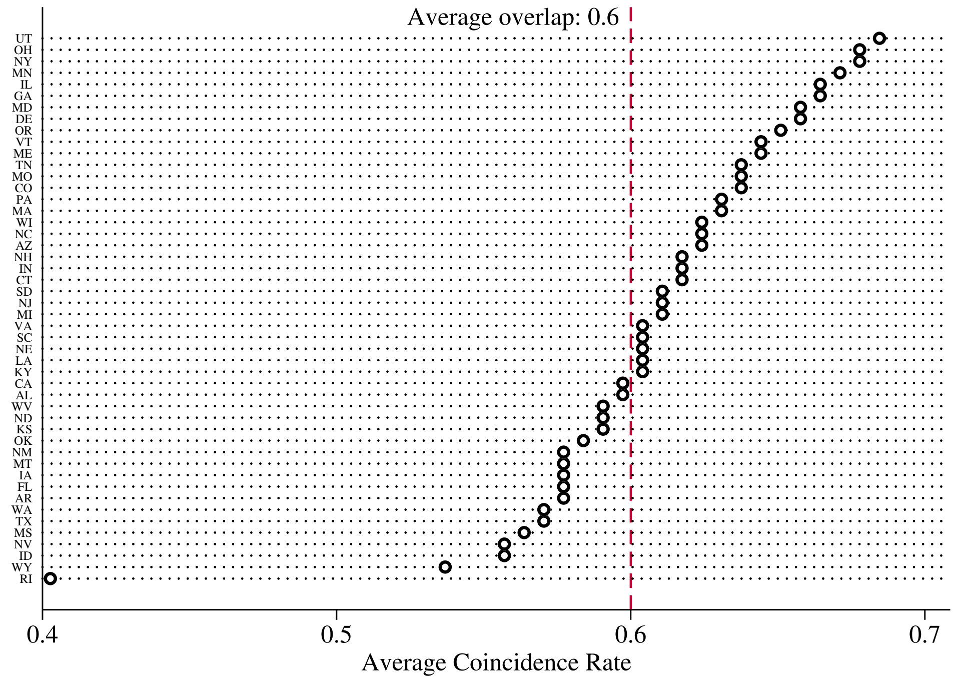
Figure 8 shows the results. States are ordered by the degree of overlap between state and

Figure 7: Decomposition of Estimated Index for Selected States



Notes: These figures decompose variation in the estimated index of economic activity for a selected number of states into five components: government finance, railroad mileage, real activity, nonfarm employment, and wealth.

Figure 8: Estimated Average Coincidence Rate by States



Notes: We define state-level recessions with the Bry and Boschan (1971) algorithm applied on our Real Economic Index (demeaned and rescaled to levels). We define national recessions as follows: Recession years from 1887 to 1991 are defined based on Table 3 of Romer (1999), with a year counted as a recession year if it reports at least one quarter within the peak-to-trough phase. Recession years prior to 1887 are defined according to Table 1 of Davis (2006), with a year counted as a recession year if it falls within the peak-to-trough phase. For years after 1991, the NBER chronology is used.

national business cycle phases, which we calculate as the fraction of times where a state and the U.S. as a whole are both signaling a recession or expansion phase. States such as Ohio or Nevada are closely aligned with the aggregate business cycle, but others such as Maine or North Dakota are not.

We calculate real GDP growth for the U.S. between 1929 and 2020 using data from the BEA, and for 1861 to 1928 using data from Williamson (2025). Equipped with this time series, we then calculate the bivariate correlation of growth in each state's economic activity index using a rolling window of five years. This approach allows us to gauge how the correlation of economic activity in individual states with the aggregate economy has changed over time.

?? plots the mean, interquartile range, minimum, and maximum for the estimated correlations over time. As one may expect, there is a steady upward trend in the synchronization of local and national business cycles over time, which is likely at least partly explained by decreases in the cost of transport and communication. That said, there is substantial heterogeneity across states, with some exhibiting high correlations with aggregate real GDP growth early on, while others still show relatively low co-movement today.

In sum, our analysis suggests substantial heterogeneity (both across space and time) in how much local economic cycles coincide with those of the U.S. as a whole. While a full-fledged study of long-run changes in local business cycle synchronization is beyond the scope of this paper, we believe it is worth examining in future work.

4.4 What Happens over State Business Cycles?

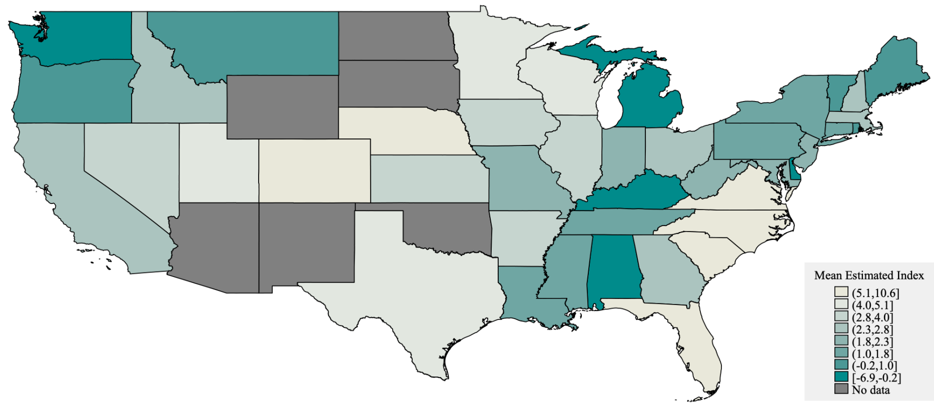
As a first step, we compare our economic activity index against select variables not included in the baseline inputs by running simple bivariate panel regressions with state fixed effects and standard errors clustered by state. In documenting the following correlates, we exploit the variation across the 48 states and over 150 years. Given that we include Manufacturing Value Added, State Government Gross Debt and the Liabilities of Failed Firms as inputs in our baseline estimation, it is reassuring that we find significant correlations with closely related variables. Second, consistent with the post-1963 state-GDP results in Van Binsbergen et al. (2024), we find that our economic activity index is positively correlated with the first lag of sentiments. In other words, an increase in sentiments is a precursor to positive growth in state-level economic activity. Thirdly, while we do not directly capture tertiary sectors in our dataset, we find a positive correlation between our real economic index and the total circulation of newspapers, as a proxy for the journalism and advertising industries. Finally, combining the long-run historical data in Berkes (2018) with our real economic index from 1871, we find a positive correlation with the Number of Patents. As noted in Berkes (2018), until recently most research papers on patenting activity have mostly focused on the past 50 years. Within this context, we confirm the well-known relationship in the literature between innovation and real economic activity historically and at the state-level. To close, while we document the on-average effects here, just as the experiences of each state are heterogeneous (Section 4.3), the above relationships vary substantially across states as well.

4.5 A New Chronology of State-Level Recessions

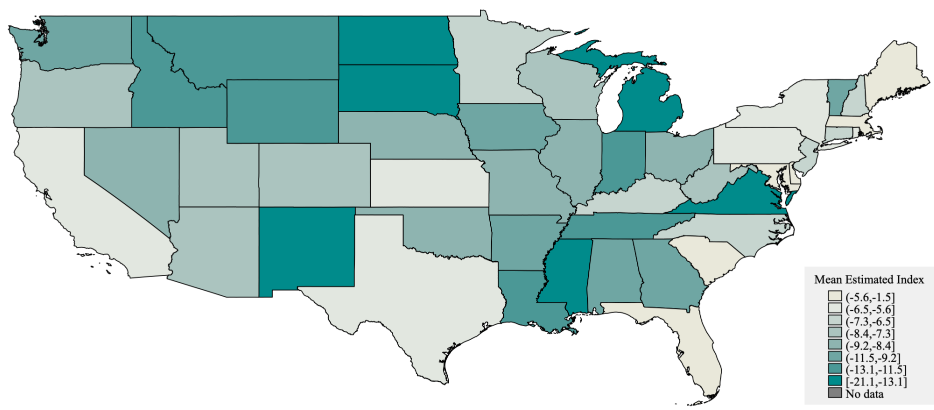
As a by-product of our estimates of economic activity, we construct a chronology of recessions since the Civil War, similar to NBER's business cycle dating, but with a focus on state-level ones. As our analysis above highlights, business cycles vary widely across states. The principal challenge is

Figure 9: Change in State-Level Economic Activity during US-wide Recessions

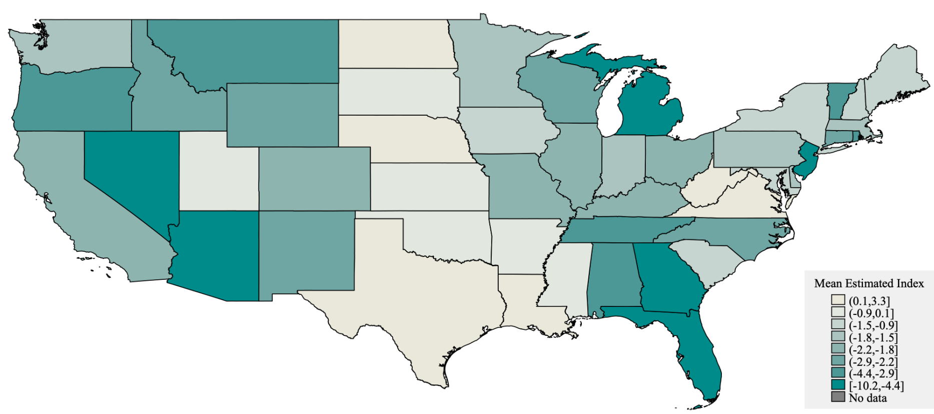
A. 1873-1875 Recession



B. 1929-1932 Recession



C. 2008-2009 Recession



Notes: We plot our state-level economic index across three national recessions. For each recession period, we report the average of our index over the recession years. We define national recessions as follows: Recession years from 1887 to 1991 are defined based on Table 3 of Romer (1999), with a year counted as a recession year if it reports at least one quarter within the peak-to-trough phase. Recession years prior to 1887 are defined according to Table 1 of Davis (2006), with a year counted as a recession year if it falls within the peak-to-trough phase. For years after 1991, the NBER chronology is used.

Table 4: Correlates of State-Level Economic Activity

Variable	$\hat{\beta}$	t-stat	Within-R^2
No. Manufacturing Employees	9.97	11.64**	0.28
Real Manufacturing Payroll	8.31	11.14**	0.20
No. Manufacturing Establishments	4.67	9.90**	0.02
Total Circulation of Newspapers	3.55	4.70**	0.03
Number of Daily Newspapers	2.08	1.12	0.01
First Difference of Sentiments (Lagged)	1.81	6.79**	0.01
Number of Patents by Inventors (First Name)	1.07	3.80**	0.00
No. Bankruptcies Terminated	-1.28	-5.25**	0.00
Real State Govt Expenditure	-2.20	-5.54**	0.01
Real State Net Debt	-2.44	-6.51**	0.01
Real State Long Term Debt	-2.90	-7.02**	0.02
No. Bankruptcies Commenced	-3.33	-7.85**	0.03
No. Business Failures	-4.98	-10.61**	0.06

Notes: This table reports the results from bivariate panel regressions of state indicators not included in our index construction on the estimated index. Variables are measured as the first difference in natural logarithm, and they are standardized to have a mean of zero and standard deviation of one. All regressions include state fixed effects. While this table does not include year fixed effects, the results are robust to their inclusion. Standard errors are clustered by state, and **, *, and + indicate statistical significance at the 1%, 5%, and 10% level, respectively.

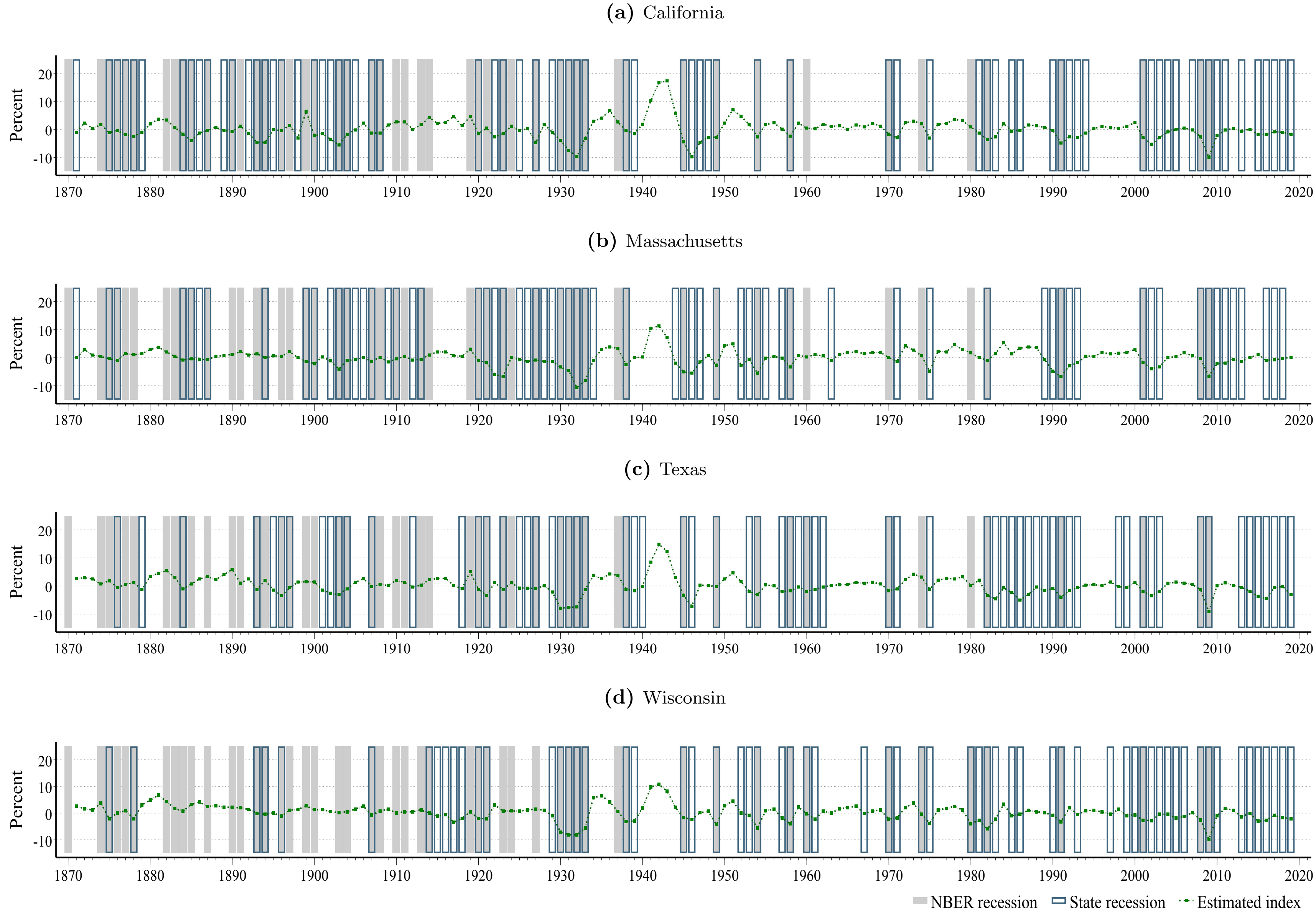
thus to identify which periods we should classify as a state-level recession. Since we are interested in creating a dataset of historical recession dates, we use the turning point algorithm first proposed by Bry and Boschan (1971), which has been applied to identify recessions (e.g., Davis, 2006).

The Bry-Boschan method has the advantage that it is straightforward, easy to implement, and has been widely used. As such, the results from applying it are also easy to understand. The main downside of Bry-Boschan is that one cannot use it for a real-time identification of recessions because it requires information about future values to determine whether any given data point should be considered a turning point. Since our paper is not concerned with forecasting, we leave the application of more sophisticated methods such as Markov regime-switching models for future work.

To implement the Bry-Boschan algorithm, we use our state-level economic indices, demeaned and in levels and ask the algorithm to identify peaks and troughs. This requires us to specify three parameters: the time window over which to identify turning points, the minimum length of expansions or contractions, and the overall duration of the cycle. Given that we have annual data, we choose a time window of two years, a minimum of one year for the length of each phase of the cycle, and an overall cycle length of two years.

One fact that stands out is that there are many local recessions not associated with NBER recessions. Similarly, many states do not experience a downturn during NBER recessions, consistent with the heterogeneity in business cycles we documented above. As such, one can think of local and U.S.-wide recessions as capturing correlated but distinct events. Figure 10 plots several examples of the identified peaks and troughs for California, Massachusetts, Texas, and Wisconsin, against NBER recessions in the background. In these case studies, state-level recessions tend to coincide with NBER recessions, but there are also exceptions. For example, California experienced a recession in 1985 that did not coincide with the NBER dating. Wisconsin, on the other hand, did not see a downturn in the early 1900s, while the other states did. Taken together, our new chronology of state-level recession dates again highlights the considerable heterogeneity in business cycles across regions.

Figure 10: Recession dates for selected states (1871–2019)



Notes: Recession dates for the states are identified by applying the Bry and Boschan algorithm (1971) to the economic condition indices (demeaned and scaled to levels). The gray bars correspond to the NBER recession dates and the dashed lines represent the demeaned economic condition indices.

5 Conclusion

This paper introduces a new historical state-level dataset for the United States, covering 65 variables from the Civil War until today. These newly constructed time series are useful because they allow us to gauge changes in economic activity in different states over time. We believe they will have many different applications in domains from economic growth to economic geography or empirical macroeconomics.

An index of economic activity based on a subset of these indicators captures the state of the business cycle well. Equipped with this new index, extracted using a mixed-frequency dynamic factor model, we document several new facts about economic fluctuations in the United States. A key finding is that state-level cycles can at times diverge quite meaningfully from national cycles, and these differences in "business cycle beta" vary across states. As a by-product of our index of state-level economic activity, we introduce an NBER-style chronology of business cycle events. Different from existing work, our dating scheme has a regional dimension. We show that many recessionary periods on the state-level do not coincide with U.S.-wide downturns, highlighting the considerable variability underlying aggregate numbers.

Our work sheds new light on the history of the U.S. economy at the local level before the advent of state-level GDP in the 1960s. As such, we view it as a starting point for more research on the nature of economic growth and fluctuations from a regional perspective, made possible by our novel dataset beyond the state-level index.

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Online Appendix for
"U.S. State-Level Business Cycles Since the Civil War"

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A Details on the Dataset

Please refer to the supplemental data appendix document Hoon et al. (2025) for all the details on constructing our dataset.

B Details on the Dynamic Factor Model

B.1 Model Derivations

B.2 An Illustrative Example

For expositional clarity, we focus on the baseline specification with N indicators reported under 5 distinct frequencies.[10] Among these indicators, N_y are reported annually, while the remaining series are reported based on one of the 4 frequency types. Let $\{N_a,\ N_b,\ N_c,\ N_d\}$ denote the number of indicators that report under the 4 frequency types, respectively. Then, matrix $\mathbf{H}_t$ of equation (5) can be written as follows:

$$\mathbf{H}_t = \begin{bmatrix} \mathbf{H}_t^a \\ \mathbf{H}_t^b \\ \mathbf{H}_t^c \\ \mathbf{H}_t^d \\ \mathbf{H}_t^y \end{bmatrix},$$

[10]Two indicators, $Y_{i,t}$ and $Y_{j,t}$, share a common reporting frequency if $\mathcal{T}_i = \mathcal{T}_j = \mathcal{T}$ and $c_t^i = c_t^j$ for all $t \in \mathcal{T}$.

where matrix $\mathbf{H}_t^x$ has N_x rows, for $x \in \{a, b, c, d, y\}$. The coefficients of these time-varying matrices are given by:

$$\mathbf{H}_t^a = \begin{bmatrix} \frac{1}{c_t^1}\lambda_1^a \mathbf{1}^\top_{[c_t^1]} & \mathbf{0}^\top_{[m_a-c_t^1]} & \frac{1}{c_t^1}\mathbf{1}^\top_{[c_t^1]} & \mathbf{0}^\top_{[m_a-c_t^1]} & \mathbf{0}^\top_{[c_t^1]} & \cdots & \cdots & \mathbf{0}^\top_{[c_t^1]} & \mathbf{0}^\top_{[m_a-c_t^1]} & \mathbf{0}^\top_{[a]} \\ \frac{1}{c_t^1}\lambda_2^a \mathbf{1}^\top_{[c_t^1]} & \mathbf{0}^\top_{[m_a-c_t^1]} & \mathbf{0}^\top_{[c_t^1]} & \mathbf{0}^\top_{[m_a-c_t^1]} & \frac{1}{c_t^1}\mathbf{1}^\top_{[c_t^1]} & \mathbf{0}^\top_{[m_a-c_t^1]} & \cdots & \mathbf{0}^\top_{[c_t^1]} & \mathbf{0}^\top_{[m_a-c_t^1]} & \vdots \\ \vdots & & \vdots & & \vdots & \ddots & & \vdots & \vdots & \vdots \\ \vdots & & \vdots & & \vdots & & \ddots & \mathbf{0}^\top_{[c_t^1]} & \vdots & \vdots \\ \frac{1}{c_t^1}\lambda_{N_a}^a \mathbf{1}^\top_{[c_t^1]} & \mathbf{0}^\top_{[m_a-c_t^1]} & \mathbf{0}^\top_{[c_t^1]} & \mathbf{0}^\top_{[m_a-c_t^1]} & \mathbf{0}^\top_{[c_t^1]} & \cdots & \cdots & \frac{1}{c_t^1}\mathbf{1}^\top_{[c_t^1]} & \mathbf{0}^\top_{[m_a-c_t^1]} & \mathbf{0}^\top_{[a]} \end{bmatrix},$$

where $\mathbf{0}_{[x]}$ and $\mathbf{1}_{[x]}$ denote column vectors of zeros and ones, each with a length of x. Furthermore, $m_a = \max(c^1) = \max\limits_{t \in \mathcal{T}_1}(c_t^1)$ denotes the largest number of lapsed years observed in the first series; in particular, we note that $m_a = 10$ in our baseline sample. In the last column of $\mathbf{H}_t^a$, vector $\mathbf{0}^\top_{[a]}$ has a length of $N_b \times m_b + N_c \times m_c + N_d \times m_d + N_y \times l_u$, where we define $m_b = \max(c^b) = \max(c^{N_a+1})$, $m_c = \max(c^{N_a+N_b+1})$, and $m_d = \max(c^{N_a+N_b+N_c+1})$, respectively. When $N_a = 1$, $\mathbf{H}_t^a$ collapses to its first row, retaining the first four and the last columns. It is likely that we do not observe all N_a growth rates in year t. In this case, we remove the rows of $\mathbf{H}_t^a$ that are associated with the missing entries. This operation ensures that $\mathbf{H}_t$ is conformable in the observation equation. We also add a superscript 'a' to the factor loadings for notational convenience. Similar to $\mathbf{H}_t^a$, matrix $\mathbf{H}_t^b$ is given by:

$$\mathbf{H}_t^b = \begin{bmatrix} \frac{1}{c_t^b}\lambda_1^b \mathbf{1}^\top_{[c_t^b]} & \mathbf{0}^\top_{[m_a+m_b-c_t^b]} & \frac{1}{c_t^b}\mathbf{1}^\top_{[c_t^b]} & \mathbf{0}^\top_{[m_b-c_t^b]} & \mathbf{0}^\top_{[c_t^b]} & \cdots & \cdots & \mathbf{0}^\top_{[c_t^b]} & \mathbf{0}^\top_{[m_b-c_t^b]} & \mathbf{0}^\top_{[b]} \\ \frac{1}{c_t^b}\lambda_2^b \mathbf{1}^\top_{[c_t^b]} & \mathbf{0}^\top_{[m_a+m_b-c_t^b]} & \mathbf{0}^\top_{[c_t^b]} & \mathbf{0}^\top_{[m_b-c_t^b]} & \frac{1}{c_t^b}\mathbf{1}^\top_{[c_t^b]} & \mathbf{0}^\top_{[m_b-c_t^b]} & \cdots & \mathbf{0}^\top_{[c_t^b]} & \mathbf{0}^\top_{[m_b-c_t^b]} & \vdots \\ \vdots & & \vdots & & \vdots & \ddots & & \vdots & \vdots & \vdots \\ \vdots & & \vdots & & \vdots & & \ddots & \mathbf{0}^\top_{[c_t^b]} & \vdots & \vdots \\ \frac{1}{c_t^b}\lambda_{N_b}^b \mathbf{1}^\top_{[c_t^b]} & \mathbf{0}^\top_{[m_a+m_b-c_t^b]} & \mathbf{0}^\top_{[c_t^b]} & \mathbf{0}^\top_{[m_b-c_t^b]} & \mathbf{0}^\top_{[c_t^b]} & \cdots & \cdots & \frac{1}{c_t^b}\mathbf{1}^\top_{[c_t^b]} & \mathbf{0}^\top_{[m_b-c_t^b]} & \mathbf{0}^\top_{[b]} \end{bmatrix},$$

where vector $\mathbf{0}_{[b]}^{\top}$ has a length of $N_c \times m_c + N_d \times m_d + N_y \times l_u$. Next, we note that matrix $\mathbf{H}_t^c$ has the following expression:

$$\mathbf{H}_t^c = \begin{bmatrix} \frac{1}{c_t^c}\lambda_1^c \mathbf{1}_{[c_t^c]}^{\top} & \mathbf{0}_{[m_a+m_b+m_c-c_t^c]}^{\top} & \frac{1}{c_t^c}\mathbf{1}_{[c_t^c]}^{\top} & \mathbf{0}_{[m_c-c_t^c]}^{\top} & \mathbf{0}_{[c_t^c]}^{\top} & \cdots & \cdots & \mathbf{0}_{[c_t^c]}^{\top} & \mathbf{0}_{[m_c-c_t^c]}^{\top} & \mathbf{0}_{[c]}^{\top} \\ \frac{1}{c_t^c}\lambda_2^c \mathbf{1}_{[c_t^c]}^{\top} & \mathbf{0}_{[m_a+m_b+m_c-c_t^c]}^{\top} & \mathbf{0}_{[c_t^c]}^{\top} & \mathbf{0}_{[m_c-c_t^c]}^{\top} & \frac{1}{c_t^c}\mathbf{1}_{[c_t^c]}^{\top} & \mathbf{0}_{[m_c-c_t^c]}^{\top} & \cdots & \mathbf{0}_{[c_t^c]}^{\top} & \mathbf{0}_{[m_c-c_t^c]}^{\top} & \vdots \\ \vdots & & \vdots & & \vdots & \ddots & & \vdots & \vdots & \vdots \\ \vdots & & \vdots & & \vdots & & \ddots & \mathbf{0}_{[c_t^c]}^{\top} & \vdots & \vdots \\ \frac{1}{c_t^c}\lambda_{N_c}^c \mathbf{1}_{[c_t^c]}^{\top} & \mathbf{0}_{[m_a+m_b+m_c-c_t^c]}^{\top} & \mathbf{0}_{[c_t^c]}^{\top} & \mathbf{0}_{[m_c-c_t^c]}^{\top} & \mathbf{0}_{[c_t^c]}^{\top} & \cdots & \cdots & \frac{1}{c_t^c}\mathbf{1}_{[c_t^c]}^{\top} & \mathbf{0}_{[m_c-c_t^c]}^{\top} & \mathbf{0}_{[c]}^{\top} \end{bmatrix},$$

where vector $\mathbf{0}_{[c]}^{\top}$ has a length of $N_d \times m_d + N_y \times l_u$. Now, matrix $\mathbf{H}_t^d$ is given by:

$$\mathbf{H}_t^d = \begin{bmatrix} \frac{1}{c_t^d}\lambda_1^d \mathbf{1}_{[c_t^c]}^{\top} & \mathbf{0}_{[m_a+m_b+m_c+m_d-c_t^d]}^{\top} & \frac{1}{c_t^d}\mathbf{1}_{[c_t^d]}^{\top} & \mathbf{0}_{[m_d-c_t^d]}^{\top} & \mathbf{0}_{[c_t^d]}^{\top} & \cdots & \cdots & \mathbf{0}_{[c_t^d]}^{\top} & \mathbf{0}_{[m_d-c_t^d]}^{\top} & \mathbf{0}_{[d]}^{\top} \\ \frac{1}{c_t^d}\lambda_2^d \mathbf{1}_{[c_t^c]}^{\top} & \mathbf{0}_{[m_a+m_b+m_c+m_d-c_t^d]}^{\top} & \mathbf{0}_{[c_t^d]}^{\top} & \mathbf{0}_{[m_d-c_t^d]}^{\top} & \frac{1}{c_t^d}\mathbf{1}_{[c_t^d]}^{\top} & \mathbf{0}_{[m_d-c_t^d]}^{\top} & \cdots & \mathbf{0}_{[c_t^d]}^{\top} & \mathbf{0}_{[m_d-c_t^d]}^{\top} & \vdots \\ \vdots & & \vdots & & \vdots & \ddots & & \vdots & \vdots & \vdots \\ \vdots & & \vdots & & \vdots & & \ddots & \mathbf{0}_{[c_t^d]}^{\top} & \vdots & \vdots \\ \frac{1}{c_t^d}\lambda_{N_d}^d \mathbf{1}_{[c_t^d]}^{\top} & \mathbf{0}_{[m_a+m_b+m_c+m_d-c_t^d]}^{\top} & \mathbf{0}_{[c_t^d]}^{\top} & \mathbf{0}_{[m_d-c_t^d]}^{\top} & \mathbf{0}_{[c_t^d]}^{\top} & \cdots & \cdots & \frac{1}{c_t^d}\mathbf{1}_{[c_t^d]}^{\top} & \mathbf{0}_{[m_d-c_t^d]}^{\top} & \mathbf{0}_{[d]}^{\top} \end{bmatrix},$$

with vector $\mathbf{0}_{[d]}^{\top}$ bearing a length of $N_y \times l_u$. Finally, the coefficients of matrix $\mathbf{H}_t^y$ are given by:

$$\mathbf{H}_t^y = \begin{bmatrix} \lambda_1^y & \mathbf{0}_{[m-1]}^{\top} & 1 & \mathbf{0}_{[l_u-1]}^{\top} & 0 & \cdots & \cdots & 0 & \mathbf{0}_{[l_u-1]}^{\top} \\ \lambda_2^y & \mathbf{0}_{[m-1]}^{\top} & 0 & \mathbf{0}_{[l_u-1]}^{\top} & 1 & \mathbf{0}_{[l_u-1]}^{\top} & \cdots & 0 & \mathbf{0}_{[l_u-1]}^{\top} \\ \vdots & & \vdots & & \vdots & \ddots & & \vdots & \vdots \\ \vdots & & \vdots & & \vdots & & \ddots & 0 & \vdots \\ \lambda_{N_y}^y & \mathbf{0}_{[m-1]}^{\top} & 0 & \mathbf{0}_{[l_u-1]}^{\top} & 0 & \cdots & \cdots & 1 & \mathbf{0}_{[l_u-1]}^{\top} \end{bmatrix},$$

and we set $m = m_1 + m_2 + m_3 + m_4$ in the second column for brevity.

Turning to the state equation in our state-space framework, we note that matrix $\mathbf{T}$ is square, where the size of both rows and columns is $(1 + N_a) \times m_a + N_b \times m_b + N_c \times m_c + N_d \times m_d + N_y \times l_u$. Let $diag(\cdots)$ denote a diagonal matrix with matrix-valued entries. Then, we note that matrix $\mathbf{T}$ has the following expression:

$$\mathbf{T} = diag\Big(\mathbf{T}^f,\ \mathbf{T}_1^a,\ \ldots,\ \mathbf{T}_{N_a}^a,\ \mathbf{T}_1^b,\ \ldots,\ \mathbf{T}_{N_b}^b,\ \mathbf{T}_1^c,\ \ldots,\ \mathbf{T}_{N_c}^c,\ \mathbf{T}_1^d,\ \ldots,\ \mathbf{T}_{N_d}^d,\ \mathbf{T}_1^y,\ \ldots,\ \mathbf{T}_{N_y}^y\Big).$$

Here, matrix $\mathbf{T}^f$ is of size $m_a \times m_a$. Assuming that $m_a > l_f$, then we can write:

$$\mathbf{T}^f = \begin{bmatrix} \phi_1 & \phi_2 & \dots & \phi_{l_f} & 0 & \dots & \dots & 0 \\ 1 & 0 & \dots & 0 & 0 & \dots & \dots & 0 \\ 0 & 1 & \dots & 0 & 0 & \dots & \dots & 0 \\ \vdots & & \ddots & & & & & \vdots \\ \vdots & & & \ddots & & \mathbf{0}_U^f & & \vdots \\ \vdots & & \mathbf{0}_L^f & & \ddots & & & \vdots \\ \vdots & & & & & \ddots & & \vdots \\ 0 & 0 & \dots & 0 & 0 & \dots & 1 & 0 \end{bmatrix},$$

where the first row captures the autoregressive structure of the commn factor. Symbol $\mathbf{0}_L^f$ represents the lower triangular part of a zero matrix with dimensions $(m_a - 4) \times (m_a - 4)$, while $\mathbf{0}_U^f$ denotes the upper triangular part of a zero matrix with the same dimension. Next, we note that:

$$\mathbf{T}_\iota^a = \begin{bmatrix} \psi_{\iota,1}^a & \psi_{\iota,2}^a & \dots & \psi_{\iota,l_u}^a & 0 & \dots & \dots & 0 \\ 1 & 0 & \dots & 0 & 0 & \dots & \dots & 0 \\ 0 & 1 & \dots & 0 & 0 & \dots & \dots & 0 \\ \vdots & & \ddots & & & & & \vdots \\ \vdots & & & \ddots & & \mathbf{0}_U^a & & \vdots \\ \vdots & & \mathbf{0}_L^a & & \ddots & & & \vdots \\ \vdots & & & & & \ddots & & \vdots \\ 0 & 0 & \dots & 0 & 0 & \dots & 1 & 0 \end{bmatrix},$$

for $\iota = 1,\ 2,\ \dots,\ N_a$. Here, we note that $\mathbf{T}^a_\iota$ is of size $m_a \times m_a$, and we have assumed that $m_a > l_u$ in the above expression. Similarly, $\mathbf{0}^a_L$ denotes a lower triangular part of a zero matrix with a size $(m_a - 4) \times (m_a - 4)$, while $\mathbf{0}^a_U$ denotes the corresponding upper triangular part of the zero matrix. Furthermore, we have:

$$\mathbf{T}^k_{\iota'} = \begin{bmatrix} \psi^k_{\iota',1} & \psi^k_{\iota',2} & \dots & \psi^k_{\iota',l_u} & 0 & \dots & \dots & 0 \\ 1 & 0 & \dots & 0 & 0 & \dots & \dots & 0 \\ 0 & 1 & \dots & 0 & 0 & \dots & \dots & 0 \\ \vdots & & \ddots & & & & & \vdots \\ \vdots & & & \ddots & & \mathbf{0}^k_U & & \vdots \\ \vdots & & \mathbf{0}^k_L & & \ddots & & & \vdots \\ \vdots & & & & & \ddots & & \vdots \\ 0 & 0 & \dots & 0 & 0 & \dots & 1 & 0 \end{bmatrix},$$

for $\iota' = 1,\ 2,\ \dots,\ N_k$ and $k = b,\ c,\ d$. Matrix $\mathbf{T}_{\iota'}$ is of size $m_k \times m_k$, and we have again assumed that $m_k > l_u$ in the above expression. In addition, $\mathbf{0}^k_L$ denotes a lower triangular part of a zero matrix with a size $(m_k - 4) \times (m_k - 4)$, while $\mathbf{0}^k_U$ denotes the corresponding upper triangular part of the zero matrix. We note that each $\mathbf{T}^y_{\iota''}$, for $\iota'' = 1,\ 2,\ \dots,\ N_y$, has a size of $(l_u + 1) \times (l_u + 1)$, and they can be expressed as follows:

$$\mathbf{T}^y_{\iota''} = \begin{bmatrix} \psi^y_{\iota'',1} & \psi^y_{\iota'',2} & \dots & \psi^y_{\iota'',l_u} & 0 \\ 1 & 0 & \dots & 0 & 0 \\ 0 & 1 & \dots & 0 & 0 \\ \vdots & & \ddots & & \vdots \\ 0 & 0 & \dots & 1 & 0 \end{bmatrix}.$$

Now, we turn to discuss square matrix $\mathbf{Q}$. Similar to $\mathbf{T}$, we show that $\mathbf{Q}$ admits the following expression:

$$\mathbf{Q} = diag\Big(\mathbf{Q}^f,\ \mathbf{Q}^a_1,\ \ldots,\ \mathbf{Q}^a_{N_a},\ \mathbf{Q}^b_1,\ \ldots,\ \mathbf{Q}^b_{N_b},\ \mathbf{Q}^c_1,\ \ldots,\ \mathbf{Q}^c_{N_c},\ \mathbf{Q}^d_1,\ \ldots,\ \mathbf{Q}^d_{N_d},\ \mathbf{Q}^y_1,\ \ldots,\ \mathbf{Q}^y_{N_y}\Big).$$

We note that $\mathbf{Q}^f$ has the same dimensions as $\mathbf{T}^f$. All elements of $\mathbf{Q}^f$ are zeros, except for the first diagonal entry, which holds the value $\omega = 1$. Similarly, each matrix $\mathbf{Q}^k_\iota$ has the same dimensions as $\mathbf{T}^k_\iota$ for $\iota = \{1,\ 2,\ \ldots,\ N_k\}$ and $k = \{a,\ b,\ c,\ d,\ y\}$. In each case, all elements of $\mathbf{Q}^k_\iota$ are zeros, except for the first diagonal entry, which stores the value σ^k_ι.

B.3 The Gibbs Sampling Algorithm

We follow Baumeister, Leiva-León and Sims (2024) to estimate the dynamic factor model using a Markov Chain Monte Carlo (MCMC) Gibbs sampling algorithm. In each iteration, we obtain a draw of the state vector, $\boldsymbol{\alpha}_t$, conditional on observing the model parameters, $\boldsymbol{\theta}$, and the entire information set, $\mathcal{F}_T$. Then, conditioning on the draws of $\boldsymbol{\alpha}_t$, and the observations $\mathcal{F}_T$, we update $\boldsymbol{\theta}$.[11] Vector $\boldsymbol{\theta}$ contains elements of the state-space system, given by:

$$\boldsymbol{\theta} = \Big(\boldsymbol{\phi},\ \boldsymbol{\psi},\ \boldsymbol{\lambda},\ \boldsymbol{\sigma}\Big)^\top,$$

where $\boldsymbol{\phi} = \Big(\phi_1,\ \phi_2,\ \ldots,\ \phi_{l_f}\Big)$, and:

$$\boldsymbol{\psi} = \Big(\boldsymbol{\psi}^a_1,\ \ldots,\ \boldsymbol{\psi}^a_{N_a},\ \boldsymbol{\psi}^b_1,\ \ldots,\ \boldsymbol{\psi}^b_{N_b},\ \boldsymbol{\psi}^c_1,\ \ldots,\ \boldsymbol{\psi}^c_{N_c},\ \boldsymbol{\psi}^d_1,\ \ldots,\ \boldsymbol{\psi}^d_{N_d},\ \boldsymbol{\psi}^y_1,\ldots,\ \boldsymbol{\psi}^y_{N_y}\Big),$$

such that:

$$\boldsymbol{\psi}^k_\iota = \Big(\psi^k_{\iota,1},\ \psi^k_{\iota,2},\ \ldots,\ \psi^k_{\iota,l_u}\Big), \quad \text{for } k = \{a,\ b,\ c,\ d,\ y\}.$$

In addition, we have:

$$\boldsymbol{\lambda} = \Big(\lambda^a_1,\ \ldots,\ \lambda^a_{N_a},\ \lambda^b_1,\ \ldots,\ \lambda^b_{N_b},\ \lambda^c_1,\ \ldots,\ \lambda^c_{N_c},\ \lambda^d_1,\ \ldots,\ \lambda^d_{N_d},\ \lambda^y_1,\ldots,\ \lambda^y_{N_y}\Big),$$

[11] Similar to Baumeister, Leiva-León and Sims (2024), we consider a total of $12,000$ iterations in our empirical exercise, and we discard the first $2,000$ iterations to ensure convergence.

with the restriction that $\lambda_1^a > 0$; and finally, we note that:

$$\boldsymbol{\sigma} = \Big(1,\ \sigma_1^a,\ \ldots,\ \sigma_{N_a}^a,\ \sigma_1^b,\ \ldots,\ \sigma_{N_b}^b,\ \sigma_1^c,\ \ldots,\ \sigma_{N_c}^c,\ \sigma_1^d,\ \ldots,\ \sigma_{N_d}^d,\ \sigma_1^y,\ \ldots,\ \sigma_{N_y}^y\Big).$$

Conditional on $\boldsymbol{\theta}$ and $\mathcal{F}_T$, the first step involves drawing $\boldsymbol{\alpha}_t$ using the Kalman filter and smoothing recursions based on our state-space framework as presented in equations (5)–(6); see Carter and Kohn (1994) and Durbin and Koopman (2012) for a detailed treatment of the Kalman filter and smoothing.[12] In the second step, we take the draws of $\boldsymbol{\alpha}_t$ as given, and proceed to update $\boldsymbol{\theta}$ based on Bayesian methods. In particular, we follow Baumeister, Leiva-León and Sims (2024) to assume that the elements of $\boldsymbol{\theta}$ are distributed by natural-conjugate priors; and therefore, the property of conjugacy ensures that the posterior distribution belongs to the same class of probability distribution as the priors. Specifically, in our baseline case, we assume that $\{\boldsymbol{\phi},\ \boldsymbol{\psi},\ \boldsymbol{\lambda}\}$ have Gaussian priors with the typical setup of zero mean and unit variances. The expressions of posterior mean and variances are derived in Baumeister, Leiva-León and Sims (2024), and are thus omitted here. Given the state equation and the assumption that $\boldsymbol{\psi}$ has a Gaussian prior, a natural-conjugate prior for $\boldsymbol{\sigma}$ is the inverse Gamma distribution. In our baseline specification, we assume that the first two parameters have values of 10 and 0.9, respectively. The associated posterior distributions are again derived in Baumeister, Leiva-León and Sims (2024), and are omitted in this exposition. We refer readers to Gelman et al. (2013) for details of the Gibbs sampler.

C Robustness Tests

C.1 Alternative Input Configurations

robustness tests: 1. 11-variable 2. using ridge to select variables for each state: left-hand side personal income 3. same indicators as baseline, but only from 1910

C.2 Alternative Model Specifications

1. multiple factors 2. time-varying parameters/subsample.

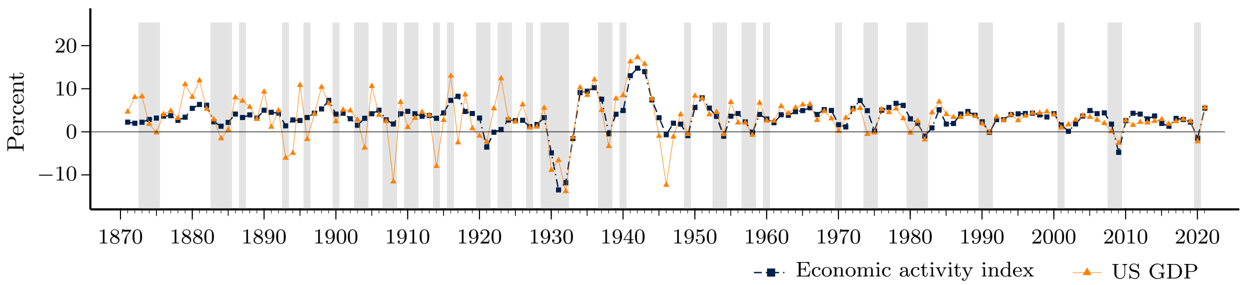
[12] We have assumed that $\boldsymbol{\eta}_t$ follows a normal distribution in the state equation. We note in passing that the Gaussian assumption is not necessary to use the Kalman filter recursion; and in fact, if the Gaussian assumption is not correct, the estimates of $\boldsymbol{\theta}$ are still consistent, albeit not efficient.

D Additional Figures and Tables

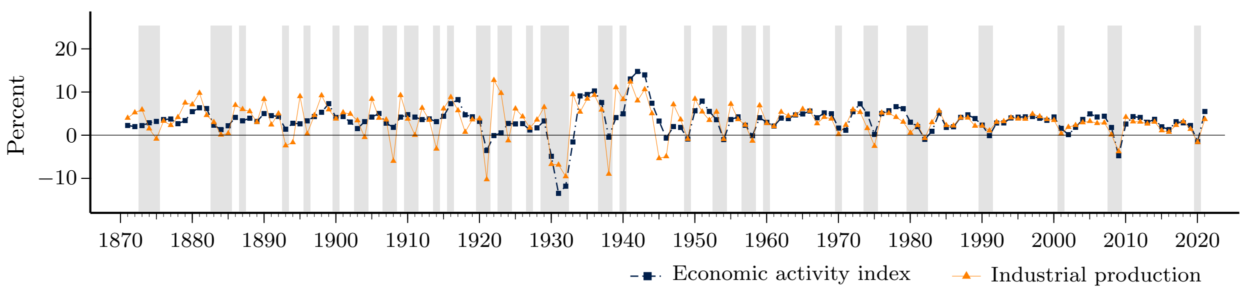
D.1 Synchronization

Figure D.1: Comparison of the aggregated economic activity index and other US-wide measures

(a) Aggregated economic activity index and US GDP

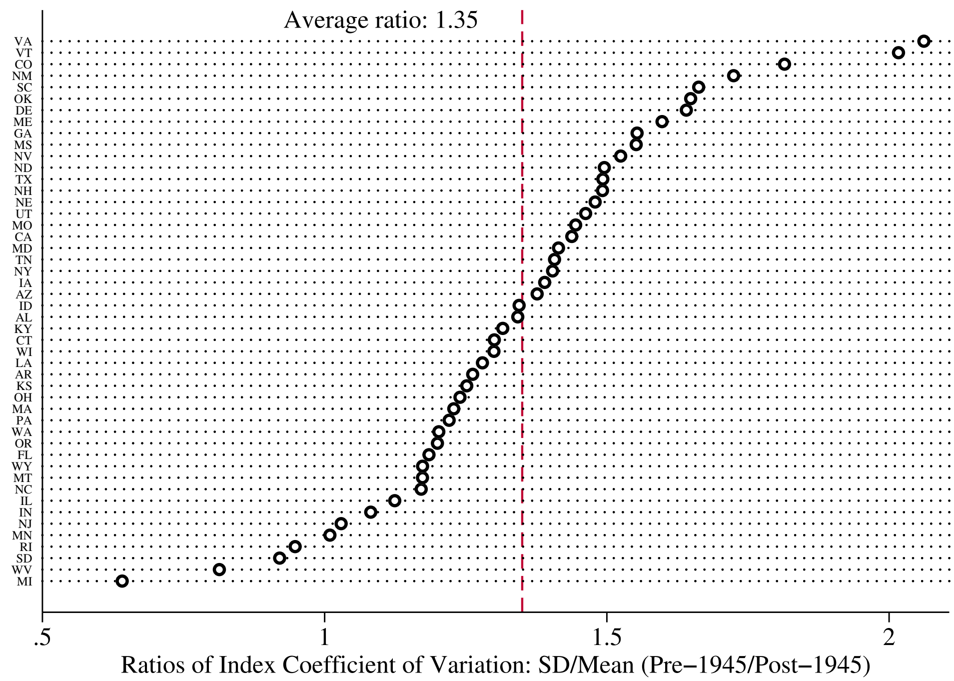


(b) Aggregated economic activity index and industrial production



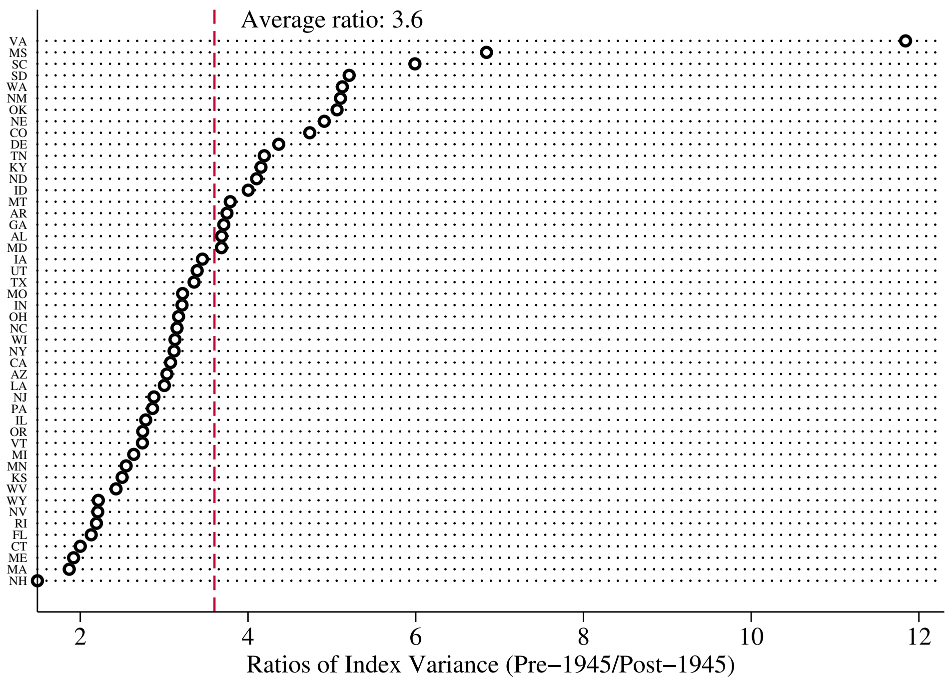
Notes: This figure plots the aggregated economic activity index alongside US GDP and industrial production from 1871 to 2019. The aggregated index is constructed by taking a weighted average of the state-level economic activity indices, with the weights based on the relative size of each state's economy compared to the sum across all 48 states. For each state, economic size is measured by the level of its economic activity index, scaled so that the 2012 value matches the state's GDP in 2012 dollars. The industrial production series is constructed by combining the data from Davis (2004) (1871–1915), Miron and Romer (1990) (1916–1919), and those published by the Fed (1920–2019). Both the aggregated index and industrial production are scaled and retrended to US GDP. The US GDP data are sourced from Williamson (2025). The shaded bars indicate recession years; see the notes to Figure 5 for their definition.

Figure D.2: Ratios of Estimated Index Coefficient of Variation: SD/Mean (Pre-1945/Post-1945) by States



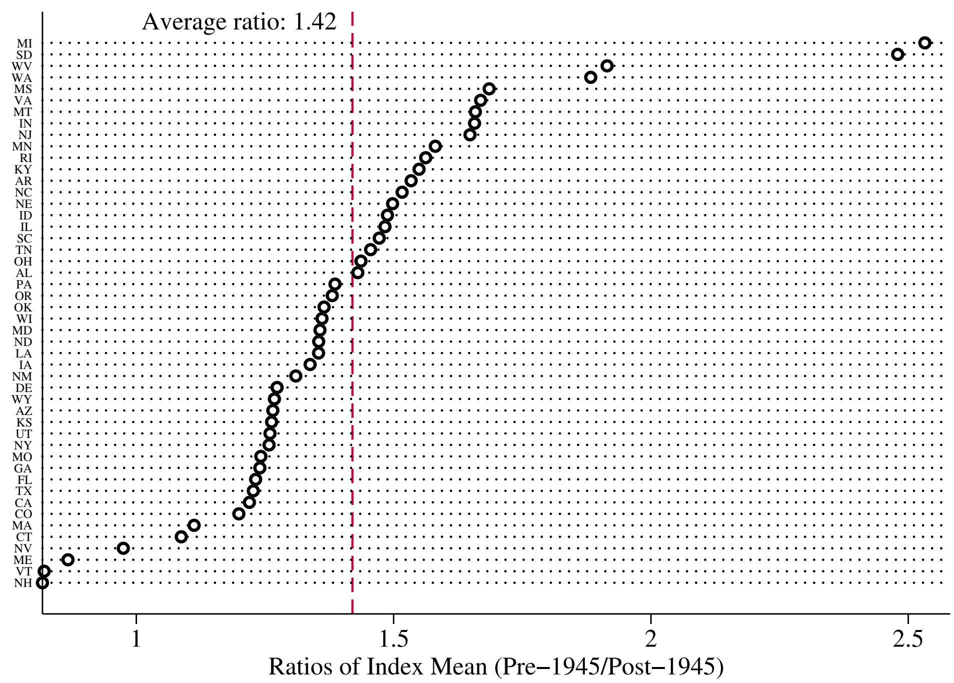
Notes: For each state, we divide the sample into 1871–1945 and 1946–2021. For each of these periods, we calculate the state-specific standard deviations and mean, before constructing the Coefficient of Variation for state i as $CV_{i,period} = \frac{SD_{i,period}}{mean_{i,period}}$. We report a ratio of $\frac{CV_{i,pre-1945}}{CV_{i,post-1945}}$ for each state. Finally, we report the cross-state average as a vertical dotted line.

Figure D.3: Ratios of Estimated Index Variance: (Pre-1945/Post-1945) by States



Notes: For each state, we divide the sample into 1871–1945 and 1946–2021. For each of these periods, we calculate the state-specific variance, for state i, $Var_{i,period}$. We report a ratio of $\frac{Var_{i,pre-1945}}{Var_{i,post-1945}}$ for each state. Finally, we report the cross-state average as a vertical dotted line.

Figure D.4: Ratios of Estimated Index Mean: (Pre-1945/Post-1945) by States



Notes: For each state, we divide the sample into 1871–1945 and 1946–2021. For each of these periods, we calculate the state-specific mean, for state i, $mean_{i,period}$. We report a ratio of $\frac{mean_{i,pre-1945}}{mean_{i,post-1945}}$ for each state. Finally, we report the cross-state average as a vertical dotted line.

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