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

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August 22, 2025

Abstract

We construct a novel dataset of 60 macroeconomic time series at the U.S. state level, spanning from the 1863 to the present, based on digitizing and harmonizing 113 historical sources. Equipped with these data, we estimate an annual index of state-level economic activity over nearly 160 years. This index aligns closely with official indicators such as state GDP and unemployment when available. Using this measure of economic activity, we uncover several new facts about state-level business cycles: (1) there is substantial heterogeneity across states in both cyclical dynamics and their underlying drivers; (2) business cycles have become more synchronized since World War II; and (3) downturns have become shorter and recoveries quicker over time.

Keywords: state-level business cycles; economic activity index; mixed-frequency dynamic factor model

JEL classification: C38, E32, N91, N92

[*]We are grateful to Robert Barro, Arnaud Costinot, Jonathon Hazell, Atif Mian, Emi Nakamura, Jonathan Payne, Christina Romer, Tom Sargent, Jón Steinsson, Bálint Szőke, and Christian Wolf for their invaluable comments and suggestions. We thank Enrico Berkes, Howard Bodenhorn, Sacha Dray, Monty Hindman, Michael McMahon, Varun Sharma, John Wallis, and Thomas Weiss for their assistance with data. We also acknowledge seminar and conference participants at Tsinghua University, Peking University, NUS RMI Macro Workshop, and NUS Macro Brownbag for helpful discussions. Liu acknowledges Singapore MOE AcRF Tier 1 Grant (FY2023-FRC1-004) for financial support. All errors are ours.

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1 Introduction

Reliable indicators on the state of the macroeconomy is the currency of research in empirical macroeconomics, economic history, and growth. Even for an advanced economy like the United States, such data is not always readily available, especially when going back in time. This is even more true for regional data, which has long been of interest to macroeconomists (e.g., Barro and Sala-i-Martin, 1991, 1992; Blanchard and Katz, 1992), and which is increasingly used to identify causal effects (Nakamura and Steinsson, 2018).

The availability of state-level economic data for the United States—particularly for annual data in historical periods—remains limited. For example, the Bureau of Economic Analysis (BEA) publishes annual estimates of state-level GDP only starting from 1963. Before that, there is no state-level annual measure of economic activity, except for a few indicators that capture limited dimensions of it, such as personal income (since 1929), agricultural output (since 1924), and value added of the manufacturing sector (since 1949). As a result, there are many open questions about state-level business cycles and growth: When did which state experience an economic downturn? How do state business cycles differ and to what extent do they coincide with national cycles? And how have state-level business cycles evolved over the long run?

This paper aims to address these questions by constructing a novel dataset containing a variety of state-level economic indicators spanning from 1863 to 2021. Based on an extensive effort to digitize 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 60 variables. 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. In many cases, we traced the availability of statistics on the production of individual mining products or state government finances through reports published by individual states. We document how we build these time series from 113 sources in a dedicated data appendix that also details the adjustments and imputations required to ensure data consistency. We believe this new dataset has many potential applications in fields such as macroeconomics, development economics, and 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. To the best of our knowledge, this is the first attempt to estimate state-level economic activity over such a long 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 naturally suggests the application of a factor model. In particular, 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 debt and revenues, housing, and transportation.

We confirm the validity of our index by comparing it with existing state-level indicators for the modern period. The index exhibits strong positive correlations with GDP, personal income, unemployment rates, and state coincident indexes. 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, or the number of patents. These findings lend credence to the reliability of the economic activity index in capturing state-level business cycle fluctuations.

Our estimated long-run state-level economic activity index sheds light on the variation of local business cycles across time and space. Three observations stand out from our analysis. First, the structure of state-level business cycles has changed over time, in line with national changes. Before 1950, recessions were longer and recoveries slower, and often concentrated in specific regions. After World War II, economic downturns became shorter and recoveries faster, perhaps they were counteracted by changes in monetary policy, fiscal policy, and broader economic diversification. Second, the co-movement between state-level economic activity and the nationwide business cycle differs considerably across states. This meshes well with existing work by Owyang, Piger and Wall (2005), but we establish it using our long-run time series dating back to the Civil War, which equips us with additional statistical power.

Third, state-level business cycles have become more synchronized, especially since the post-war period. We examine two statistics to track variation in synchronicity over time. We begin by calculating the dispersion of the index across states, which directly measures the extent of variation in economic conditions across states in a given year. As an alternative measure, 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. For both measures, we observe large increases in business cycle synchronization across states since World War II.

Given the documented considerable heterogeneity in state business cycles, our state economic activity index lends itself to constructing indicators for state-level recessions by applying existing algorithms such as that of Bry and Boschan (1971*b*). Preliminary findings suggests that, while many recessions align with NBER recession dates, there are also many "forgotten recessions," with more localized downturns. Going forward, this list of recession dates will be potentially useful in the study of local business cycle dynamics among other related applications.

Literature. The primary contribution of this paper is to introduce a novel state-level dataset for the United States comprising dozens of indicators since just after the Civil War, and using these time series to estimate an indicator of regional economic activity. Our work mainly builds upon three strands of literature.

ADD Fulford and Schiantarelli (2025)

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 existing work, our study examines a much longer sample period and utilizes regionally 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), 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 state-level GDP in 1963. Similarly, Bokun et al. (2023) introduce a real-time database with 28 indicators per state, also only for recent decades. We contribute to this literature by constructing new time series pre-dating the official statistics, providing data on 60 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. In spirit, our work also builds on a growing strand of literature using regional identification for answering questions in macroeconomics (for a review of this literature, see Nakamura and Steinsson (2018)).

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 existing work. A companion data appendix documents further details on the dataset.

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, especially at the state level. This issue is especially pronounced for the SA, where state-level statistics are often not included in existing digitization efforts. We utilize Optical Character Recognition (OCR) technology as implemented by Amazon Textract to process the scanned documents, and then check for transcription errors with manual verification. Note that past data is frequently revised in later issues of the SA, based on revision 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 in the SA or Census are presented in less detail than in the original underlying publications, or they do not span the entire 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 work in the economic history literature. Much of this data is difficult to obtain and only available in print or PDF format. As a result, a major contribution of our work is to digitize many data sources previously not available in digital format.

The total number of sources we use is 113, of which 84 were newly digitized, while the remainder is compiled from scattered but already digitized sources. Section I in the supplementary data appendix provides a full list of all the variables together with their sources and coverage across states and time.[1]

Taken together, we provide a comprehensive and consistent set of state-level historical series that are comparable with their modern counterparts. They are not only the key inputs in the dynamic factor estimation we will focus on later, but will likely be of interest to researchers studying the economic history of U.S. states.

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 60 individual variables, which can be grouped into seven broad categories: Real Activity, Government Finances, Labor Market, Transportation, Wealth, Housing, and Miscellaneous.

Real Activity. Our dataset covers real economic activity across three major sectors that are especially important in the earlier years of our sample: agriculture, mining, and manufacturing. The variables we construct include the value of agricultural products sold, the value of minerals, and the value added by the manufacturing sector. Within the agriculture and mining sectors, we

[1] For additional information on these data sources, we refer interested readers to the appendix, 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.

collect data on major products, which are usually reported separately annually, and use them to estimate total values in these sectors whenever they are not reported on an annual basis in the early years.[2] 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 the 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 based on their customs district. Given that only some states have ports, we would expect these measures to matter for economic activity in certain states more than others.

Local 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 are not available throughout our sample period, we include motor vehicle registrations, which are 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 the mileage of railway tracks, rural roads, and state highways.

Government Finances. Our dataset reports several 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) outlines the changing importance of the different levels of governments over time, and in particular the move from state and local funding to a federal system. Building upon Sylla, Legler and Wallis (1993), our dataset

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

includes regional variation in state and federal government activity with detailed personal and corporate income tax data.

Labor Market, Wealth, Bankruptcies, Miscellaneous. We cover measures of the labor market, including total non-farm employment, manufacturing employment, and manufacturing payroll, which allow us to track local economic dynamics via labor market fluctuations. We also report measures of personal income and the value of farmland and buildings. We extend the official BEA data on personal income that starts in 1929 back to 1880 at decennial intervals, and from 1919-1921 and in 1927-1928 annually. We also use several miscellaneous series. The number of bankruptcies includes both corporate and personal bankruptcies. Our banking sector data include bank assets, deposits, capital, liabilities and loans of national and state banks that stretch back to 1863, taken from Hoon et al. (2025). We report annual data on population starting from 1870, where we estimate 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

This section describes our approaches in constructing consistent and coherent state-level time series data.

Territorial Changes. 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."

Consistency of Variable Definitions. Considering the length of the sample period and the breadth of the sources we draw on, we pay attention to maintaining consistent variable definitions across time and data sources. Whenever possible, we manually harmonize the raw data to account for definitional changes over time. This process typically entails checking source documents and data files. 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 the 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.

As an illustration of this harmonization process, Panel (a) of Figure 1 displays our long-run series of harmonized value added of manufacturing production for New York and Texas. Another example in our dataset is the state government general revenue series shown in Panel (b) of Figure 1, where we combine multiple data sources and carefully verify variable definitions across time to ensure consistency.

When the nature of definitional changes is unclear, or when there is insufficient information to perform manual harmonization, we resort to ratio splicing the raw data from multiple sources. As an example, our coverage of the number of business failures series 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) for 1998-2007 and from US Bankruptcy Court reports for 2008-2021. We perform the ratio splice using overlapping data in 1998. Multiple other ratio splices are involved in constructing the business failure series, as illustrated in Panel (c) of Figure 1 for Ohio. Specifically, the imputed series incorporates four ratio splices for the pre-1934 data, three for 1934, two for 1935–38, one for 1939–1983, and two for 1984–96. Details of each ratio splice are provided in the companion data appendix.

Imputation. Our raw data series still remain incomplete after these changes, with most series containing missing data points that occur randomly, at regularly intervals, or both. For sporadic gaps involving only a single year, we use linear interpolation as a simple rule-of-thumb imputation method. For longer gaps—typically occurring at five- or ten-year intervals in the earlier years of our sample—we recover the missing observations through the factor model estimation, which produces these annual values as a by-product of the factor estimates.

An exception is the total output 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 sold 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). Despite the absence of annual totals for much of this period, we have annual sales receipts data for major crop and livestock commodities covering 1870–1924. The aggregate of these individual receipts contains useful information regarding the fluctuations of the total value of agricultural products sold. We therefore use the growth rates of these individual receipts to impute the missing annual observations of the total value of agricultural products sold, following a constrained minimization approach in the spirit of Denton (1971). We describe the imputation details in Data Appendix 2.2, and display the results for California and Massachusetts in Panel (d) of Figure 1. We also conduct several robustness exercises, including one using the value-weighted growth of individual crops as proxies for growth in total agricultural products sold. We find that the imputed time series is fairly robust across these alternative approaches.

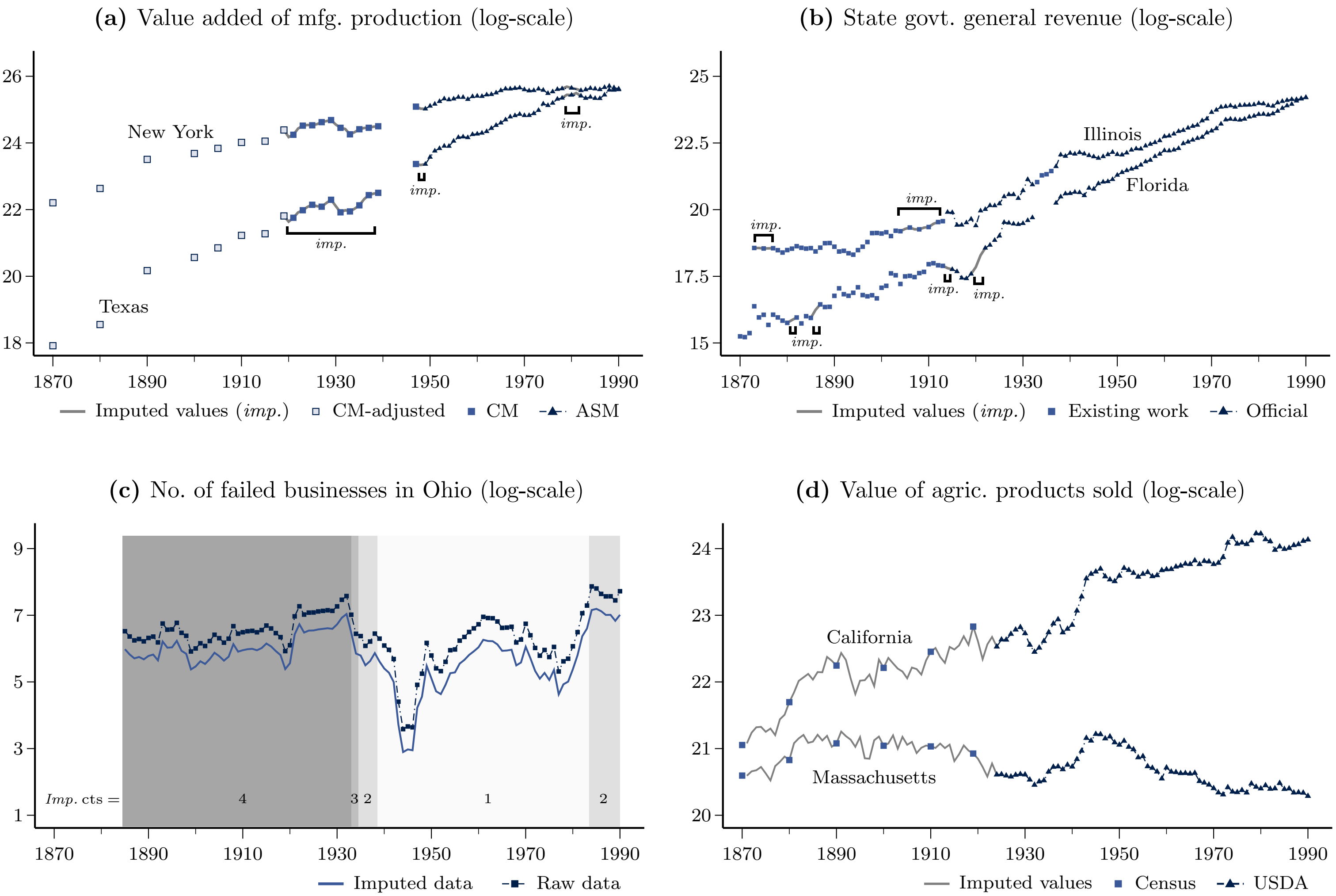
In total, we report 60 time-series variables that span economic activity across multiple sectors. To illustrate the structure and completeness of our dataset, Figure A.1 displays the fraction of variables available for each year by state, which underscores both the depth and breadth of our state-level panel that we construct.

2.4 Comparison with Existing Datasets

Table 1 compares our new dataset with existing state-level and U.S.-wide historical datasets capturing economic activity. For the former, our data provide an entirely new historical perspective, adding around 100 years of data that are useful in studying state-level economic dynamics from a long-run perspective. Additionally, the dataset we construct is much more comprehensive in terms of the number of 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 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 coverage. 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. Official U.S. GDP estimates from the BEA start in 1929. Different from these efforts, our dataset emphasizes a regional dimension and takes a "big data" approach by covering a large number of individual economic indicators.

Figure 1: Imputed and Harmonized Historical Time Series: Selected Examples



Notes: This figure displays examples of the constructed time series for selected states from 1870 to 1990. In Panel A, manufacturing value added is constructed using production output and cost data from the Census of Manufactures for 1870, 1880, 1890, 1900, 1905, 1910, 1915, 1947, and biennially for 1919–1939 (inclusive). Data pre-1921 are adjusted to match the product coverage of later years. Comparable output and cost data are drawn from the Annual Survey of Manufactures for 1949–1978, 1980, and the post-1982 years. Missing values for 1948, 1979, 1981, and biennial gaps for 1920–1938 are imputed using linear interpolation between adjacent years. In Panel B, the official sources for Illinois include the Financial Statistics of States (FSS; 1915–1919, 1921–1932, 1937–1950), State Government Finances (SGF; after 1950), and individual state reports (1914 and 1920). Non-official sources are from Hindman (2010) for 1873, 1875, 1877–1904, 1906, 1908, 1910, 1912, and 1913, and from Sylla, Legler and Wallis (1993) for 1933–1936. Missing values for 1874, 1876, and biennial gaps 1905–1911 are imputed using linear interpolation as before. For Florida, general revenue data are sourced from FSS and SGF for the same periods, with the exception for 1921, for which no records are available. Non-official sources are from Hindman (2010), covering 1870–1880, 1882–1885, and 1887–1913. Missing observations for 1881, 1886, and 1920–1921 are imputed via linear interpolation, while the 1914 observation is imputed based on implied growth rates from the 1913–1914 data in Sylla, Legler and Wallis (1993). In Panel C, the number of failed businesses is compiled from various Dun & Bradstreet (D&B) reports spanning the displayed period. In addition to the raw D&B data, we provide an imputed series with consistent variable definitions across the full sample. The imputation details are outlined in the Data Appendix, and the imputation counts (labeled *Imp. cts*) are reported in the plot for reference. Panel D shows the value of agricultural products sold, sourced from the USDA (yearly after 1923) and the Census (1870, 1880, 1890, 1900, 1910, and 1919), with the latter harmonized to match USDA definitions. Intercensal observations prior to 1924 are imputed using sales receipts from individual crop, livestock, and forest products. Finally, the values in Panels A, B, and D are in 2012 dollars, deflated using the U.S. price index from Williamson (2025).

Table 1: Comparison with Existing Datasets

	Variable	Frequency	Coverage
A. State-Level			
This paper	Economic activity index	Annually	1871–2021
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	Annually	1790–1915
Miron and Romer (1990)	Industrial production	Monthly	1884–1940
Federal Reserve	Industrial production	Monthly	1919–2023
Williamson (2025)	GDP	Annually	1790–2023
Balke and Gordon (1989)	GNP	Annually	1869–1929
BEA	GDP	Annually	1929–2023

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 occurs 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 until 1949, and annually afterwards. To take full advantage of the available data, we need an estimation framework that accommodates frequency variation across both the cross-section and time. 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.[3]

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. 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,

[3] 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.

let N_i^y denote those that report only at annual frequency, and let $N_i - N_i^y$ denote those that report 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:

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

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

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 Crone and Clayton-Matthews (2005, p. 594) 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 $t - \mathcal{T}_{i,j,t}$ in terms of $f_{i,t}$ as follows:

$$\begin{aligned}
&\frac{1}{\mathcal{T}_{i,j,t}} \left(\ln Y_{i,j,t} - \ln Y_{i,j,(t-\mathcal{T}_{i,j,t})} \right) \\
&= \frac{1}{\mathcal{T}_{i,j,t}} \left(z_{i,j,t} + z_{i,j,t-1} + \cdots + z_{i,j,(t-\mathcal{T}_{i,j,t}+1)} \right) \\
&= \frac{1}{\mathcal{T}_{i,j,t}} \lambda_{i,j} \left(f_{i,t} + f_{i,t-1} + \cdots + f_{i,(t-\mathcal{T}_{i,j,t}+1)} \right) + \frac{1}{\mathcal{T}_{i,j,t}} \left(u_{i,j,t} + u_{i,j,t-1} + \cdots + u_{i,j,(t-\mathcal{T}_{i,j,t}+1)} \right),
\end{aligned} \tag{4}$$

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 term. 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:

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

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). 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.[4]

Estimation Strategy. For notational simplicity, we omit the index i from equations (5)–(6). The state-space system is estimated using a Bayesian MCMC approach via Gibbs sampler. The procedure is standard: in each MCMC iteration, we first obtain a draw of the state vector conditional on the model parameters and the full information set $\mathcal{F}_T \equiv (\mathbf{y}_1^\top, \mathbf{y}_2^\top, \ldots, \mathbf{y}_T^\top)^\top$. Then, conditioning on the draw of the state vector and the observations $\mathcal{F}_T$, we update the model parameters. Further details on the estimation algorithm and the assumed priors 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:

$$\tilde{f}_i = (\boldsymbol{\lambda}_i^\top \boldsymbol{\lambda}_i)^{-1} \boldsymbol{\lambda}_i^\top \mathbf{y}_i^P, \tag{7}$$

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, p. 488), using $\tilde{f}_i$ in place of the median 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, and (ii) the contribution of the jth input series to $\tilde{f}_{i,t}$ can be conveniently computed 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 rescaled 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) and 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

[4] 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).

obtained by the following affine transformation:

$$s_{i,t} = \beta_{1,i} + \beta_{2,i}\tilde{f}_{i,t}, \qquad \text{for} \quad t = 1, 2, \ldots, T, \tag{8}$$

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 $\tilde{f}_{i,t}$ 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 state-level indicators for our baseline estimation based on two criteria. First, we choose indicators that are economically relevant and tend to comove with business cycles. Second, we include indicators with long historical coverage and few missing observations in the early years of the sample. While our method is flexible and can accommodate missing observations, choosing indicators with more complete coverage helps improve the estimation's accuracy. 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 plots our factor estimates against BEA GDP growth rates (available post 1963) for a few selected states. We observe a strong linear relationship between the factor estimates and GDP growth, suggesting that our estimated factor effectively captures economic activity at the state level. This observation validates the linear transformation in equation (8) 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 4 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

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	1910–2021
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. The final column presents the years in which the inputs are available for at least one state. Intercensal values of agricultural products sold from 1871 to 1924 are imputed using annual growth rates from 16 major crop and livestock commodities; see Section 2.2 of the companion data appendix for imputation details.

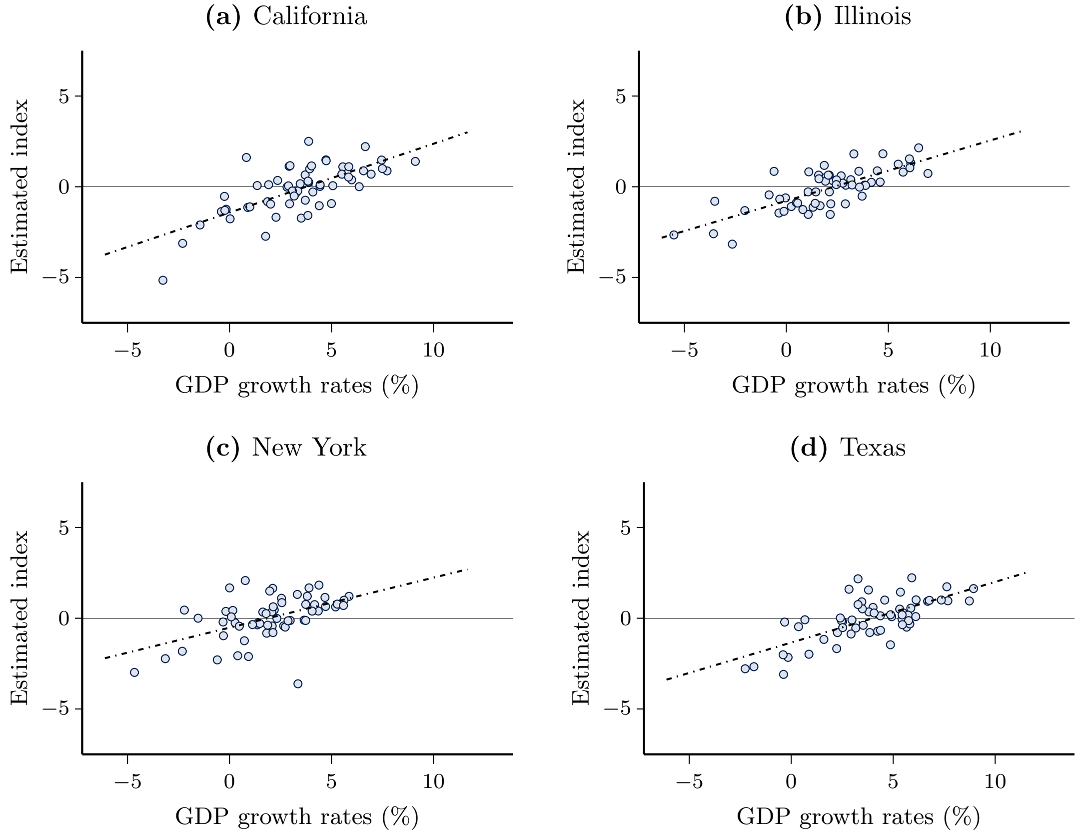
Oklahoma, Kansas, and Nebraska suffered due to the Dust Bowl. Thanks to the wide coverage of historical data, we also capture earlier recessions, including the Long Depression (1873-1896) and the Panic of 1893, that show significant declines particularly in railroad-dependent and farming states. More 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-World War II 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 a clear message regarding cross-state variation, with some states experiencing frequent boom-bust cycles while others show long-term stability.[5] Energy-dependent

[5]Table C.1 in the appendix offers a complementary perspective to the heat map by presenting descriptive statistics on

Figure 2: Factor Estimates v.s. GDP Growth Rates



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

states such as North Dakota, Wyoming, and West Virginia exhibit high volatility, likely due to the highly volatile commodity prices important to their local economies. 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 World War II, 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 na-

the estimated economic activity indices across states, providing static evidence on cross-state variation.

ture 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 that our estimates capture state-level business cycles, we compare them with existing measures that are available for a shorter period of time in a binscatter plot Figure 3. These data include: (i) state GDP from the BEA; (ii) the State Coincident Index from Philadelphia Fed;[6] (iii) the state-level unemployment rate from the BLS Local Area Unemployment Statistics; and (iv) state-level personal income from the BEA. As shown before, our factor estimates line up well with GDP, so it is not surprising that a linearly-transformed version also strongly correlates with GDP, displayed in Panel (a) of Figure 3. 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.

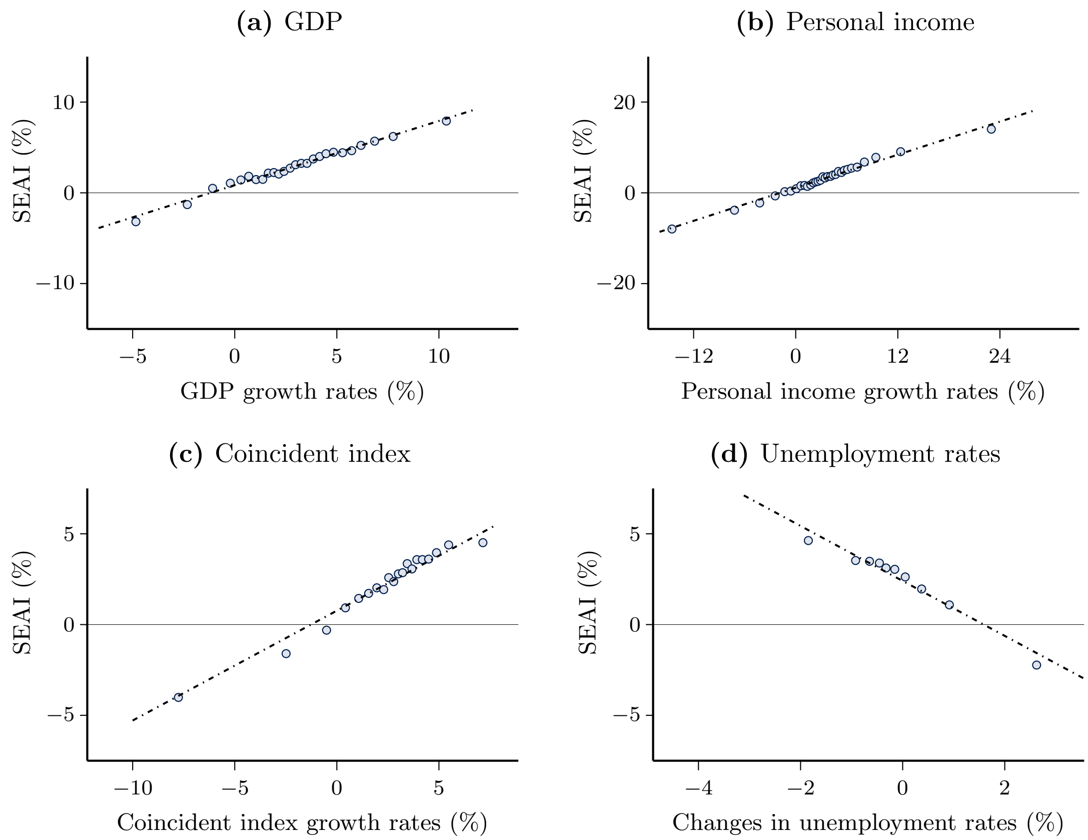
Alternative Input Specifications. We examine two alternative input specifications. The first specification augments the baseline set of indicators listed in Table 2 with three additional series: (i) total bank assets and liabilities from Hoon et al. (2025), and (ii) changes in lagged sentiment indicators from Van Binsbergen et al. (2024). The first two series capture dynamics in the financial sector, while the sentiment series provides a proxy for local economic expectations. As shown in Figure C.2, including these additional indicators does not materially alter the qualitative features of the estimated indices. State-level indices obtained under this extended specification remain highly correlated with their baseline counterparts, particularly in the case of New York.

As a further robustness check, we implement a data-driven selection of input indicators using ridge regression. For each state, we regress personal income—an independent measure of economic activity—on a large pool of potential input variables, including those in the extended baseline and additional candidates listed in Table 4. We explore 1,000 logarithmically spaced values for the ridge penalty parameter between 10^{-4} and 10^{4}, compute the corresponding slope coefficients, and use their absolute averages to evaluate indicator relevance. Specifically, we retain indicators whose average absolute coefficients exceed the 30th percentile across all regressors. We then use this subset of input indicators to re-estimate the state-level economic activity indices. Despite relying on a smaller and automatically selected set of inputs, the ridge-based estimates remain highly consistent

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

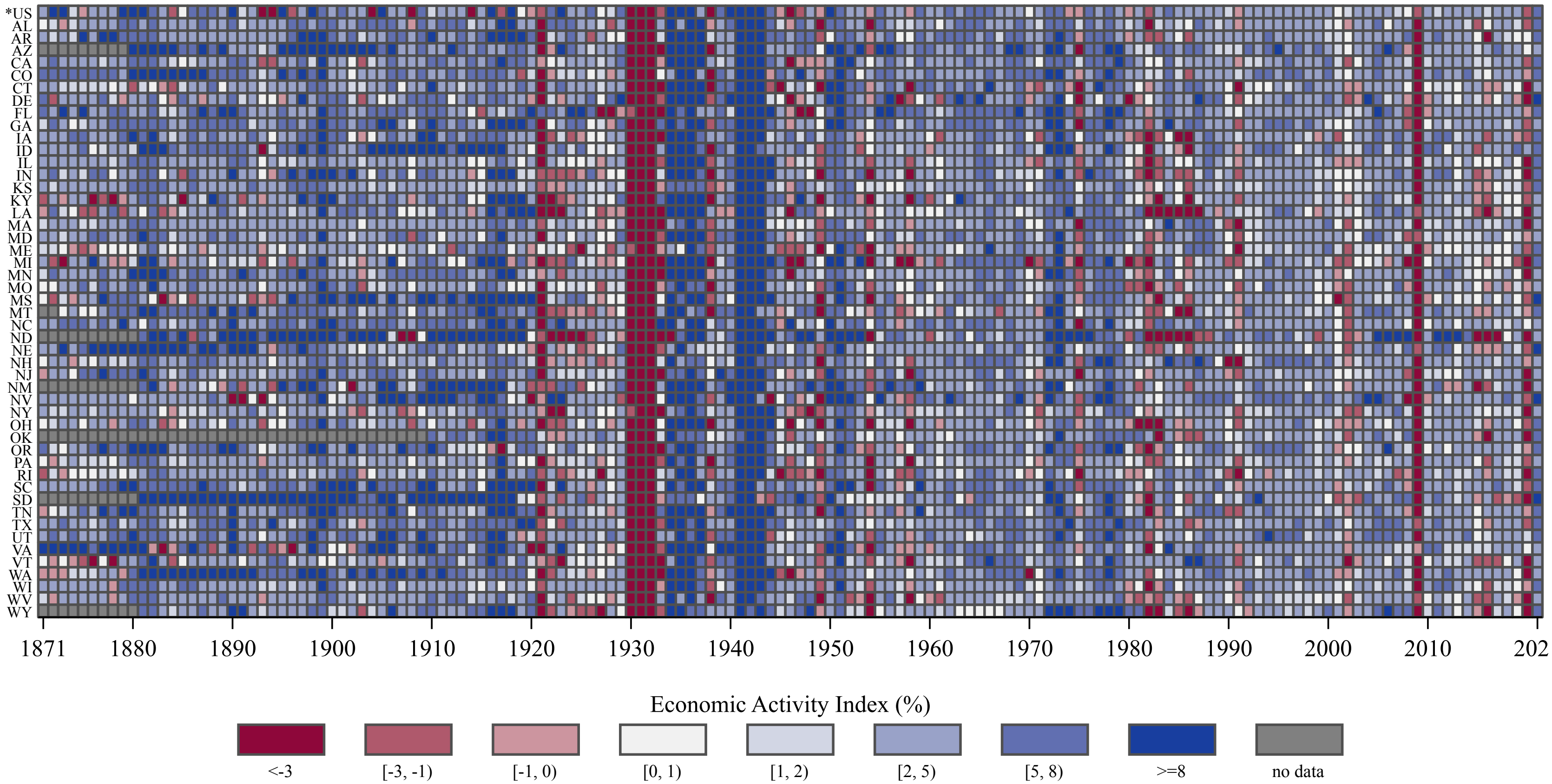
with those from the baseline specification, reinforcing the robustness of our approach to alternative input choices.

Figure 3: 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 (1964–2021), personal income (1929–2021), and the coincident index (1980–2021) are calculated as log differences, while changes in unemployment rates (1977–2021) 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.

Figure 4: State-Level Indices of Economic Activity



Notes: Each cell represents the estimated state-level index of economic activity (in percentages). Gray cells indicate years for which the index is not estimated, often due to limited data availability before statehood. For reference, the first row reports US GDP growth rates from Williamson (2025), labeled as "*US".

4 150 Years of State-Level Business Cycles

Our estimated index provides various novel insights into state-level business cycles from a very long-run perspective. In this section, we discuss the drivers of our estimated index, the time-varying nature of state business cycles and their relationship with the national one, and the broader fluctuations in alternative economic indicators over the state business cycles.

4.1 Decomposition of the Estimated State Economic Activity

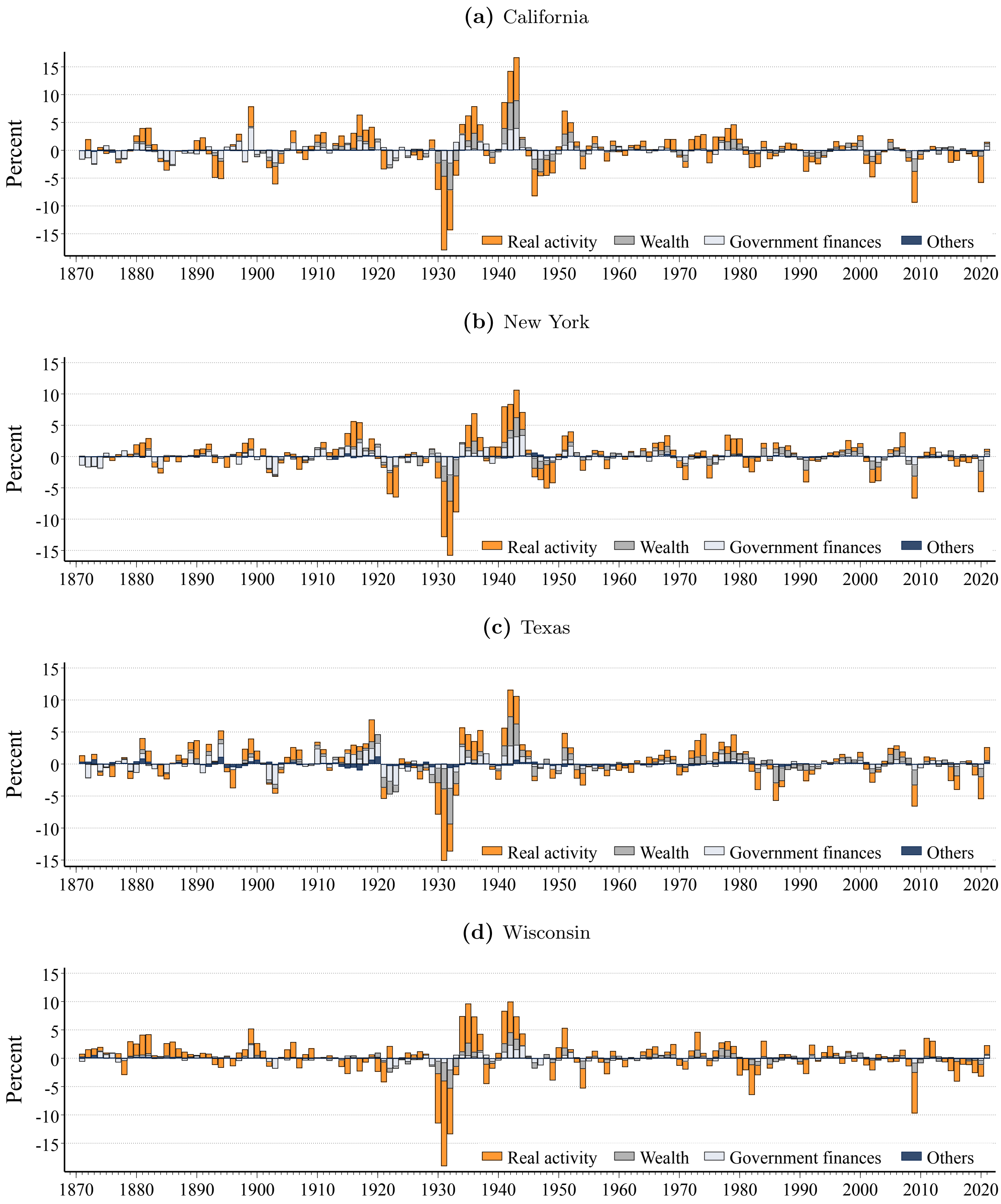
Our factor model allows for a decomposition of the estimated index into the factors that contribute to its variation over time. Figure 5 plots changes in economic activity for a selection of states together with changes in the underlying indicators grouped into four buckets: real activity, wealth, government finances, and others. This decomposition reveals several interesting patterns. In general, and perhaps not surprisingly, variables referring to real activity are the primary contributors to the estimated index both across states and over time. Other variables in the categories of government finances and wealth play a relatively more important role only in the earlier sample, but with considerable heterogeneity across states. For example, government finances play an important role in shaping California and New York's pre-1920 economic dynamics compared to the other three states, while in Wisconsin, fluctuations in variables directly related to real activity appear to be the primary drivers.

4.2 Heterogeneity, Volatility and Synchronization

In Figure 6, we present graphs of the estimated annual economic activity indices for selected states from 1871 to 2021, overlaid by NBER recession bars shaded in gray. This figure reveals similarities, but also key differences in the state-level business cycles, both within and across different regions. For example, for the states of Florida and Texas in the South, the economic indexes show strong comovement over the entire sample period, but they also exhibit very different dynamics in specific scenarios such as the post-World War II recovery period and the Great Recession. With the exception of the Great Depression, New Deal, and World War II, state-level business cycles do not appear to be more volatile before and after 1960, an observation consistent with that of Romer (1986).

However, we observe a dramatic variation over time in the synchronization of the estimated economic activity indices across states. Figure 7 shows this by plotting the cross-state standard

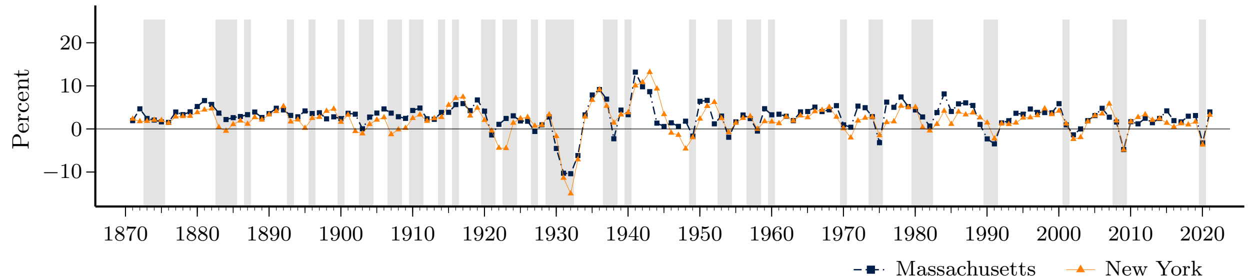
Figure 5: Decomposition of Economic Activity Indices for Selected States



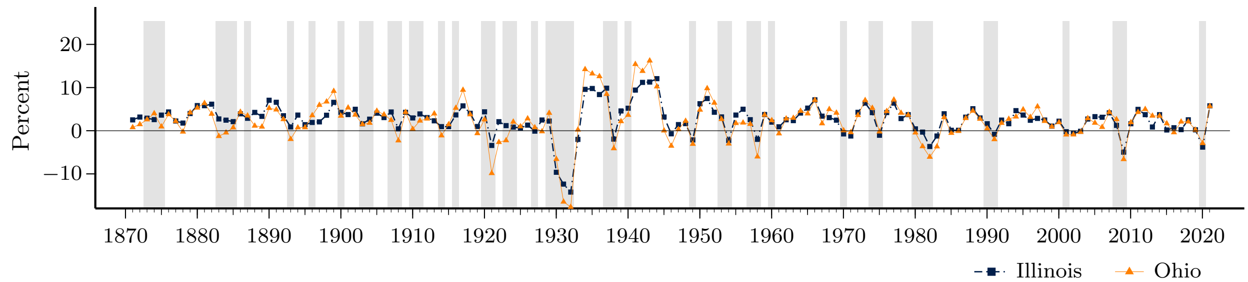
Notes: This figure decomposes the variation in the economic activity index for selected states into four categories: real activity, wealth, government finances, and others. The specific input series within each category are detailed in Table 2. Note that the economic activity index is normalized to have a mean of zero in this figure.

Figure 6: Annual Index of Economic Activity for Selected States

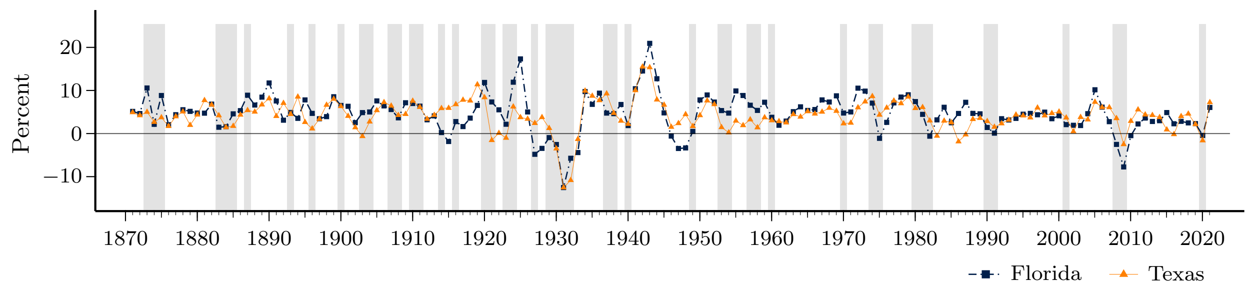
(a) Northeast



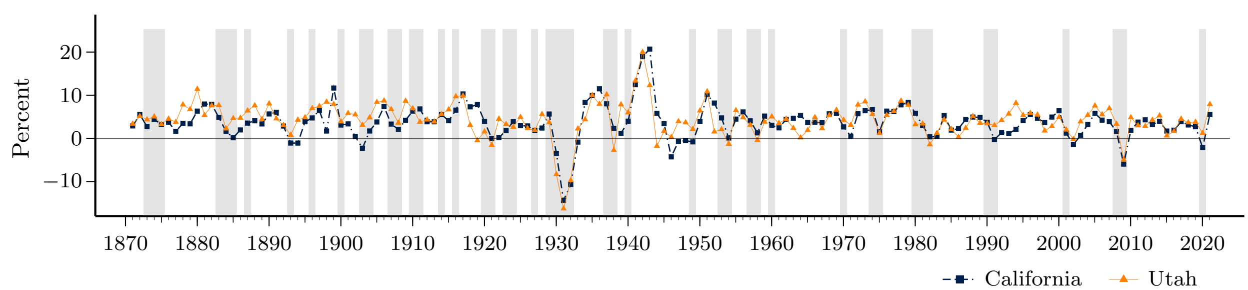
(b) Midwest



(c) South

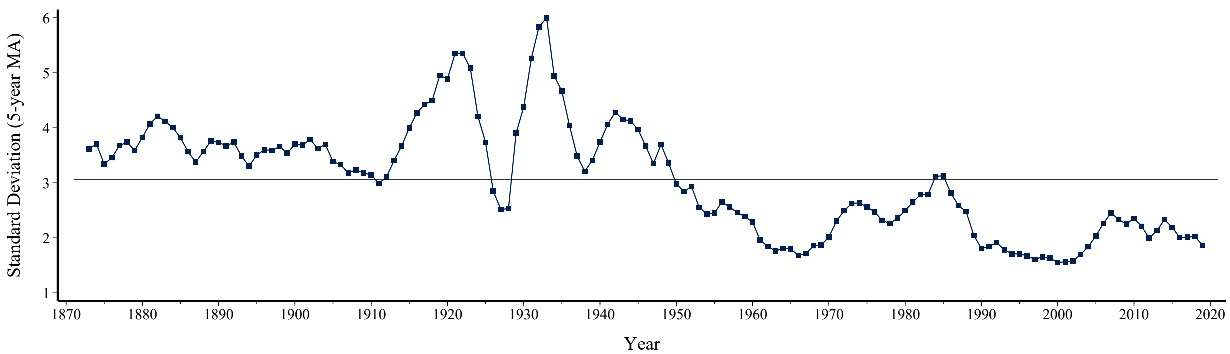


(d) West



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.

Figure 7: Dispersion of State-Level Economic Activities Over Time



Notes: This figure shows the standard deviation of our estimated economic activity indices across states as a proxy for business cycle synchronization, averaged over a five-year moving window. The horizontal line represents the average value over time, which is about 3.

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 6.

deviation of changes in economic activity over time. We find that the cross-state standard deviation in economic activity is notably higher in the pre-World War II period compared to afterwards, and that the Great Depression and to a lesser extent the 2007-08 Global Financial Crisis saw a dramatic increase in this measure. Table 3 further illustrates this pattern by summarizing the average dispersion of the state-level economic activity indices across four periods: 1871–1905, 1906–1940, 1945–1980, and 1981–2019. This exercise also shows a steady increase in business cycle synchronization after World War II, and this increase does not seem to be specific to expansion and recession periods. In Appendix C.1, we develop an alternative measure of business cycle synchronization based on Kalemli-Özcan, Papaioannou and Peydró (2013), which yields similar conclusions.

To sum up, our estimated historical state-level index of economic activity shows three interesting facts: (1) state cycles exhibit substantial heterogeneity; (2) state-level business cycle volatility has not changed much over the past 150 years, excluding the Great Depression; and (3) state-level cycles have become more synchronized after World War II.

4.3 The Correlates of State Business Cycles

Business cycle research typically explores the extent to which fluctuations in GDP co-move with changes in a range of economic indicators. We compare our economic activity index against select variables *not* included in the index's inputs by running simple bivariate panel regressions with state fixed effects. In particular, we regress changes in state-level economic activity on the log-difference of several indicators, and then report the resulting coefficients, t-statistics, and (within-) R^2. We cluster standard errors by state.

Table 4 plots the results. The economic activity index we construct is highly correlated with changes in manufacturing payroll and employment, with an R^2 upwards of 0.2 and t-statistics exceeding 10. Business failures and bankruptcies are also highly predictive of changes in economic activity. We also find that a measure of state-level sentiment from Van Binsbergen et al. (2024) predicts economic activity over the more than 150-year period we consider, consistent with Van Binsbergen et al. (2024), who show a similar result for state-level GDP growth after 1963.

Importantly, we also find some indirect evidence suggesting that our measure of economic activity is correlated with output in the tertiary sector. Changes in the circulation of newspapers, which captures variation in part of the services sector that is historically important, attract a t-statistic of 4.70, suggesting a strong statistical link with our index. We also draw on the long-run historical data on patenting activity from Berkes (2018), and find a positive correlation with economic activity, suggesting strong procyclicality of innovation activities.

4.4 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 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, state-level business cycles are far from perfectly coinciding, although they seem to become more so during national downturns. The 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. Figure C.5 plots the change in our economic activity index across states during three major nationwide recessions:

Table 4: Association of State-Level Economic Activity and Other Economic Indicators

Indicator	$\hat{\beta}$	t-stat	Within-R^2
Manufacturing payroll	8.31***	11.14	0.20
Number of manufacturing employees	9.97***	11.64	0.28
Number of manufacturing establishments	4.67***	9.90	0.02
Number of patents	1.07***	3.80	0.00
Number of bankruptcies commenced	−3.33***	−7.85	0.03
Number of bankruptcies terminated	−1.28***	−5.25	0.00
Number of business failures	−4.98***	−10.61	0.06
Total circulation of newspapers	3.55***	4.70	0.03
Change in lagged sentiments	1.81***	6.79	0.01

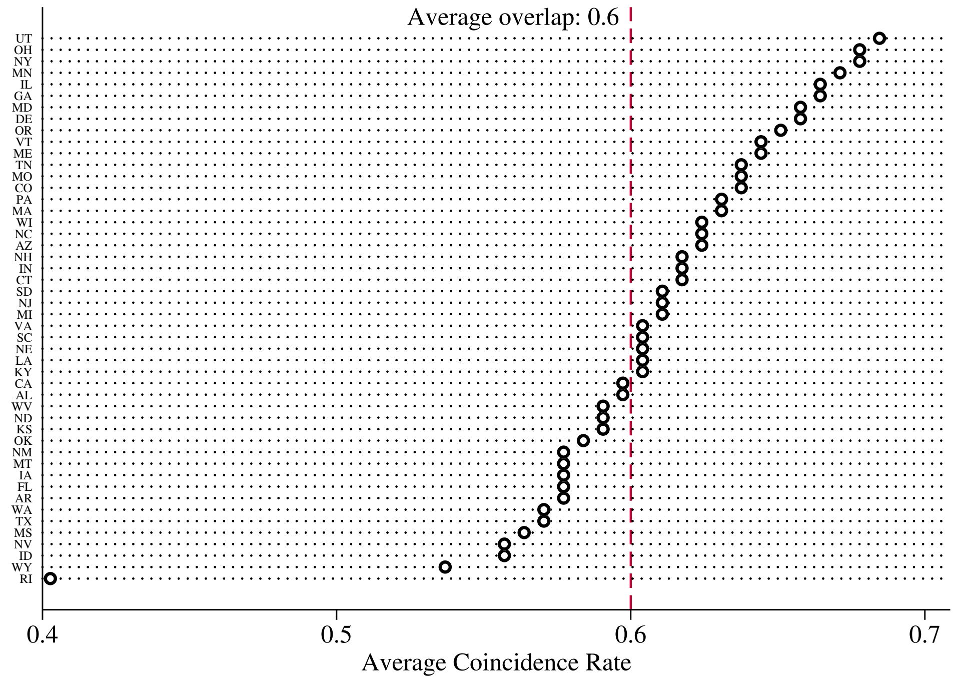
Notes: This table presents the results of bivariate panel regressions of the state-level economic activity index on several indicators not included in the baseline estimation (see Table 2). t-statistics are based on standard errors clustered by state. All indicators, except for the change in lagged sentiments, are log-transformed and standardized to have zero mean and unit variance. The change in lagged sentiments is computed as $S_{t-1} - S_{t-2}$, where S_t denotes the standardized sentiments index with zero mean and unit variance. All regressions include state fixed effects, with standard errors clustered at the state level. Statistical significance is indicated by $***$, $**$, and $*$ for the 1%, 5%, and 10% levels, respectively.

1873, 1929, and 2007. For each event, we calculate the mean change in the index for the recession years. These maps highlight that economic downturns are highly unequal in space: while most states experienced downturns, the extent to which they do 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 U.S. business cycle turning points using NBER recession dates. Figure 8 shows the results. States are ordered by the degree of overlap between state and 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.

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.

Figure 8: Estimated Average Coincidence Rate by States



Notes: We define state-level recessions with the Bry and Boschan (1971*a*) algorithm applied to our Economic Activity 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.

4.5 Dating State-Level Recessions

One can use our estimates of state-level economic activity to date state recessions, similar to NBER's business cycle dating. As our analysis above highlights, business cycles vary widely across states and may differ from nationwide upswings and recessions. The principal challenge is thus to identify which periods we should classify as a state-level recession. As an illustrative method, we use the turning point algorithm first proposed by Bry and Boschan (1971*a*), a workhorse method for identifying recessions (e.g., Davis, 2006).

To implement the Bry-Boschan algorithm, we use our state-level economic indices, demeaned and in levels, and use 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.

Figure C.6 plots several examples of the identified peaks and troughs for California and Massachusetts, against U.S.-wide recession events in the background. We define U.S. recessions in three steps. Recession years prior to 1887 are defined according to Table 1 of Davis (2006). From 1887 to 1991, they are defined based on Table 3 of Romer (1999). In both cases, a year counts as a recession if at least one quarter (or the whole year) falls within the peak-to-trough phase. After 1991, we use the NBER to identify recession dates. In these case studies, state-level recessions tend to coincide with national recessions, but there are also exceptions. For example, California experienced a recession in 1985 that did not coincide with the dating in Romer (1999). Put differently, local and U.S.-wide recessions are clearly correlated but distinct events.

Taken together, our new chronology of state-level recession dates again highlights the considerable heterogeneity in business cycles across regions. This simple "0 or 1" measure has the potential to be a simplified indicator for local booms and busts. It is worth noting that while the Bry-Boschan method is straightforward to implement and simple to interpret, 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.

5 Conclusion

We introduce a new historical state-level dataset for the United States, covering 60 variables from the Civil War until today. These newly constructed time series, based on 113 unique sources and a large-scale digitization effort, allow us to gauge changes in the spatial distribution of economic activity over a long span of time. In this paper, we apply this dataset to the analysis of state-level business cycles.

We estimate an annual index of state-level economic activity based on a subset of these indicators using a mixed-frequency dynamic factor model, and show that the resulting index is a reliable measure of state business cycles. Equipped with this new index, we document several new facts about economic fluctuations at the states. First, state-level business cycles exhibit substantial heterogeneity over the long run. Second, state-level business cycle volatility has not changed much over the past 150 years apart from the Great Depression and World War II periods. Third, state cycles have become more synchronized after World War II, suggesting stronger risk sharing across states.

We also show 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 regional 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 and historical perspective, made possible by our novel dataset as well as the state-level index.

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

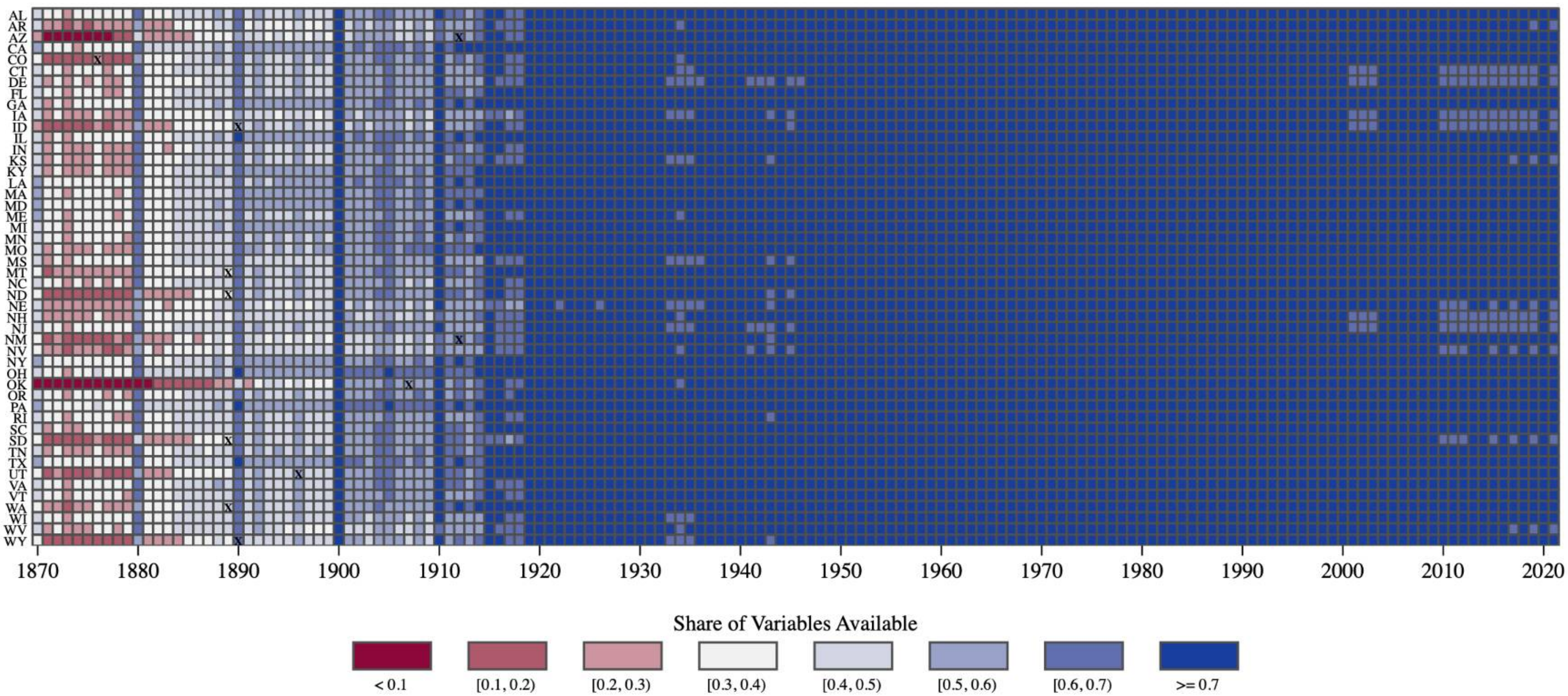
Joseph Hoon Chang Liu Karsten Müller Zhongxi Zheng

August 22, 2025

A Details on the Dataset

Figure A.1 displays the fraction of available input variables for each state-year observation. Data availability is more limited in the earlier years. Nonetheless, the dataset exhibits relatively strong coverage in core sectors—namely agriculture, mining, and manufacturing—which collectively represent the bulk of economic activity during that period. Additional details on data construction, variable definitions, and source documentation are provided in the supplementary appendix by Hoon, Liu, Müller and Zheng (2025).

Figure A.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. We observe that for the majority of states, including but not limited to Arizona (admitted in 1912) and Oklahoma (admitted in 1907), variable coverage improves post-admission.

B The Gibbs Sampling Algorithm

Let $\boldsymbol{\theta}$ collect the model parameters in the state space system (5)–(6). Conditional on $\boldsymbol{\theta}$ and $\mathcal{F}_T$, the first step involves drawing $\boldsymbol{\alpha}_t$ using the Kalman filter and smoothing recursions; see Carter and Kohn (1994) and Durbin and Koopman (2012) for a detailed treatment of the Kalman filter and smoothing.[7] It is likely that we do not observe all indicators in a given year t. In this case, we remove the rows of $\mathbf{H}_t$ that are associated with the missing entries. This operation ensures that $\mathbf{H}_t$ is conformable in the observation equation when we perform the first step. 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. We assume that $\{\boldsymbol{\phi},\ \boldsymbol{\psi},\ \boldsymbol{\lambda}\}$ have Gaussian priors with the typical setup of zero mean and unit variances. 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. We refer readers to Gelman et al. (2013) for details of the Gibbs sampler.

C Additional Figures and Tables

[7] 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.

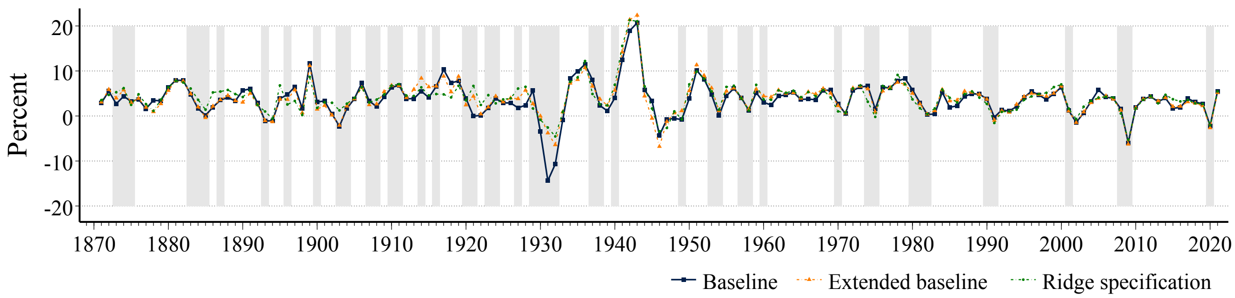
Table C.1: Descriptive Statistics of the Estimated SEAI

State	Average	Volatility	25th Percentile	Median	75th Percentile
Alabama	3.35	4.41	1.78	3.50	5.39
Arkansas	4.00	4.35	2.34	3.98	6.20
Arizona	5.38	5.31	3.17	5.21	8.34
California	3.70	3.97	1.83	3.78	5.65
Colorado	4.52	4.50	2.48	4.72	6.17
Connecticut	2.75	4.18	0.92	2.75	4.92
Delaware	3.11	4.82	0.31	2.95	5.71
Florida	4.64	4.29	2.53	4.75	7.07
Georgia	4.36	4.67	2.48	4.86	6.61
Iowa	3.09	4.89	1.25	3.72	5.44
Idaho	4.48	5.34	1.98	4.57	7.26
Illinois	2.58	3.57	0.95	2.82	4.21
Indiana	3.08	5.17	0.41	2.99	6.23
Kansas	2.91	2.98	1.61	2.91	4.55
Kentucky	3.18	5.34	0.45	3.47	5.12
Louisiana	2.33	4.95	0.28	2.60	4.92
Massachusetts	2.83	3.11	1.64	3.11	4.37
Maryland	3.52	3.75	1.80	3.47	5.12
Maine	1.99	3.39	0.30	1.59	3.64
Michigan	2.49	7.04	−0.37	1.93	5.71
Minnesota	3.89	3.94	2.24	4.14	5.86
Missouri	2.50	3.72	0.85	2.70	4.32
Mississippi	3.47	6.28	0.65	3.16	6.30
Montana	3.09	4.91	0.87	3.18	6.06
North Carolina	4.43	4.03	2.89	4.38	6.59
North Dakota	4.52	10.37	0.41	5.36	11.15
Nebraska	3.60	4.64	1.47	3.29	5.98
New Hampshire	3.31	3.63	1.78	3.27	5.53
New Jersey	3.11	3.84	1.61	3.12	5.10
New Mexico	4.11	5.87	1.94	3.88	6.64
Nevada	4.36	5.20	2.01	4.16	6.56
New York	2.03	3.33	1.09	2.33	3.34
Ohio	2.28	4.59	0.19	2.46	4.30
Oklahoma	3.06	4.15	1.62	3.33	5.02
Oregon	4.07	4.58	1.49	4.27	6.85
Pennsylvania	2.23	3.37	1.03	2.30	3.80
Rhode Island	2.23	3.86	0.60	2.50	4.24
South Carolina	4.46	4.21	2.51	4.68	6.92
South Dakota	5.49	7.28	1.26	4.39	10.33
Tennessee	4.12	5.06	2.15	4.38	6.73
Texas	4.15	3.50	2.53	4.21	6.10
Utah	4.31	3.94	2.65	4.36	6.42
Virginia	4.27	7.08	1.11	3.90	6.70
Vermont	2.48	4.57	0.73	2.72	4.38
Washington	4.59	5.59	1.94	4.50	7.23
Wisconsin	2.93	3.49	1.62	3.23	4.26
West Virginia	2.20	3.54	0.76	2.39	4.49
Wyoming	2.91	5.11	1.16	3.01	5.77

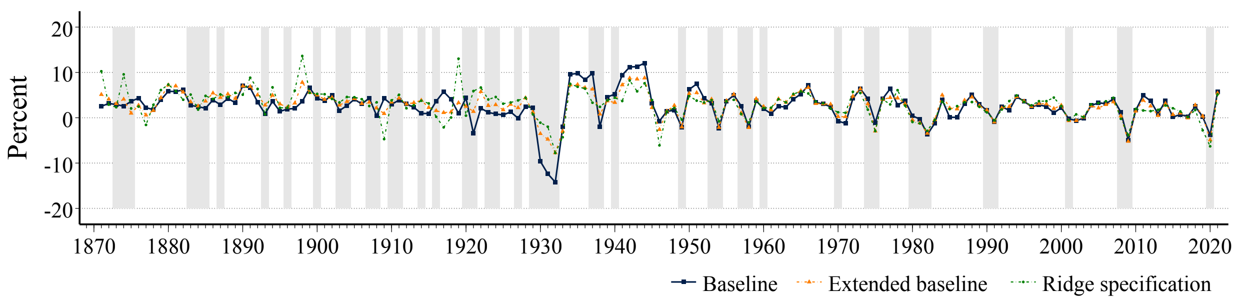
Notes: This table presents the descriptive statistics for the state-level economic activity indices from 1871 to 2021.

Figure C.2: Alternative Estimates of Economic Activity Indices for Selected States

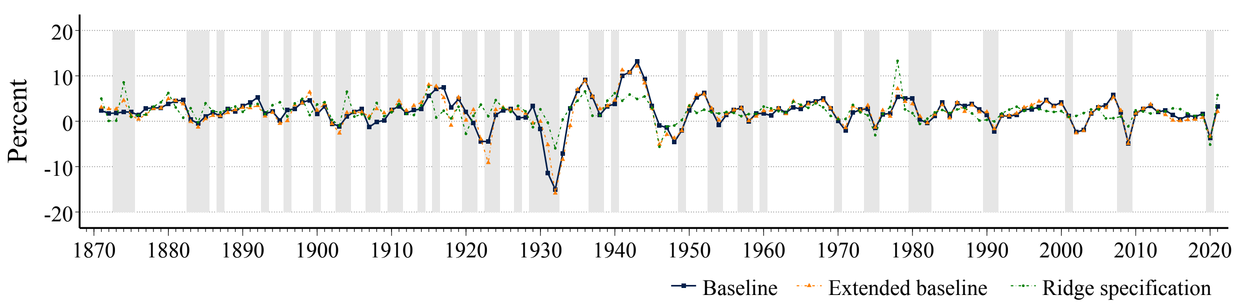
(a) California



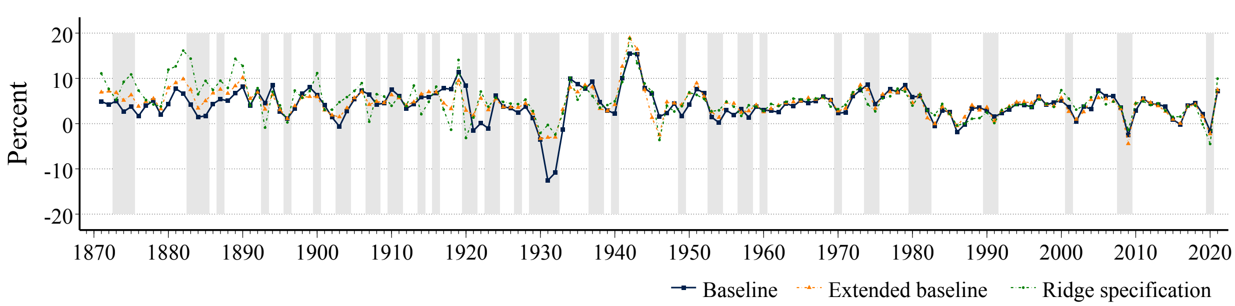
(b) Illinois



(c) New York



(d) Texas



Notes: In this figure, *Baseline* refers to the estimation using input indicators listed in Table 2, while *Extended baseline* adds (i) total bank assets and liabilities from Hoon, Liu, Payne, Müller and Zheng (2025) and (ii) changes in lagged sentiments from Van Binsbergen et al. (2024). See the notes in Table 4 for details on constructing changes in lagged sentiments. *Ridge specification* refers to the estimation using input indicators selected via ridge regression, where, for each state, state-level personal income is regressed on a pool of indicators, including those in the *Extended baseline* and Table 4. The procedure is as follows: (i) pick 1000 logarithmically spaced ridge parameters between 10^{-4} and 10^{4}; (ii) regress state-level personal income on this pool of indicators for each ridge parameter and obtain the regression slope coefficients; (iii) compute the absolute average of the coefficients for each indicator; (iv) include an indicator if its coefficient exceeds the 30th percentile of all coefficients.

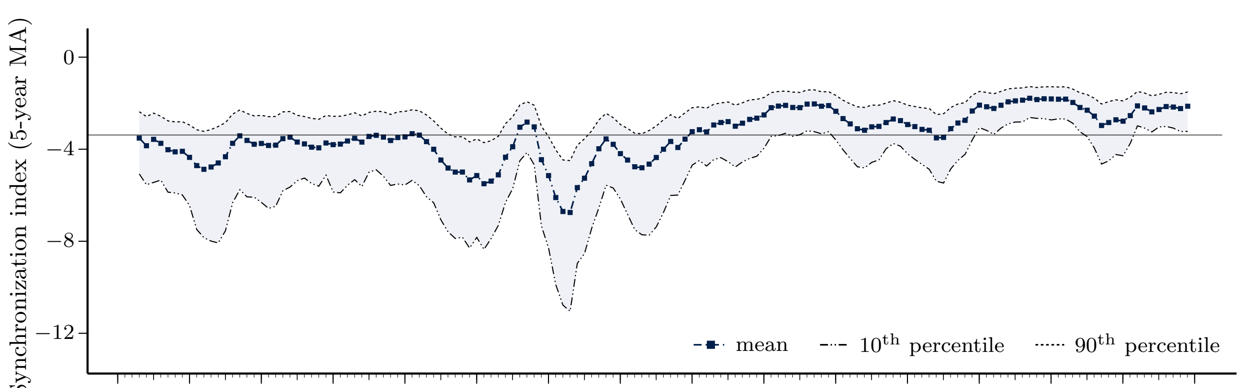
C.1 Synchronization

For our baseline estimation of business cycle synchronization, we calculate the cross-state standard deviation of changes in economic activity in each year. In this section, we use an alternative approach following Kalemli-Özcan, Papaioannou and Peydró (2013). In particular, we calculate a synchronization measure for state i as the sum of negative absolute differences between the state's economic activity index and those of all other states in a given year, scaled by the total number of state pairs:

$$Synchronization_{i,t} = -\frac{\sum_{i \neq i'} |s_{i,t} - s_{i',t}|}{S_t - 1}, \tag{C.1}$$

where $s_{i,t}$ and $s_{i',t}$ refer to the scaled economic activity index, according to equation (8), for states i and i' in year t. $S_t \leq 48$ denotes the number of states for which the scaled economic activity index is available in year t. From equation (C.1), state i's economic activity is more synchronized with those of the other states as $Synchronization_{i,t}$ approaches zero. In Figure C.3, we report the mean, 10th, and 90th percentiles of $Synchronization_{i,t}$ over time. From this figure, we see that the economic activity indices seem to exhibit a mild U-shape pattern, where the states' business cycles are least synchronized during the 1930s–40s, and they are increasingly more synchronized after the 1950s.

Figure C.3: Synchronization of state-level economic activity over time

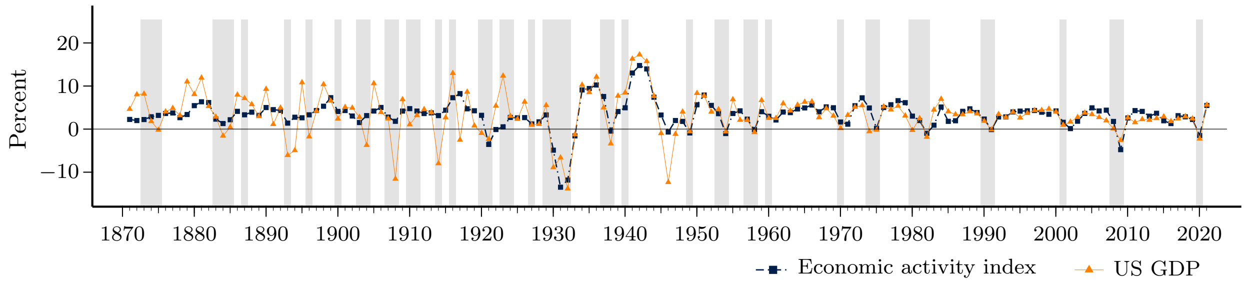


Notes: This figure presents the mean, 10th, and 90th percentiles of the synchronization index, averaged over a five-year moving window. The synchronization index is computed using Equation (C.1), where the number of states, S_t, ranges from 41 to 48, depending on the availability of economic activity indices shown in Figure 4. The solid line denotes the average of the mean index level over time, which is approximately −3.4.

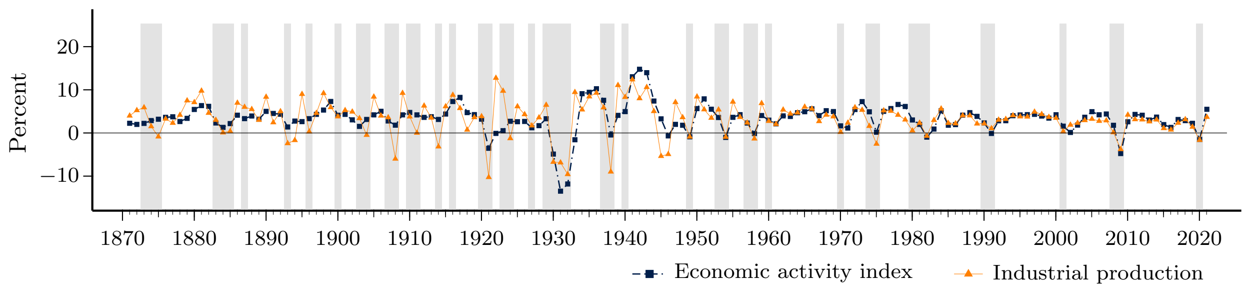
C.2 Aggregated State-Level Index vs U.S. Measures

Figure C.4: Comparison of the Aggregated SEAI and Other US-Wide Measures

(a) Aggregated economic activity index and US GDP



(b) Aggregated economic activity index and US industrial production

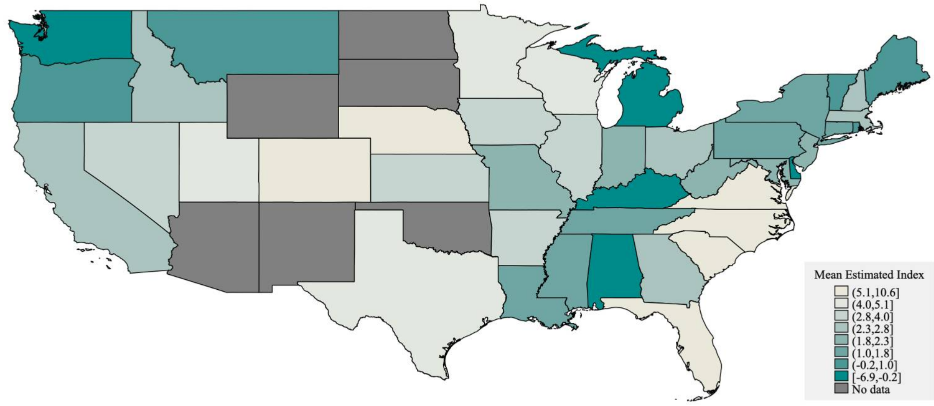


Notes: This figure plots the aggregated economic activity index alongside US GDP and industrial production from 1871 to 2019. The aggregated index is constructed by taking a weighted average of the state-level economic activity indices, with the weights based on the relative size of each state's economy 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 6 for their definition.

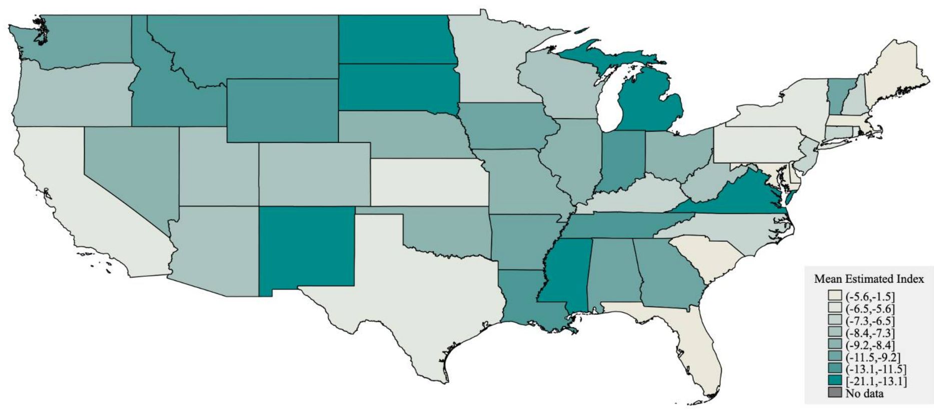
C.3 State-Level Economic Activity During US-Wide Recessions

Figure C.5: Changes in State-Level Economic Activity During US-Wide Recessions

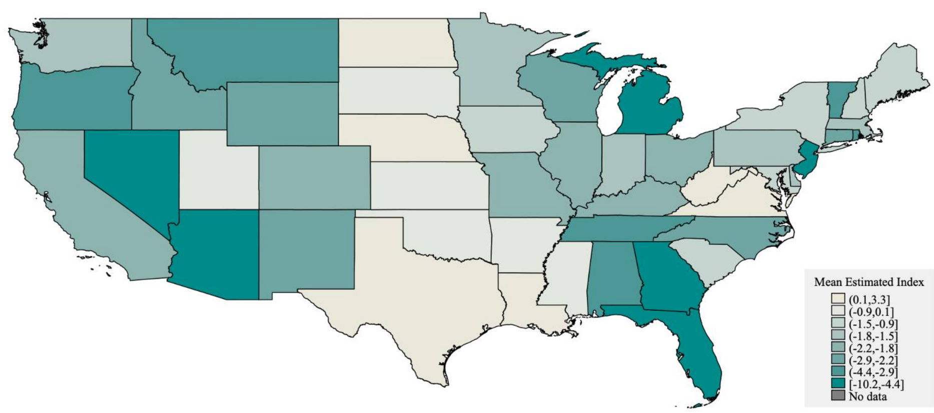
A. 1873-1875 Recession



B. 1929-1932 Recession



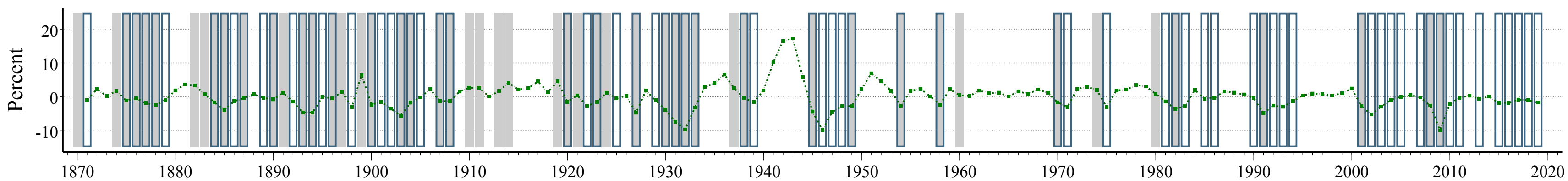
C. 2008-2009 Recession



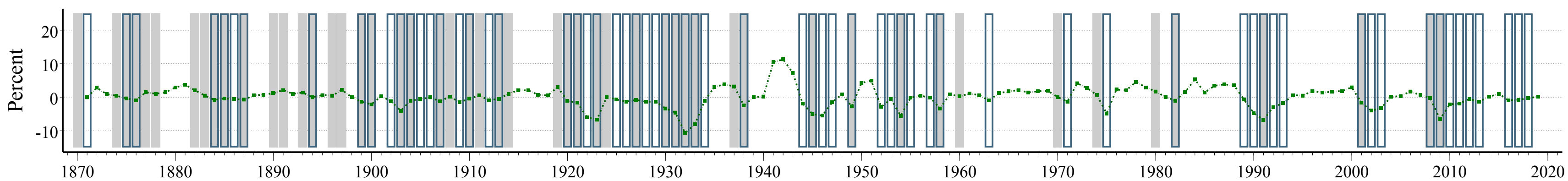
Notes: This figure shows the average percentage changes in economic activity indices during three national recession episodes: the 1873–75 Recession, the Great Depression (1929–32), and the Great Recession (2008-09). See the notes in Figure 6 for the definition of national recessions.

Figure C.6: Recession dates for selected states (1871–2019)

(a) California



(b) Massachusetts



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.

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