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

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Abstract

We present a novel dataset of 62 state-level macroeconomic time series for the United States, spanning from 1870 to the present, assembled by digitizing and harmonizing 135 historical sources. Using these data, we estimate an annual index of state-level economic activity over the past 150 years and validate it in a variety of ways. We document four facts. First, business cycles exhibit substantial heterogeneity across states, both historically and today. Second, the comovement of state business cycles has increased since World War II. Third, average state-level volatility has declined since the 1980s, but likely not much beforehand. Fourth, over a third of the recessions are state-specific rather than national, and such idiosyncratic downturns tend to be shorter and milder.

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

JEL classification: C38, E32, N91, N92

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1 Introduction

Reliable indicators on the state of the macroeconomy are the primary inputs for empirical research in macroeconomics, economic history, and growth. Yet even for the United States, consistent long-run data are limited, especially at the regional level. The paucity of regional data is particularly consequential because such data have long been used in macroeconomics (e.g., Barro and Sala-i-Martin, 1991, 1992; Blanchard and Katz, 1992) and are increasingly used to identify causal effects (Nakamura and Steinsson, 2018). The official state-level GDP series published by the Bureau of Economic Analysis (BEA), for example, only begin in 1963.[1] As a result, there are many open questions about state-level business cycles and growth: How have state-level business cycles evolved over the long run? When did each state experience an economic downturn? How do business cycles differ across states, and to what extent do they coincide with national cycles?

This paper addresses these gaps by constructing a new dataset of state-level economic indicators spanning from 1870 to 2021. Drawing on historical publications produced by U.S. federal, state and private agencies, we digitize and harmonize a comprehensive panel covering 62 variables. Only about 22% of the observations in our compilation are available in existing official statistics; the remainder are newly digitized or assembled from a range of official and private sources. In many instances, we reconstruct the historical availability of key statistics, such as output of specific mining products and state government finances, by tracing them through reports published by individual states. A dedicated data appendix documents the 135 underlying sources and describes the adjustments and imputations required to ensure data consistency. We anticipate that the dataset will be useful for many applications in macroeconomics, development economics, and economic history.

Equipped with our dataset spanning over 150 years of U.S. regional economic history, we estimate an annual index of state-level economic activity for 1871–2021. To the best of our knowledge, this is the first attempt to estimate an annual state-level measure of economic activity over such a long horizon. Following the spirit of Burns and Mitchell (1946) and Stock and Watson (1989), we view business cycles as common movements across a broad set of underlying indicators, which naturally motivates a dynamic factor framework. In particular, we estimate a dynamic factor model that accommodates randomly missing observations and allows for time-varying volatility in

[1] For the period before 1963, there is no comprehensive state-level annual measure of economic activity. A few indicators capture limited dimensions, such as personal income (since 1929), agricultural output (since 1924), and value added of the manufacturing sector (since 1949).

both the latent and series-specific innovations. Both features are essential in our setting: historical sources often contain substantial and irregularly missing observations, and the long sample plausibly covers periods of differing macroeconomic volatility. In our baseline specification, we estimate an index from 23 core indicators for each state, including real activity measures (such as agriculture, mining, and manufacturing output) as well as series capturing local labor markets, public finances, transportation, and business statistics.

We assess the validity of our estimation approach in three ways. First, we compare our factor estimates with state-level GDP growth once these data become available in 1963 and find these to be highly correlated in all states. This result indicates that the estimated factor is a useful proxy for state-level economic activity and motivates a linear transformation of our index that can be interpreted as a measure of economic growth. Second, the resulting state economic activity index is strongly positively correlated with other measures of local economic conditions, including personal income and state coincident indexes, and negatively correlated with unemployment rate. These correlations provide additional support for the index as a measure of state-level business-cycle fluctuations. Third, we construct a nationwide version of our economic activity index based on the same model but U.S.-wide analogues of the state-level series. Comparing this national index with U.S. real GDP growth using historical GDP data from Williamson (2025), we find that it tracks aggregate growth closely from 1871 to 2021. Taken together, these validation exercises show that our state economic activity index provides a reliable characterization of regional economic conditions.

Beneath aggregate booms and busts, our index reveals pronounced regional heterogeneity in both the timing and severity of state business cycles. For example, Florida's economic activity surged during the 1920s land boom, turning positive in 1922, peaking at roughly 13%, and remaining elevated through 1926, before reversing sharply in 1927–28, years ahead of the national collapse. Even during nationally recognized expansions and contractions, the magnitude and timing of state-level fluctuations vary widely: in the post-WWII economic expansion, Sunbelt states such as California, Texas and Florida stood out with strong persistent growth, while northeastern states such as New York and Massachusetts recorded only modest expansion. Notably, localized booms and busts are more common in the earlier part of our sample, when idiosyncratic shocks, such as local banking crises and shocks to the agricultural sector, are more pronounced and harder to be absorbed.

Our index further speaks to the evolution of volatility and synchronization of business cycles across states. Average state-level volatility declines only modestly from the immediate prewar to the postwar period once measurement issues are properly accounted for in our framework, echoing the view by Romer (1999). Since the 1980s, however, there is clear evidence of lower volatility. Importantly, these changes in business cycle volatility are highly uneven across states: some became markedly more stable after 1945, while others grew more volatile. After 1945, we also find a sharp increase in business cycle synchronization across states. Specifically, the correlation between states' economic activity and national GDP growth rose substantially, and cross-state dispersion fell, indicating a meaningful secular increase in business cycle synchronization, likely due to more integrated regional economies and better risk sharing mechanisms in modern times.

Finally, we construct state recession indicators based on a simple turning-point algorithm, which allows us to investigate how regional cycles are related to national fluctuations. State and national recessions often overlap, but not always, and there is considerable heterogeneity across states. While local recessions overlap with nationwide ones 72% of the time on average, this coincidence rate is much lower for states such as Oklahoma and North Dakota, and higher for Connecticut and Ohio. Importantly, idiosyncratic state-level recessions are different from those coinciding with nationwide ones: they are shorter and associated with smaller economic downturns. Together, these results show that regional data provide a much richer lens for understanding both the propagation of national shocks and the incidence of localized recessions outside nationally dated downturns.

Literature. The primary contribution of this paper is to introduce a new state-level dataset spanning the Civil War to the present and to construct an indicator of regional economic activity that provides new insights into regional business cycles. Our work mainly builds upon and contributes to three strands of literature.

First, we contribute to the literature on historical business cycle fluctuations in the United States. 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. 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 the BEA's state-level GDP in 1963. Similarly, Bokun et al. (2023) introduce a real-time database with 28 indicators per state but focus on recent decades. Fulford and Schiantarelli (2025) study the spatial distribution of county-level GDP since 1870 using decadal data. We contribute to this literature by compiling new time series pre-dating the official statistics, providing data on 62 indicators, and estimating an annual economic activity index that covers a much longer time span. Our estimation framework builds on recent developments in the dynamic factor literature, such as Del Negro and Otrok (2008), Marcellino, Porqueddu and Venditti (2016), Antolin-Diaz, Drechsel and Petrella (2017), and Baumeister, Leiva-León and Sims (2024).

Third, 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).

The remainder of this paper proceeds as follows. Section 2 introduces our historical state-level macro dataset. Section 3 describes our approach in estimating the state economic activity index. Section 4 provides a descriptive analysis of the evolution of U.S. state-level business cycle over the past 150 years. Section 5 concludes.

2 Data

In this section, we introduce our new state-level historical dataset that covers the 48 contiguous states for the period 1870–2021. 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. We document further details on this dataset in a companion data appendix.

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 in these files have 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. Since past data are frequently revised in later issues, we always use the data from the latest issue in which a given year's data is reported.

Table 1: Classification and Examples of Sources

Source (Variable)	**Start**	**End**	**Freq.**
Panel A. Examples of Newly Digitized Sources (98 total)			
Statistical Abstract (e.g., value of imports of merchandise)	1870	2018	Annual
Books and almanacs (7 total)			
American Almanac and Treasury of Facts, Statistical, Financial, and Political (e.g., state government gross debt)	1880	1889	Annual
Company surveys (7 total)			
Poor's Manual of the Railroads of the United States (e.g., railroad mileage)	1870	1884	Annual
Government reports (78 total)			
Livestock on Farms (e.g., sheep value)	1869	1935	Annual
Existing studies (3 total)			
Leven (1925) (personal income)	1919	1921	Annual
Panel B. Examples of Existing Sources (37 total)			
Census Compendium (e.g., non-farm employment)	1870	2021	Decennial
BEA (personal income)	1929	2021	Annual
USDA (e.g., crop receipts)	1924	2021	Annual
Van Binsbergen et al. (2024) (sentiments)	1850	2019	Annual

Notes: This table provides examples of the sources we use to construct our dataset, along with variables collected in parentheses, and the period and frequency for which we collect data from each source. Panel A lists examples of newly digitized sources; Panel B lists examples of existing sources. We separate our 98 newly digitized sources into four categories: books and almanacs, company surveys, government reports, and existing studies. We digitize data from the Census Compendium from 1870–1930 and use existing Census data thereafter. For more details, please refer to the data appendix.

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 these data are difficult to obtain and only available in print or PDF format. As a result, a major part of our contribution is to digitize many data sources previously not available in digital format.

We draw on a grand total of 135 sources, of which 98 were newly digitized. The remainder was compiled from scattered but already digitized sources. We provide a classification of these sources along with examples in Table 1. For further details, Section 3 in the supplementary data appendix provides a comprehensive overview of all variables together with their sources, coverage across states and time, and imputation methods. 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 independent 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 consistently reported data on retail sales (reported in SA) for the prewar period, we do not include it in our dataset. That said, to the best of our knowledge, our dataset is the most comprehensive state-level dataset that has ever been constructed over such a long time horizon. In fact, most variables have close to universal coverage, spanning from 1870s until today. Others are available later, such as the number of motor vehicle registrations, or appear with lower frequency in the earlier years, such as manufacturing payrolls.

Our dataset contains a total of 62 variables, which can be grouped into seven broad categories as listed in Table 2: production and trade, transportation, employment and earnings, household income and housing, business statistics, public finances, and others. The "production and trade" category covers production statistics 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 mining production, and the value added of the manufacturing sector. For the agriculture and mining sectors, we collect data on major products, such as the value of sheep, lumber, petroleum at mines or sweet potato receipts. For the

Table 2: Overview of the state-level dataset

Production and trade		*Business statistics*	
1.	Value added of manufacturing production	18.	No. of manufacturing establishments
2.	Value of agricultural products sold	19.	No. of business concerns
3.	Value of fishery products	20.	No. of business failures
4.	Value of mining production	21.	Liabilities of failed businesses
5.	Production of electric energy	22.	No. of bankruptcies commenced
6.	Value of exported merchandise	23.	No. of bankruptcies terminated
7.	Value of imported merchandise		
Transportation		*Public finances*	
8.	No. of motor vehicle registrations	24.	State government revenue
9.	Railroad mileage	25.	State government expenditure
10.	State highway mileage	26.	State government gross debt
11.	Rural and municipal mileage	27.	Federal internal revenue
Employment and earnings		*Others*	
12.	Nonfarm employment	28.	Population
13.	Manufacturing employment	29.	Newspaper circulation
14.	Manufacturing wage and salary	30.	No. of daily newspapers
		31.	No. of patents
Household income and housing			
15.	Personal income		
16.	Value of farmland and buildings		
17.	House price index		

Notes: In addition to the indicators listed above, we collect 29 sector-specific series for agriculture and mining, which we use to impute missing observations in *Value of agricultural products sold* and *Value of mining production*, respectively. Of these sector-specific series, we report 21 series in our final dataset, along with the sub-components *Value of Crops Sold*, *Value of Animal Products Sold*, and *Value from Forest Products Sold*. We additionally report the *Number of Farm Operations* and the *Quantity of Fishery Products*. Details on the sectoral series are provided in the data appendix. We also report sub-components for several public finance indicators, including personal and corporate income taxes (components of federal internal revenue), automobile tax receipts (state government revenue), and state government long-term and net debt. In total, our dataset comprises 62 state-level indicators. In addition to the 62 variables, we obtain the rent price index from Lyons et al. (2024) and sentiments from Van Binsbergen et al. (2024) for use in further analysis.

early years, there is no annual data on total sectoral value added, and the data on these individual commodities allows us to estimate them; we provide details on this procedure in Section 2.3. In addition, we gather data on the total value of fishery products, total production of electric energy, as well as 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.

Given the importance of transportation networks in facilitating the flow of goods and people—therefore, economic growth (e.g., Donaldson and Hornbeck, 2016)—our dataset includes measures of transportation. Specifically, we include the mileage of railroad, rural and municipal roads, and state highways. We also cover the number of motor vehicle registrations as a measure for transportation, which can also be interpreted as a proxy for durable goods consumption given its importance in U.S. households.[2]

The category "employment and earnings" reports measures of the local labor market, including total non-farm employment, manufacturing employment, and manufacturing payroll. These statistics allow us to track local economic conditions through the lens of labor market fluctuations. For "household income and housing", we report personal income, as well as measures related to housing markets, namely the value of farmland and buildings and a house price index. Building upon the work of economic historians, we extend the official BEA data on personal income that starts in 1929 back to 1880 at the decennial frequency, and annually for 1919, 1920, 1921, 1927 and 1928. The house price index is drawn from Lyons et al. (2024) for 1890–1975 and the FHFA House Price Index for 1976–2021.

Our data on "business statistics" include business indicators such as the number and liabilities of business failures, which have been recognized as important indicators of economic crises (Simpson and Anderson, 1957), and the total number of business concerns. The fact that they have been consistently reported since the late 19$^{\text{th}}$ century makes them especially suitable for our long-run study of the business cycle. Similar cyclical metrics include the number of bankruptcies, which includes both corporate and personal bankruptcies, with the former used to supplement the number of business failures.

Government finance variables, which interact with the local economy in various ways, contain useful information on the state of the economy. For "public finances", our dataset includes state-level fiscal variables, including state government revenue, federal government internal revenue (including personal and corporate income tax revenues), state government expenditure, and state government debt (gross, net, and long-term). 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.

In miscellaneous series, we report annual data on population starting from 1870, where we estimate the intercensal years following the approach outlined in the Census Bureau's technical

[2]Local consumption data have been notoriously difficult to obtain even for the post-war period. 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 cycle fluctuations. While direct expenditure data are not available throughout our sample period, our motor vehicle registration data, which are available since 1900, can thus be a proxy for durable goods consumption.

reports. We include state-level measures of patents and newspaper circulation, the bulk of which are drawn from existing work. Table 1 in our data appendix 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

Because the time series we collect are from many disparate sources, they require adjustments to be usable. Here, we briefly summarize 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, information for Oklahoma and the Indian Territory were 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 the historical 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 \$5,000. 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 \$5,000 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.

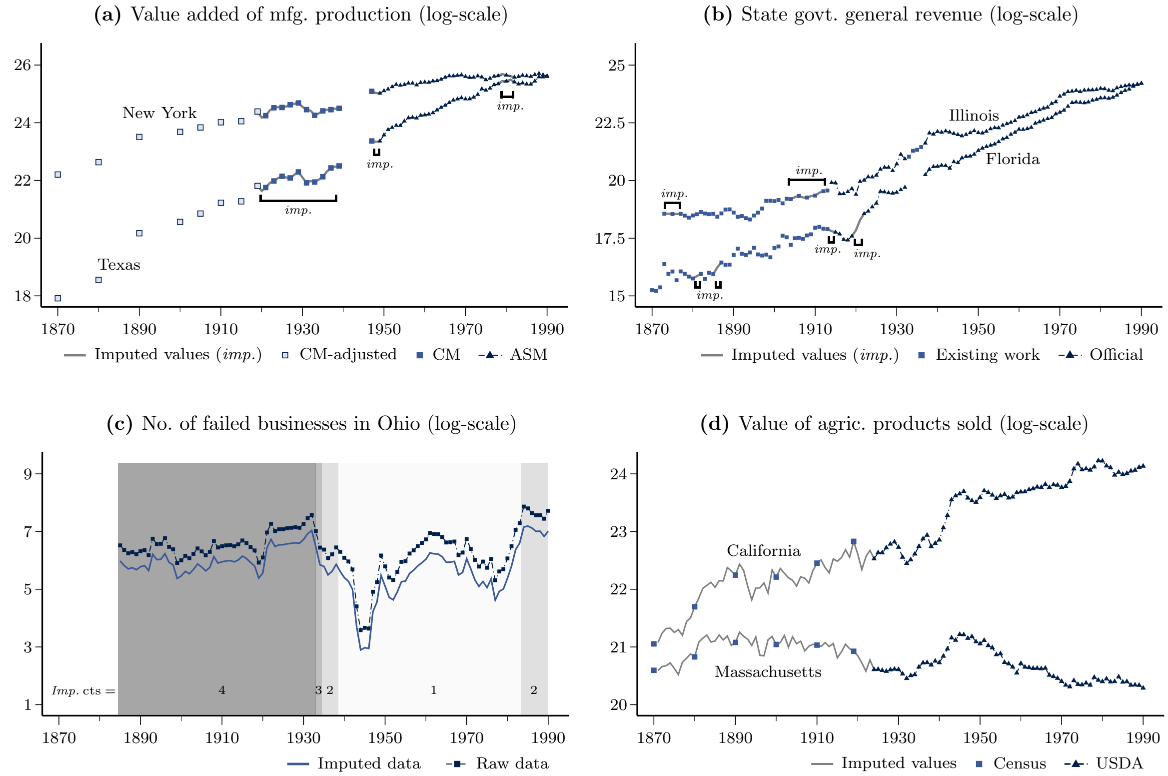
As an illustration of this harmonization process, Panel (a) of Figure 2.1 displays our long-run series of harmonized value added of manufacturing production for New York and Texas, which requires some imputation. Another example are the state government general revenue series for Illinois and Florida shown in Panel (b), 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 U.S. 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 2.1 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. Even after the above procedures, our raw data series still sometimes remain incomplete, with many series containing missing data points that occur randomly, at regularly intervals, or both. In principle, an approach such as the dynamic factor model we use later could easily accommodate such missing observations, but they make the raw time series for individual indicators less useful. For sporadic gaps involving only a single year, we thus 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 as unobserved states in the state-space model.

An exception is the data on total value of the agricultural and mining sectors, where we estimate lower-frequency aggregate values using their annually-available underlying component data. 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, which contain 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).[3] We describe the imputation details in Data Appendix 2.2, and display the results for California and Massachusetts in Panel (d) of Figure 2.1.

[3] We conducted 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.

Figure 2.1: 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 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.

In total, we report 62 time series variables that span economic activity across multiple sectors. To illustrate the structure and completeness of our dataset, Figure B.1 displays the fraction of variables available for each state and year. After 1920, typically more than three-quarters of variables are available for a given state, which underscores the depth and breadth of the state-level panel that we construct.

3 Constructing the State-Level Economic Activity Index

We follow Baumeister, Leiva-León and Sims (2024) and employ a dynamic single-factor model to construct indices of economic activity at the state level.[4] Our specification incorporates stochastic volatility in the innovations to both the common factor and the idiosyncratic components, following Del Negro and Otrok (2008), thereby allowing the model to accommodate shifts in volatility across historical regimes over our sample period. Using our new state-level dataset, we estimate the model for each of the 48 contiguous U.S. states separately.[5]

3.1 The Model

Let $Y_{s,i,t}$ denote the level of indicator i for state s in year t, where $s \in \{1, \ldots, 48\}$, $i \in \{1, \ldots, N_s\}$, and $t \in \{1, \ldots, T_s\}$. Here, N_s is the number of indicators used in the estimation for state s, and T_s is the length of the estimation period.[6] For each indicator i, we use lowercase letters to denote the year-over-year log growth rate, $y_{s,i,t} = \ln Y_{s,i,t} - \ln Y_{s,i,t-1}$.[7] When $y_{s,i,t}$ is available, we assume it can be decomposed into two latent components: one that captures cyclical fluctuations common to all N_s indicators, and one that accounts for idiosyncratic variation specific to indicator i. Formally,

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

where $f_{s,t}$ is the common factor, $\lambda_{s,i}$ the loading for indicator i, and $u_{s,i,t}$ the idiosyncratic component. Equation (1) corresponds to the measurement equation in Baumeister, Leiva-León and Sims (2024, eq. 6), adapted here to an annual setting. To simplify notation, we drop the subscript s for the remainder of this section because the model structure is identical across states. We also write $N \equiv N_s$ and $T \equiv T_s$.

We model the dynamics of the common factor and the idiosyncratic components as autoregres-

[4] The model in Baumeister, Leiva-León and Sims (2024) extends the single-index model of Stock and Watson (1991) to accommodate mixed-frequency indicators and missing observations in a state-level setting. Because our dataset is based on annual indicators, we adapt the framework to an annual specification while retaining a treatment of missing observations.

[5] We exclude Alaska and Hawaii due to limited data availability.

[6] In the baseline estimation, N_s ranges from 19 to 23, and T_s equals 151 for most states, covering the period 1871–2021.

[7] $y_{s,i,t}$ is unobserved when the underlying level series is missing, which primarily reflects gaps in historical coverage.

sive processes of orders p and q_i, respectively:

$$f_t = \phi_1 f_{t-1} + \ldots + \phi_p f_{t-p} + \sigma_{f,t} v_t, \tag{2}$$

$$u_{i,t} = \psi_{i,1} u_{i,t-1} + \ldots + \psi_{i,q_i} u_{i,t-q_i} + \sigma_{i,t}\epsilon_{i,t}, \qquad i = 1, \ldots, N, \tag{3}$$

where v_t and $\epsilon_{i,t}$ are independent standard normal innovations, i.e., $v_t \overset{iid}{\sim} \mathcal{N}(0,1)$ and $\epsilon_{i,t} \overset{iid}{\sim} \mathcal{N}(0,1)$ for all i. As noted in Baumeister, Leiva-León and Sims (2024, p. 485), modeling the idiosyncratic dynamics explicitly is useful in state-level applications because doing so helps separate series-specific episodes from broader statewide fluctuations. In our dataset, one such episode arises from the sharp and persistent increases in vehicle registrations across several states following the introduction of motor vehicle registration laws in the early 1900s. These increases primarily reflect changes in legal requirements rather than a sustained surge in vehicle use.

We follow Del Negro and Otrok (2008) and specify the volatilities of the common factor and the idiosyncratic components as the product of a scale parameter and a time-varying term: $\sigma_{f,t} = \sigma_f e^{\zeta_{f,t}}$ and $\sigma_{i,t} = \sigma_i e^{\zeta_{i,t}}$, with $\sigma_f > 0$ and $\sigma_i > 0$. The latent log-volatilities follow drift-less random walks:

$$\zeta_{j,t} = \zeta_{j,t-1} + \sigma_{\omega_j}\omega_{j,t}, \qquad j = f, 1, \ldots, N, \tag{4}$$

where $\omega_{j,t} \overset{iid}{\sim} \mathcal{N}(0,1)$. This specification allows for permanent shifts in volatility without imposing mean reversion, making it well suited to a long historical sample spanning multiple eras.[8]

Identification and normalization. We impose three normalizations for identification.[9] First, we set $\sigma_f = 1$ to fix the scale of the factor and its loadings. Second, because the level of $\zeta_{j,t}$ is not separately identified from the scale parameter σ_j, we pin down this level by setting $\zeta_{j,0} = 0$ for all $j \in \{f, 1, \ldots, N\}$. Finally, because the sign of the factor and its loadings is indeterminate, we pick a reference indicator and require its loading to be positive, i.e., $\lambda_{\text{ref}} > 0$, throughout estimation.

State-space representation. The model in equations (1)–(4) can be written in state-space form:

$$\mathbf{y}_t = \mathbf{G}\boldsymbol{\alpha}_t, \tag{5}$$

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

[8] The random walk specification is widely used in factor models with stochastic volatility, particularly in national and international business-cycle and forecasting applications (see, e.g., Del Negro and Otrok, 2008; Marcellino, Porqueddu and Venditti, 2016; Antolin-Diaz, Drechsel and Petrella, 2017; Eckert et al., 2025). While a random walk process can in principle wander without bound, it is typically innocuous over a finite time horizon when the innovation variance $\sigma^2_{\omega_j}$ is small; for related discussion, see, Antolin-Diaz, Drechsel and Petrella (2017, p. 346).

[9] See Del Negro and Otrok (2008, Sec. 2.1) for related normalization choices in factor models with stochastic volatility.

$$\boldsymbol{\zeta}_t = \boldsymbol{\zeta}_{t-1} + \boldsymbol{\omega}_t, \qquad \boldsymbol{\omega}_t \sim \mathcal{N}(\mathbf{0}, \mathbf{R}), \tag{7}$$

where $\mathbf{y}_t = (y_{1,t}, \ldots, y_{N,t})'$ collects the growth rates of the N indicators. The state vector $\boldsymbol{\alpha}_t$ stacks the common factor and the idiosyncratic components (and their lags), while $\boldsymbol{\zeta}_t = (\zeta_{f,t}, \zeta_{1,t}, \ldots, \zeta_{N,t})'$ stacks the log-volatilities. The matrices $\mathbf{G}$ and $\mathbf{H}$ are implied by equations (1)–(3), with $\mathbf{H}$ collecting the autoregressive coefficients in companion form. The time-varying covariance matrix $\mathbf{Q}_t$ is diagonal, with entries $e^{2\zeta_{f,t}}, \sigma_1^2 e^{2\zeta_{1,t}}, \ldots, \sigma_N^2 e^{2\zeta_{N,t}}$ in the positions associated with f_t and $(u_{1,t}, \ldots, u_{N,t})$. Finally, $\mathbf{R}$ governs innovations in $\boldsymbol{\zeta}_t$. See Appendix A for more details on the state-space system.

3.2 Model Estimation

We estimate the model in a Bayesian framework using a Markov Chain Monte Carlo Gibbs sampler. The sampler proceeds in six blocks, which we summarize below. More details on the Gibbs sampler and implementation are provided in Appendix A.

1. *Draw the state sequence.* Draw $\{\boldsymbol{\alpha}_t\}_{t=1}^T$ using the forward-filtering backward-sampling algorithm of Carter and Kohn (1994) conditional on matrices $(\mathbf{G}, \mathbf{H})$ and $\{\mathbf{Q}_t\}_{t=1}^T$. Missing observations are handled by dropping the missing entries of $\mathbf{y}_t$ and the corresponding rows of $\mathbf{G}$ at each t.

2. *Draw AR coefficients of the factor.* Draw $(\phi_1, \ldots, \phi_p)'$ conditional on $\{f_t\}_{t=1}^T$ and $\{\zeta_{f,t}\}_{t=1}^T$ (with σ_f normalized to 1) by rescaling the factor transition equation to obtain a linear regression with homoskedastic errors. Under a conjugate Normal prior, the conditional posterior is Normal. We reject draws that imply a non-stationary AR(p) process.

3. *Draw idiosyncratic AR coefficients and innovation scale parameters.* For each indicator i, draw $(\psi_{i,1}, \ldots, \psi_{i,q_i})'$ and σ_i^2 conditional on $\{u_{i,t}\}_{t=1}^T$ and $\{\zeta_{i,t}\}_{t=1}^T$ by rescaling the idiosyncratic transition equation. Under a conjugate Normal prior for the AR coefficients and an inverse-gamma prior for σ_i^2, the conditional posteriors are Normal and inverse-gamma. As in Block 2, we reject draws of the idiosyncratic AR coefficients that imply a nonstationary AR(q_i) process.

4. *Draw factor loadings.* For each i, draw λ_i conditional on $\{f_t\}_{t=1}^T$, the idiosyncratic parameters, and $\{\zeta_{i,t}\}_{t=1}^T$ by filtering the measurement equation with the lag polynomial $\Psi_i(L) = 1 - \psi_{i,1}L - \ldots - \psi_{i,q_i}L^{q_i}$ and rescaling by $e^{-\zeta_{i,t}}$, which together yield a linear regression with homoskedastic errors. Under a Normal prior, the conditional posterior is also Normal. Missing observations are handled by dropping rows for which $\Psi_i(L)y_{i,t}$ is undefined. We impose the sign normalization by rejecting draws with $\lambda_{\text{ref}} \leq 0$ (i.e., rejecting nonpositive draws of the reference loading).

5. *Draw log-volatilities.* For each $j \in \{f, 1, \ldots, N\}$, draw $\{\zeta_{j,t}\}_{t=1}^{T}$ conditional on the current state draws and parameters using the algorithm of Kim, Shephard and Chib (1998), implemented via the ten-component Normal mixture approximation of Omori et al. (2007).

6. *Draw log-volatility innovation variances.* For each $j \in \{f, 1, \ldots, N\}$, draw $\sigma^2_{\omega_j}$ from its inverse-gamma conditional posterior given $\{\Delta\zeta_{j,t}\}_{t=1}^{T}$, where $\Delta\zeta_{j,t} = \zeta_{j,t} - \zeta_{j,t-1}$ with $\zeta_{j,0} = 0$.

3.3 Economic Activity Indices

Let $\tilde{f}_t$ denote the posterior median of the common factor in year t. Because the factor is identified up to scale, we rescale $\tilde{f}_t$ to obtain an interpretable index of state-level economic activity. Following Clayton-Matthews and Stock (1998), we linearly transform $\tilde{f}_t$ so that, over 1964–2021, the resulting index matches the sample mean and standard deviation of the state's real GDP growth over the same period. Specifically, we define

$$s_t = \beta_1 + \beta_2 \tilde{f}_t, \tag{8}$$

where $\beta_1 = \hat{\mu} - \beta_2 \hat{\mu}_{\tilde{f}}$ and $\beta_2 = \frac{\hat{\sigma}}{\hat{\sigma}_{\tilde{f}}}$. Here, $\hat{\mu}$ and $\hat{\sigma}$ are the sample mean and standard deviation of the state's real GDP growth over 1964–2021, and $\hat{\mu}_{\tilde{f}}$ and $\hat{\sigma}_{\tilde{f}}$ are the corresponding moments of $\tilde{f}_t$ over the same period.[10]

3.4 Baseline Specification

Our baseline specification sets the factor lag order to $p = 2$ and imposes $q_i = 2$ for each idiosyncratic component. We use the same prior distributions across states and summarize the associated set of hyperparameters in Appendix A.3.

We use all indicators reported in Table 2, excluding those in the *Others* category and the series "number of bankruptcies terminated." For the *Business statistics* category, rather than using "number of business concerns", "number of business failures", and "liabilities of failed businesses" separately, we construct two indicators to better capture cyclical business distress: (i) the "failure rate", defined as the number of failed businesses in year t divided by the number of business concerns in year $t-1$, and (ii) the "severity of failure", defined as liabilities of failed businesses in year t divided by the number of failed businesses in year t. These transformations separate

[10] In the empirical application, we also consider alternative scaling choices, including (i) a regression-based method that uses the fitted values from a regression of state real GDP growth on $\tilde{f}_t$ over 1964–2021, and (ii) scaling based on U.S. real GDP growth over 1871–2021. These alternatives yield indices that are very similar to those from equation (8).

failure incidence from liabilities per failure, which help distinguish the extensive and intensive margins of business distress. In addition, for each state we drop an indicator if it is observed for fewer than about two-thirds of the sample (i.e., fewer than 100 years over the period 1871–2021). This coverage rule ensures that each retained indicator has enough historical overlap with the other baseline indicators within the state to inform the common factor. After these selections, the baseline indicator count ranges from 19 to 23 across states. We demean and standardize each indicator series to have unit variance prior to estimation, so differences in measurement units and scale do not influence the factor estimates.

Because several states are admitted to the Union after 1871, the estimation start year can differ across states. When pre-statehood series are available for the same geographic area and provide sufficient coverage (i.e., at least three indicator categories in Table 2), we begin estimation in the earliest such year.[11] Figure 3.1 compares the posterior median factor $\tilde{f}_t$ with annual real GDP growth (available from 1964) for selected states. We observe the two series comove closely in the post-1964 period. The same pattern holds across all states, as shown in Figure C.3. This observation suggests that our estimation framework generates factor estimates that are highly correlated with the widely-used economic indicator, and supports our scaling approach in equation (8) to construct an index that is comparable to GDP growth.

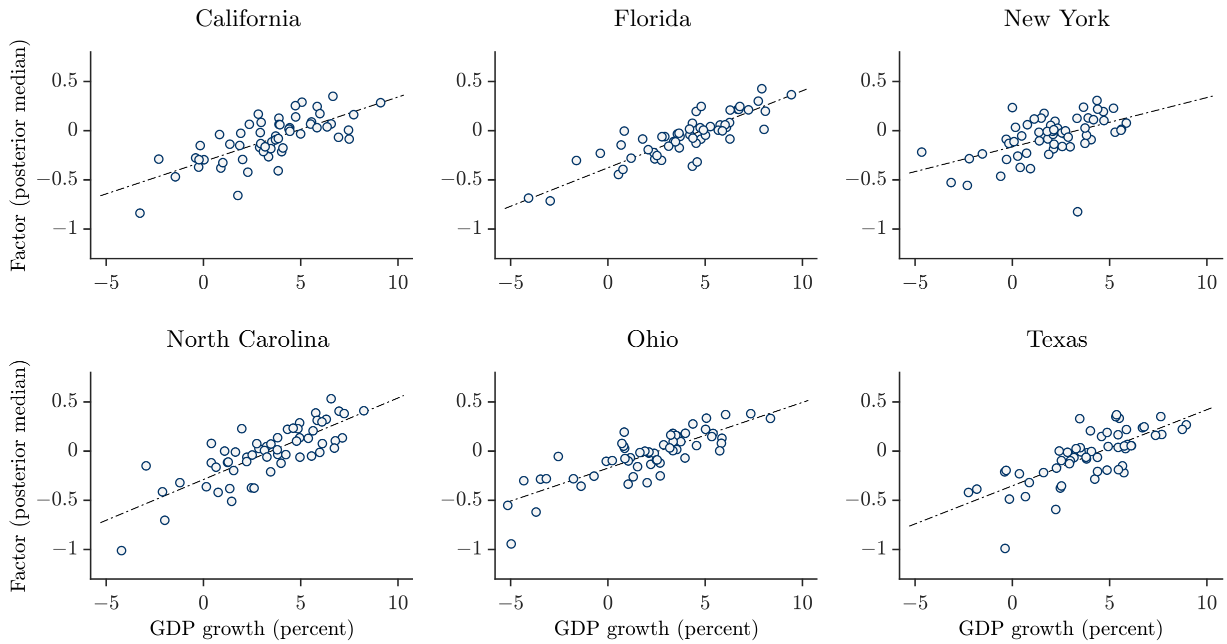
To further validate that our estimates capture state-level business cycles, we compare them with existing measures that are available for a shorter period of time in a binscatter plot Figure C.1. These data include: (i) state GDP from the BEA; (ii) the State Coincident Index from Philadelphia Fed;[12] (iii) the state-level unemployment rate from Fieldhouse et al. (2022); 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 C.1. Similarly, our index exhibits a strong positive correlation with established economic indicators, including personal income, State Coincident Indexes, and a negative correlation with the unemployment rate. This consistency supports the validity of our index in capturing economic fluctuations over an extended period.

To complement these state-level comparisons, we also assess how the same model framework performs when using aggregate data, given the availability of U.S. GDP estimates dating back

[11] For example, Washington is admitted to the Union in 1889, but we begin its estimation in 1873 using territorial series for the same geographical area.

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

Figure 3.1: Factor Estimates and GDP Growth



Notes: This figure documents the association between the posterior median of the common factor, $\tilde{f}_t$, and annual GDP growth for selected states from 1964 to 2021. State GDP data are from the Bureau of Economic Analysis.

to 1800s.[13] While our primary objective is to measure state-level business cycles, applying the same framework to the aggregate data could provide a useful benchmark for the model input and estimation procedure. Accordingly, we assemble national analogues of the main series used in the state-level estimation (see the data appendix for more details), and estimate the same dynamic factor model to obtain a nationwide economic activity index. Figure C.2 in the appendix shows that this national index comoves closely with U.S. real GDP growth over 1871–2021 (with $R^2 = 0.54$). This exercise provides additional validation that our model together with its specification choices extract sensible estimates of economic activities over a very long span of time.

3.5 Alternative Specifications

We assess robustness in five ways: (i) imposing AR(1) rather than AR(2) dynamics for the common factor and idiosyncratic components, (ii) modifying the prior calibration for the log-volatility innovation variances, (iii) expanding the baseline indicator set to include the U.S. real GDP growth, (iv) shutting down stochastic volatility, and (v) re-estimating the model using data from 1920 onward. The results for these alternative specifications are reported in Appendix C.3. Overall, these exer-

[13] We would like to thank Christiane Baumeister for this useful suggestion.

Table 3: 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

cises indicate that our baseline estimates are robust to a range of plausible modeling assumptions, indicator choices, and sample start years, while highlighting the practical value of incorporating stochastic volatility in a long historical sample.

3.6 Comparison with Existing Datasets

Table 3 summarizes how our state economic activity indices compare with existing state-level and U.S.-wide historical measures in terms of coverage and frequency. Relative to prior state-level series, our indices extend coverage by roughly a century, allowing analyses of long-run dynamics in state business cycle and growth. The underlying dataset also brings together a broader set of indicators than is typical in this literature. Taken together, our contribution is a longer and richer state-level panel of economic conditions than previously available.

Our data effort echoes studies that 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. Our contribution is complementary: we bring the long historical perspective to the state level by combining many regional indicators and extracting a common component of regional economic activity.

4 150 Years of State-Level Business Cycles

Our state-level economic activity index (SEAI) provides novel insights into business cycles from a regional and very long-run perspective. In this section, we offer a descriptive analysis of the evolution of state business cycles, and their relationship with the nationwide cycles.

4.1 Narrative Evidence

As shown in Table 3, our state-level annual economic activities index spans 150 years, much longer than the BEA's state-level GDP or other statewide indices estimated in existing literature. These extended series allow a unique quantitative insight into the economic history of U.S. states.

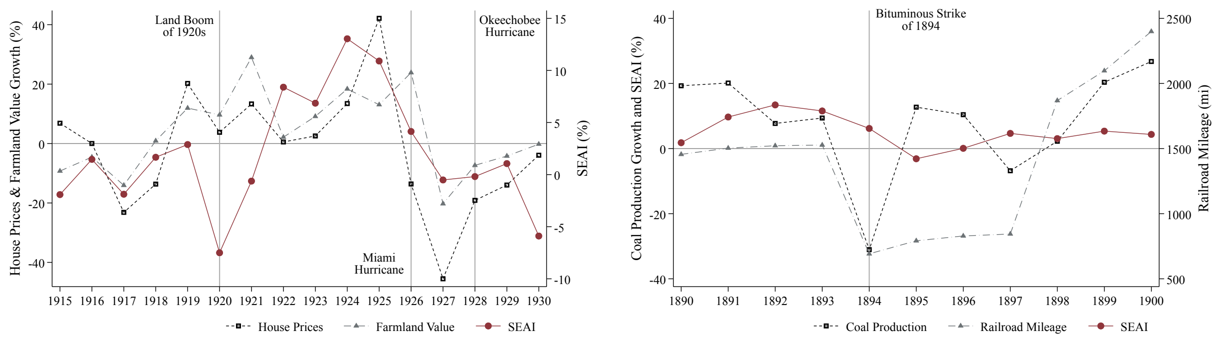
The dynamics of the estimated state-level economic activity index (SEAI) align with narrative evidence documented by historians. We provide two examples to illustrate this. First, Figure 4.1a traces Florida's experience during the "Florida Land Boom" of the 1920s. Consistent with narratives of a frenzy of land speculation in Florida, we observe sharply positive growth in both house prices and farmland values, with elevated growth rates persisting through the early to mid-1920s. These developments are mirrored in the estimated SEAI: growth turned positive in 1922, peaked at roughly 13%, and remained elevated through 1926. While signs of fragility emerged as early as 1925[14], the collapse of the real estate bubble is commonly dated to a series of hurricanes: the Miami hurricane of 1926, and subsequently, the Okeechobee Hurricane of 1928. These two disasters destroyed substantial real estate holdings and were followed by sharp declines in house prices and farmland values. Consistent with this narrative, the SEAI records negative growth in 1927 and 1928, a marked reversal from the boom years, plunging Florida into a deep depression years ahead of the rest of the nation.

Second, Figure 4.1b documents Oklahoma's experience during 1890–1900, a period preceding statehood. During this period, the land that would later become Oklahoma state was divided into Indian Territory and Oklahoma Territory. Voss (2013) describes a fragile equilibrium between Native Americans and "Euro-Americans", shaped in large part by the interplay of railroads and coal. This balance unraveled during the Bituminous Strike of 1894, when as many as $225,000$ miners walked out in response to a nationwide decline in coal prices, leading to the closure of all mines in Indian Territory. We detect the strike's economic footprint in Figure 4.1b, which documents

[14] For instance, *Forbes* cautioned that Florida land prices rested primarily on expectations of resale rather than underlying fundamentals. See floridahistory.com for additional background.

Figure 4.1: Narratives and the State Economic Activity Index

(a) Florida: 1915–1930 **(b)** Oklahoma: 1890–1900



Notes: In panel (a), we plot the growth rates of house prices and farmland value (on the left y-axis), against the estimated state economic activity index (on the right y-axis) for Florida, from 1915-1930. In panel (b), we plot the growth in the nominal value of coal produced and the estimated state economic activity index (on the left y-axis) as well as the railroad mileage (on the right y-axis) for Oklahoma, from 1890-1900.

pronounced declines in both coal output and railroad mileage. In the wake of the shutdowns, Native American coal leaseholders and operators appealed to the federal government for assistance. Voss (2013) contends that this episode was pivotal not only to the strike's resolution, but also as a major challenge to Native American economic authority, one that ultimately contributed to the dissolution of Indian Territory and the establishment of the state of Oklahoma in 1907. These historical accounts align closely with the movements in Oklahoma's SEAI, which fell in 1894–1895, coinciding with the Bituminous Strike, and then returned to positive territory from 1896 onward, reflecting the relatively rapid resolution of the conflict.

Taken together, this narrative evidence underscores the usefulness of the new dataset we construct. The case studies of Florida and Oklahoma highlight how the granular state-level time series can be used to track historical events using quantitative data, which will hopefully be useful for future work as well.

4.2 State-Level Business Cycles, 1871–2021

To provide a broader view of the economic fluctuations across states and time, Figure 4.2 plots the estimated state-level economic activity index in a heat plot. This 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 U.S. history. States reliant on manufacturing, such as Michigan, Pennsylvania, and Ohio, experienced deep contractions, while agricultural states like Oklahoma, Kansas, and Nebraska suffered likely due to the Dust Bowl. Thanks to the extensive coverage of our historical data, we also capture earlier recessions, including the Long Depression (1873–1896) and the Panic of 1893 that show significant declines in some states, and the 1920–21 Depression that was very severe across most states but short-lived. More recent recessions, such as the 2008 Great Recession, also display nationwide impacts, with financial hubs (e.g., New York) and real estate-heavy states (e.g., Florida, Arizona, and Nevada) suffering severe contractions. Periods of strong economic growth are also evident. The post-World War II boom from the 1950s to the 1960s saw widespread economic expansion. The 1990s also mark a period of significant economic expansion, largely due to the rise of the technology sector, especially benefiting states like California, Washington, and Massachusetts.

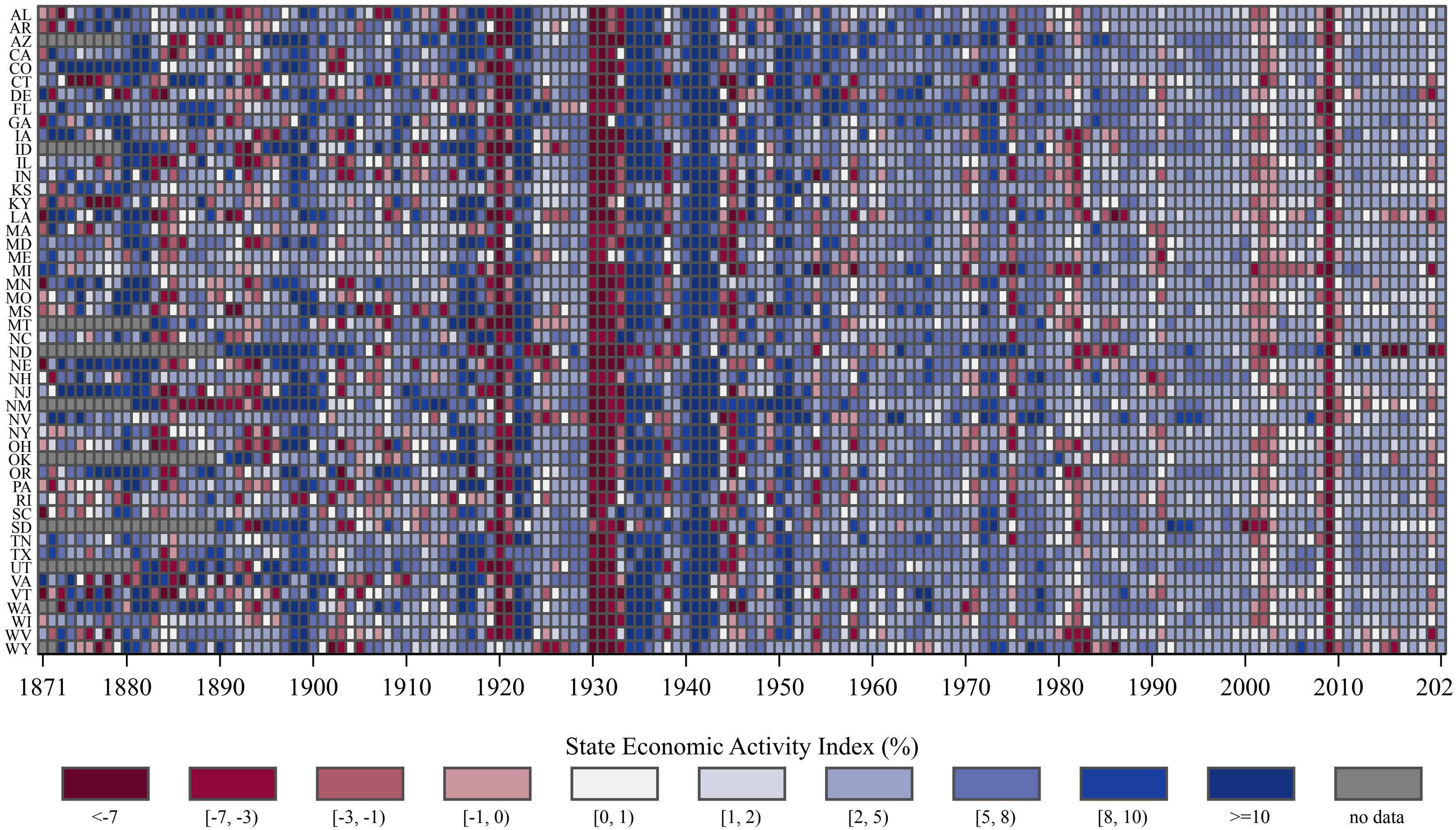
This plot suggests considerable regional heterogeneity of business cycles. First, some states experienced more frequent boom-bust cycles than others. For example, resource-dependent states have experienced persistent volatility: Texas, Oklahoma, and North Dakota enjoyed oil boom expansions in the 1970s–early 1980s, then suffered sharp contractions when oil prices collapsed in 1986. In contrast, states like California and New York demonstrate relatively consistent growth and more resilience due to their diversified economies. Second, in nationwide booms and busts, regional business cycles can exhibit dramatic difference in magnitudes. For instance, while the Great Depression was a nationwide event, the intensity and recovery paths varied, with the Midwest and Plains states hit hardest and longest. Similarly, in the post-WWII economic expansion, Sunbelt states such as California, Texas and Florida stand out with strong persistent growth, while northeastern states such as New York and Massachusetts record more modest expansions. Third, regional cycles need not coincide with nationwide fluctuations when regional shocks are pronounced enough. For instance, during the 1920s, many farm states were mired in low growth or decline even as the nation saw overall prosperity, owing to collapsing crop prices. Similarly, Midwest farm states faced a severe crisis in the 1980s, yet this agricultural recession did not coincide with any official nationwide downturn. Another case is North Dakota during the 2010s: the state enjoyed an oil fracking boom that insulated it from the 2007–09 recession, but later, when oil prices tumbled in 2015, North Dakota suffered a sharp contraction even as the national economy continued to grow.

In the postwar period, overall economic downturns became less frequent, and expansions longer, consistent with the observation made by Romer (1999), although, as discussed above, regional heterogeneity remains. This is potentially made possible by broader use of federal stabilization policies such as monetary policy and government stimulus, and better integration of regional economies via trade and migration. In the prewar era, recessions occurred often. Recessions, in particular those which coincided with US-wide recessions such as in 1919 and 1930, were often long and deep. By contrast, the postwar period is characterized by fewer recessions, alongside substantially longer expansions, including exceptionally long booms in the late 20th and early 21st centuries.

Figure 4.2 also shows broader and more simultaneous boom-bust episodes in the postwar era, contrasting sharply with the more fragmented and regionally uneven patterns observed before World War II. This suggests that regional business cycles have become increasingly synchronized, which we investigate in more detail next, potentially reflecting greater economic integration via either stronger presence of aggregate shocks or better risk sharing of idiosyncratic regional shocks.

Taken together, the heatmap of state-level economic activity from 1871 to 2021 offers rich insights into the uneven and evolving economic dynamics of U.S. states. It highlights enduring regional differences—some states being consistently more volatile or crisis-prone, others relatively stable or quick to rebound—as well as the convergence of business cycles in the modern era. Yet even in the integrated postwar economy, idiosyncratic, localized recessions have punctuated the landscape, a point we will return to later.

Figure 4.2: State Economic Activity Index



Notes: Each cell represents the estimated state-level economic activity index (in percentages). Gray cells indicate years for which the index is not estimated, often due to limited data availability before statehood.

4.3 Business Cycle Volatility

Romer (1986*a*,*b*,*c*, 1989, 1999) posits that the post-World War II era has not been dramatically more stable than pre-World War I, once measurement errors are properly accounted for, such that economic indicators like unemployment, GNP, industrial production, and commodity output are consistently measured. An investigation of the dynamics of our estimated state-level index echoes this point from a state-level perspective.

The first line in Table 4 presents the average volatility across states for two pre-World War II periods, following Romer (1999), and two periods after World War II. Due to the Great Depression, the 1920–1940 period saw substantial volatility. Between the three decades in the pre-World War I and post-World War II eras, average volatility declined but only modestly from 4.60% to 3.41%. As discussed in Section 3.1, our estimation framework allows for time-varying idiosyncratic volatility, which may be especially useful early in the sample when the data are likely noisier. Consistent with the argument in Romer's aforementioned works, once these measurement limitations are accounted for, average state-level economic volatility does not exhibit a significant fall in the immediate postwar period.

That said, the experiences of individual states differ. Table C.2 displays substantial variation in how volatility has changed over time for individual states. States such as Arizona and Illinois experienced substantially more stable economies in the postwar period, whereas in states such as Michigan and Nevada, economic volatility has in fact increased. One reason for such heterogeneous trends across states could be sector-specific shocks, such as the decline in the manufacturing sector and fluctuations in resource supplies and prices. Therefore, this result offers a more nuanced take on changes in business cycle volatility through regional data than aggregate data alone can provide. Our data also suggest a state-level "Great Moderation", a significant reduction in macroeconomic volatility commonly believed to have taken place since the 1980s. Most states did in fact experience less variance in economic activity since the 1980s. In this regard, we confirm the results in Owyang, Piger and Wall (2008), who document the Great Moderation at the state level around the same time.

In summary, our estimated historical state-level index of economic activity suggests no clear and systematic change in overall business cycles between the immediate pre- and post-World War II periods, but also confirms patterns consistent with a moderation post-1980. Most importantly, however, these dynamics vary widely across states.

Table 4: Volatility and Dispersion of State-Level Economic Activity Index

	Pre-WWII		Post-WWII	
	1886–1916	1920–1940	1948–1980	1981-2019
Avg. volatility across states (%)	4.60	8.06	3.41	2.79
	(1.64)	(2.22)	(0.88)	(0.78)
Avg. corr. with US GDP across states	0.30	0.78	0.67	0.65
	(0.17)	(0.09)	(0.21)	(0.17)
Avg. dispersion across time (%)	4.24	3.81	2.54	1.89
	(0.92)	(1.19)	(0.59)	(0.60)

Notes: This table summarizes the volatility and cross-sectional dispersion of the state economic activity index in the prewar and postwar eras. The choice of prewar window follows Romer (1999). In the first row, we compute volatility for each state as the within-period standard deviation of the index, and then report the cross-state mean. In parentheses, we report the cross-state standard deviation of these state-specific volatility estimates. In the second row, we measure co-movement with the national economy by calculating, for each state and within each subsample, the correlation between the SEAI and US real GDP growth, drawn from Williamson (2025). We report the cross-state average correlation, and the cross-state standard deviation in parentheses. Finally, we quantify cross-state dispersion by computing, for each year, the cross-sectional standard deviation of the state indices. The third row reports the time-series average of this annual dispersion measure over each subsample, with the standard deviation over time in parentheses.

4.4 Business Cycle Synchronization

Our dataset also allows us to trace the evolution of comovement in state business cycles over the past 150 years. The second row of Table 4 reports the average correlation between each state's economic activity index and U.S. real GDP growth. We find that this correlation is nearly twice as large in the post–World War II era as in the prewar period, with the exception of the period 1920–1940 that includes the Great Depression and onset of World War II. This pattern indicates substantially greater synchronization of local fluctuations, consistent with the evidence in Figure 4.2. Measures of cross-state dispersion, reported in the third row, lead to the same conclusion: the average dispersion in economic activity declines markedly from the prewar to the postwar subsample. In Appendix C.4, we complement Table 4 by plotting (i) the cross-state standard deviation of changes in economic activity and (ii) an alternative synchronization measure over time. These series similarly show substantially higher dispersion—and correspondingly lower synchronization—prior to World War II. From roughly 1945 onward, cross-state dispersion remains low, with notable reversals in the 1970s and in the years preceding the Great Recession.

Taken together, these results provide robust evidence that regional business cycles have become more synchronized in the postwar period. Several mechanisms could underlie this secular trend. Declining trade frictions and migration costs may have facilitated greater integration of goods and labor markets across regions, while more integrated financial markets may have strengthened cross-state risk sharing. In addition, early twentieth-century policy changes that deepened the fiscal union, including the introduction of the federal income tax, the New Deal, the expansion of federal spending, and the growth of interstate transfer programs, may have contributed to the pronounced increase in business cycle comovement. These developments likely enhanced automatic fiscal stabilizers, improved cross-state risk sharing, and reduced regional disparities (Liu, 2021).

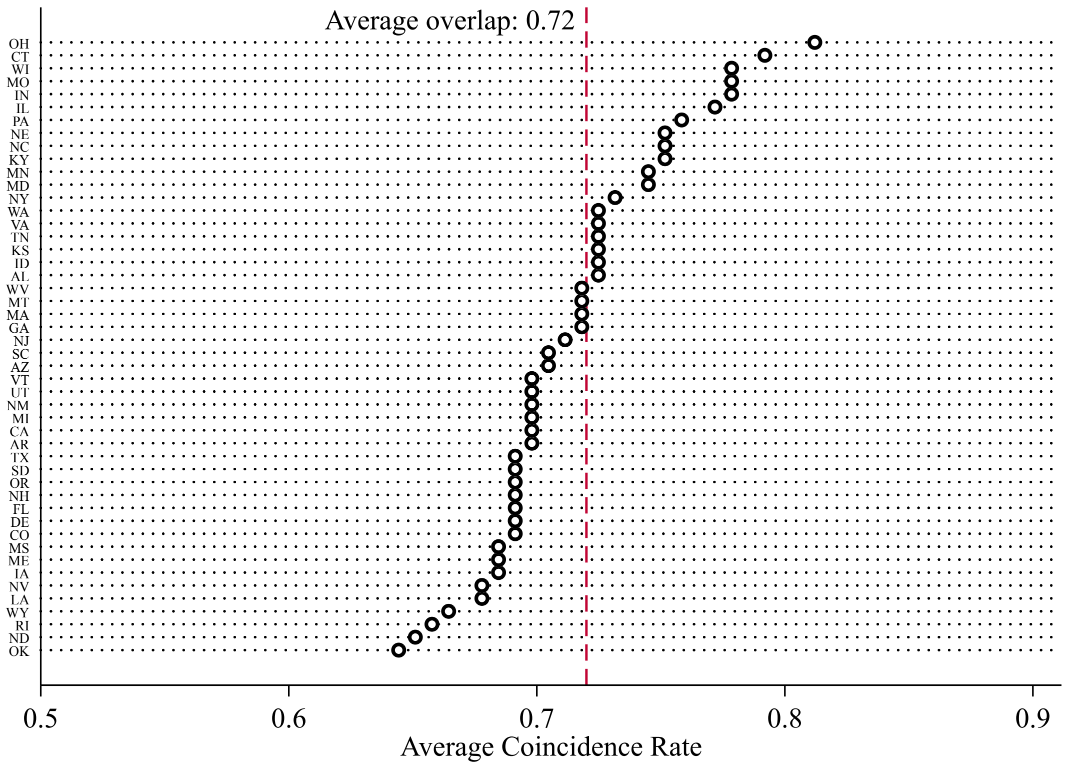
4.5 State vs. National Recessions

States can experience recessions well outside nationwide downturns. For example, our analysis has highlighted the experience of Florida's real estate crash that preceded the start of the Great Depression, usually dated as 1929. Equipped with our estimates of state-level economic activity, we can date state recessions similar to NBER's business cycle dating. As our analysis highlights, business cycles vary widely across states and may differ significantly 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), and later used widely for identifying recessions with historical data (e.g., Davis, 2006).

We use our state-level economic indices, in levels, and implement the Bry-Boschan 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.10 plots several examples of the identified peaks and troughs, for Ohio, Connecticut, North Dakota, and Oklahoma, against U.S.-wide recessions in the background.[15] In these case studies, state-level recessions tend to coincide with national recessions, but there are also exceptions. For example, Oklahoma experienced a recession in 1986 that did not coincide with the NBER dating. Put differently, local and U.S.-wide recessions are clearly correlated but distinct events. In total, we identify 1345 state recession years, out of which 871 years or 64.8% occur during NBER recessions. Even when state-level recessions do coincide, which appears more so during national downturns, their magnitudes can vary a lot. Figure C.9 plots the change in our

[15] We report Ohio and Connecticut as the two states with the highest and North Dakota and Oklahoma with the lowest coincidence rates with the U.S. business cycle in Figure 4.3.

Figure 4.3: Estimated Average Coincidence Rate by State



Notes: We define state-level recessions with the Bry and Boschan (1971) algorithm applied to our state economic activity index (rescaled to levels). We define national recessions using NBER business cycle dates.

economic activity index across states following three major nationwide recessions in 1874, 1930, and 2008. 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 gain insights into how closely each state's economy is aligned with the U.S. business cycle overall, 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 the recession dates from NBER. Figure 4.3 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 and Connecticut are closely aligned with the aggregate business cycle, but others such as Oklahoma and North Dakota are much less so.

Next, we document the characteristics of "nationwide" episodes, i.e. state recessions which coincide with US-wide recessions, against "idiosyncratic" episodes, or state recessions which occur outside of US-wide recessions. We first examine the relative length of state recessions in and outside of US-wide recessions by plotting histograms of peak-to-trough time in Figure C.11. We observe that "idiosyncratic" downturns are in general shorter compared to "nationwide" episodes: the former exhibits a higher fraction of recessions which last one year, and a lower fraction of recessions lasting two to four years. Second, we compare the amplitude of the two recession types, using two density plots of the cumulative loss of state recessions, for "idiosyncratic" episodes and for "nationwide" episodes. Figure C.12 shows that the density plot of "idiosyncratic" recessions has a fatter right tail (near 0), compared to the plot of "nationwide" recessions, which has more mass on the left. This difference suggests that "idiosyncratic" recessions are in general less severe compared with their "nationwide" counterparts.

In summary, our new chronology of state-level recession dates further highlights the local nature of business cycles. This binary indicator offers a parsimonious summary measure of local booms and busts. A caveat, however, is that although the Bry–Boschan algorithm is straightforward to implement and easy to interpret, it is not designed to identify real-time recession probabilities: identifying turning points requires information about subsequent observations. We leave the development and application of more sophisticated dating procedures, such as Markov regime-switching models (e.g., Morley and Piger, 2012), to future work.

4.6 Sentiments and Economic Activity

Having documented economic fluctuations across the 48 states and 150 years, we turn to investigating the relationship between state-level business cycles and economic sentiment across our long panel. To do so, we employ the news-based economic sentiment measure from Van Binsbergen et al. (2024), who construct state-level time series spanning from 1850-2019.[16] Van Binsbergen et al. (2024) show that national economic sentiments predict national economic activity from 1850–2017. They find a similarly positive relationship using state-level data, but their analysis is limited to recent years due to the availability of state GSP data from the BEA. As such, we view this as exactly the type of analysis that is enabled by our long-run dataset.

Specifically, we document that the state-level comovement of sentiments and economic activity persists through the nearly 150 years of our sample. In particular, we run a set of regressions of

[16] We thank the authors for kindly sharing the data with us in personal correspondence.

the following form:

$$Y_{s,t} = \alpha_s + \beta_1 \triangle \text{State Sent.}_{s,t} + \gamma_1 Y_{s,t-1} + \gamma_2 \triangle \text{US GDP}_{t-1} + \gamma_3 \triangle \text{Nat. Sent.}_{t-1} + \epsilon_{s,t} \tag{9}$$

where $Y_{s,t}$ refers to either state GSP in first differences or our SEAI, and $\triangle\text{Sentiment}_{s,t}$ refers to changes in state-level economic sentiments. We include state fixed effects (α_s) to account for time-invariant differences across states and, following Van Binsbergen et al. (2024), report results which additionally control for one lag of the dependent variable ($Y_{s,t-1}$), changes in national GDP ($\triangle\text{US GDP}_{t-1}$), and changes in national economic sentiment ($\triangle\text{US Sentiment}_{t-1}$).

Table 5 presents the results. Column 1 confirms the positive and significant relationship between changes in sentiments and changes in state GSP, for the modern period from 1978-2019, which echoes the result in Van Binsbergen et al. (2024). The coefficient of 0.501 indicates that a one standard deviation increase in sentiment predicts a 0.5% increase in state GSP growth in the same year. Similarly, column 2 shows that state-level sentiment is positively correlated with state GSP growth even after controlling for state GSP and national GDP growth, as well as changes in national sentiments.

In columns 3 and 4, we extend the sample back to 1871 and replace the dependent variable with our SEAI. We find that the coefficient on the contemporaneous changes in state-level sentiment remains both positive and significant: in column 3 it rises to 1.199, nearly double the corresponding estimate for the modern sample in column 1. In column 4, the relationship continues to be positive and significant, with a magnitude of 0.763, even after controlling for lags of the SEAI, national GDP growth and changes in national sentiments.

In sum, our findings are consistent with the view that sentiments play a role in state-level business cycles (see, e.g., Lagerborg, Pappa and Ravn, 2023), and that this relationship is evident not only in recent times but also throughout history. In fact, the data suggest a much stronger pattern statistically and economically in the longer-run sample, which highlights the benefits of having more statistical power.

Table 5: SEAI and State-Level Economic Sentiment, 1871–2019

Dependent var.:	$100 \times \Delta$ State $\text{GSP}_{s,t}$		$\text{SEAI}_{s,t}$	
	(1)	(2)	(3)	(4)
$\triangle\text{Sentiment}_{s,t}$	0.501***	0.367***	1.199***	0.763***
	(0.113)	(0.099)	(0.195)	(0.133)
$\triangle \ln(\text{State GSP}_{s,t-1})$		0.065		
		(0.097)		
$\triangle \ln(\text{National GDP}_{t-1})$		0.170		-0.022
		(0.111)		(0.016)
$\triangle\text{National Sentiment}_{t-1}$		0.835***		1.815***
		(0.095)		(0.072)
$\text{SEAI}_{s,t-1}$				0.464***
				(0.019)
Observations	1252	1252	6032	6032
State Fixed Effects	Yes	Yes	Yes	Yes

Notes: This table reports the results from a regression of the log change in real State Gross State Product per-capita (in columns 1-2) or the State Economic Activity Index per-capita (in columns 3-4) on the changes in State Economic Sentiments ($\triangle\text{Sentiment}_{s,t}$). For ease of comparison with real State GSP per-capita, we report the SEAI in per capita terms. To do so, we scale the SEAI to levels and divide by annual population figures for each state. Next, we take log-differences and multiply by 100. In columns 2 and 4, we include additional controls, the lagged log change in National GDP ($\triangle \ln(\text{National GDP}_{t-1})$), National Economic Sentiments ($\triangle\text{National Sentiment}_{t-1}$), and lagged measures of changes in State economic activity - namely, State GSP ($\triangle \ln(\text{State GSP}_{s,t-1})$) in column 2, and the SEAI ($\text{SEAI}_{s,t-1}$) in column 4. We include state fixed effects and report state-clustered standard errors throughout. ***, **, * denote significance at the 1%, 5%, and 10% levels. We find that the results are robust to controlling for the first lag of the change in sentiments ($\triangle\text{Sentiment}_{s,t-1}$). We source data on state-level Economic Sentiments and national-level Economic Sentiments from Van Binsbergen et al. (2024). The economic sentiment series have been standardized and residualized, as detailed in Van Binsbergen et al. (2024). The national-level sentiments data are originally reported at a quarterly frequency, and we aggregate to annual frequency by taking a simple sum over quarterly first differences. We report State GSP and National GDP in units of 2012 dollars, and source the data from the Bureau of Economic Activity and Williamson (2025) respectively. We adjust the GSP and GDP series using population figures from our dataset. For more details, please refer to the data appendix. In columns 1 and 2, we restrict the sample to 1978–2019 to parallel the sample used in Van Binsbergen et al. (2024), which sources state GSP data from SAGDP9 only. However, the results in column 1 and 2 are robust to using the full state GSP sample from 1963–2019. In columns 3 and 4, we include the full sample from 1871-2019.

5 Conclusion

We introduce a new historical state-level dataset for the United States, covering 62 variables from the Civil War to the present. These newly constructed time series, constructed across 135 unique sources through a large-scale digitization and harmonization effort, allow us to gauge changes in the spatial distribution of economic activity over the long run. 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 from a subset of indicators using a dynamic factor model that flexibly accommodates missing data and time-varying volatility. We show that the resulting index is a reliable measure of state-level economic conditions. Using this index, we document four new stylized facts about regional economic fluctuations. First, business cycles exhibit substantial heterogeneity across states. Second, the state-level business cycle volatility did not decline much between the period immediately before and after World War II, but has seen some reduction since the 1980s. Third, since the 1940s, there has been an increasing synchronization of U.S. state-level business cycles. Fourth, state-level downturns can at times diverge sharply from the national cycle: many state-level recessions do not coincide with U.S.-wide downturns, highlighting the considerable cross-state variation in the timing and severity of downturns underlying aggregate fluctuations.

Our results provide new evidence on the regional evolution of the U.S. economy prior to the availability of state GDP beginning in the 1960s. More broadly, we view this work as a foundation for further research on long-run growth and fluctuations from a regional and historical perspective, enabled by the new dataset and the state-level economic activity 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 Estimation Procedure

This section describes the estimation procedure for the dynamic factor model with stochastic volatility. Section A.1 sets out the state-space representation of the model. Section A.2 presents the Gibbs sampling algorithm, and Section A.3 summarizes the prior choices used in the baseline estimation.

A.1 State-Space Representation

For ease of reference, we restate the model here (dropping the state subscript s). The measurement equations are given by

$$y_{i,t} = \lambda_i f_t + u_{i,t}, \qquad i = 1, \ldots, N.$$

The common factor and idiosyncratic components follow autoregressive laws of motion,

$$f_t = \phi_1 f_{t-1} + \cdots + \phi_p f_{t-p} + \sigma_f e^{\zeta_{f,t}} v_t \qquad \text{and} \qquad u_{i,t} = \psi_{i,1} u_{i,t-1} + \cdots + \psi_{i,q_i} u_{i,t-q_i} + \sigma_i e^{\zeta_{i,t}} \epsilon_{i,t},$$

where $v_t \overset{iid}{\sim} \mathcal{N}(0,1)$ and $\epsilon_{i,t} \overset{iid}{\sim} \mathcal{N}(0,1)$, and we set $\sigma_f = 1$ for identification. The log-volatilities are modeled as driftless random walks,

$$\zeta_{j,t} = \zeta_{j,t-1} + \sigma_{\omega_j} \omega_{j,t}, \qquad j = f, 1, \ldots, N,$$

where $\omega_{j,t} \overset{iid}{\sim} \mathcal{N}(0,1)$ and $\zeta_{j,0} = 0$. Putting these equations in state-space form yields

$$\mathbf{y}_t = \mathbf{G}\boldsymbol{\alpha}_t, \tag{A.1}$$

$$\boldsymbol{\alpha}_t = \mathbf{H}\boldsymbol{\alpha}_{t-1} + \boldsymbol{\eta}_t, \qquad \boldsymbol{\eta}_t \sim \mathcal{N}(\mathbf{0}, \mathbf{Q}_t), \tag{A.2}$$

$$\boldsymbol{\zeta}_t = \boldsymbol{\zeta}_{t-1} + \boldsymbol{\omega}_t, \qquad \boldsymbol{\omega}_t \sim \mathcal{N}(\mathbf{0}, \mathbf{R}), \tag{A.3}$$

where $\mathbf{y}_t = (y_{1,t}, \ldots, y_{N,t})'$ collects the growth rates of the N indicators, and the state vector is

$$\boldsymbol{\alpha}_t = (f_t, \ldots, f_{t-p+1}, u_{1,t}, \ldots, u_{1,t-q_1+1}, \ldots, u_{N,t}, \ldots, u_{N,t-q_N+1})'.$$

The matrix $\mathbf{G}$ maps the common factor and the contemporaneous idiosyncratic components to $\mathbf{y}_t$: its first column contains the factor loadings $\boldsymbol{\lambda} = (\lambda_1, \ldots, \lambda_N)'$, and the remaining columns select $(u_{1,t}, \ldots, u_{N,t})'$ from $\boldsymbol{\alpha}_t$. The matrix $\mathbf{H}$ is block-diagonal, with blocks collecting the autoregressive coefficients for f_t and $u_{i,t}$ in companion form. Specifically,

$$\mathbf{H} = \operatorname{diag}\big(\mathbf{H}_f, \mathbf{H}_{u,1}, \ldots, \mathbf{H}_{u,N}\big),$$

where

$$\mathbf{H}_f = \begin{bmatrix} \phi_1 & \phi_2 & \cdots & \phi_{p-1} & \phi_p \\ 1 & 0 & \cdots & 0 & 0 \\ 0 & 1 & \cdots & 0 & 0 \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ 0 & 0 & \cdots & 1 & 0 \end{bmatrix} \quad \text{and} \quad \mathbf{H}_{u,i} = \begin{bmatrix} \psi_{i,1} & \psi_{i,2} & \cdots & \psi_{i,q_i-1} & \psi_{i,q_i} \\ 1 & 0 & \cdots & 0 & 0 \\ 0 & 1 & \cdots & 0 & 0 \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ 0 & 0 & \cdots & 1 & 0 \end{bmatrix},$$

for $i = 1, \ldots, N$. The covariance matrix $\mathbf{Q}_t$ is diagonal, with entry $e^{2\zeta_{f,t}}$ in the position associated with f_t and entries $\sigma_i^2 e^{2\zeta_{i,t}}$ in the positions associated with $u_{i,t}$ for $i = 1, \ldots, N$. All other diagonal entries (corresponding to lagged states) are set to zero. Finally, equation (A.3) governs the evolution of volatility vector $\boldsymbol{\zeta}_t = (\zeta_{f,t}, \zeta_{1,t}, \ldots, \zeta_{N,t})'$, with $\mathbf{R} = \operatorname{diag}(\sigma^2_{\omega_f}, \sigma^2_{\omega_1}, \ldots, \sigma^2_{\omega_N})$.

A.2 Details on the Gibbs Sampler

We estimate the model in (A.1)–(A.3) using a Markov Chain Monte Carlo (MCMC) Gibbs sampling algorithm, in which conditional draws of the latent state vector, model parameters, and stochastic volatilities are obtained sequentially at each iteration. The collection of draws across a large number of iterations provides an approximation to the posterior distribution of each unknown in the model, from which point estimates and credible intervals for the latent variables and model parameters are readily obtained. The algorithm proceeds in six blocks, as described below.

Block 1: Draw state sequence $\{\boldsymbol{\alpha}_t\}_{t=1}^T$. Conditional on matrices $\mathbf{G}$ and $\mathbf{H}$ and the sequence $\{\mathbf{Q}_t\}_{t=1}^T$, the state-space system in (A.1)–(A.2) is linear Gaussian. We therefore draw $\{\boldsymbol{\alpha}_t\}_{t=1}^T$ using the forward-filtering backward-sampling (FFBS) algorithm of Carter and Kohn (1994) and initialize the Kalman filter with $\boldsymbol{\alpha}_0 \sim \mathcal{N}(\mathbf{0}, \mathbf{I})$. At each t, we handle missing observations by restricting the Kalman filter and backward-sampling step to the observed components of $\mathbf{y}_t$; that is, by dropping missing entries of $\mathbf{y}_t$ and the corresponding rows of $\mathbf{G}$.

Block 2: Draw AR coefficients of the common factor. Conditional on $\{f_t\}_{t=1}^T$ and $\{\zeta_{f,t}\}_{t=1}^T$, the factor law of motion can be rewritten as a linear regression with homoskedastic innovations:

$$y_t^f = (x_t^f)'\boldsymbol{\Phi} + \sigma_f v_t, \qquad v_t \overset{iid}{\sim} \mathcal{N}(0,1), \qquad t = p+1, \ldots, T,$$

where $\boldsymbol{\Phi} = (\phi_1, \ldots, \phi_p)'$, $y_t^f = e^{-\zeta_{f,t}} f_t$, and $x_t^f = e^{-\zeta_{f,t}}(f_{t-1}, \ldots, f_{t-p})'$. Setting $\sigma_f = 1$ and stacking over $t = p+1, \ldots, T$ yields $\mathbf{y}^f = \mathbf{X}^f\boldsymbol{\Phi} + \mathbf{v}$, where $\mathbf{v} \sim \mathcal{N}(\mathbf{0}, \mathbf{I}_{T-p})$. Here, $\mathbf{y}^f = (y_{p+1}^f, \ldots, y_T^f)'$ and $\mathbf{X}^f$ collects $(x_t^f)'$ as rows. Under the Normal prior $\boldsymbol{\Phi} \sim \mathcal{N}(\mathbf{m}_{f,0}, \mathbf{V}_{f,0})$, the conditional posterior is also Normal:

$$\boldsymbol{\Phi} \mid \mathbf{y}^f, \mathbf{X}^f \sim \mathcal{N}(\mathbf{m}_{f,1}, \mathbf{V}_{f,1}),$$

where $\mathbf{V}_{f,1} = \big(\mathbf{V}_{f,0}^{-1} + (\mathbf{X}^f)'\mathbf{X}^f\big)^{-1}$ and $\mathbf{m}_{f,1} = \mathbf{V}_{f,1}\big(\mathbf{V}_{f,0}^{-1}\mathbf{m}_{f,0} + (\mathbf{X}^f)'\mathbf{y}^f\big)$. We sample $\boldsymbol{\Phi}$ from this posterior and reject draws that imply a nonstationary AR(p) process.

Block 3: Draw idiosyncratic AR coefficients and innovation scale parameters. Fix an indicator i and let $\boldsymbol{\Psi}_i = (\psi_{i,1}, \ldots, \psi_{i,q_i})'$. Conditional on $\{u_{i,t}\}_{t=1}^T$ and $\{\zeta_{i,t}\}_{t=1}^T$, the idiosyncratic law of motion can be written as

$$y_t^{u_i} = (x_t^{u_i})'\boldsymbol{\Psi}_i + \sigma_i \epsilon_{i,t}, \qquad \epsilon_{i,t} \overset{iid}{\sim} \mathcal{N}(0,1), \qquad t = q_i+1, \ldots, T,$$

where $y_t^{u_i} = e^{-\zeta_{i,t}} u_{i,t}$ and $x_t^{u_i} = e^{-\zeta_{i,t}}(u_{i,t-1}, \ldots, u_{i,t-q_i})'$. Stacking over $t = q_i+1, \ldots, T$ yields the regression $\mathbf{y}^{u_i} = \mathbf{X}^{u_i}\boldsymbol{\Psi}_i + \sigma_i\boldsymbol{\epsilon}_i$, with $\boldsymbol{\epsilon}_i \sim \mathcal{N}(\mathbf{0}, \mathbf{I}_{T-q_i})$, where $\mathbf{y}^{u_i} = (y_{q_i+1}^{u_i}, \ldots, y_T^{u_i})'$ and $\mathbf{X}^{u_i}$ stacks $(x_t^{u_i})'$ row-by-row.

Draw $\boldsymbol{\Psi}_i$. Given σ_i^2 and under the prior $\boldsymbol{\Psi}_i \sim \mathcal{N}(\mathbf{m}_{\psi,i,0}, \mathbf{V}_{\psi,i,0})$, the conditional posterior is

$$\boldsymbol{\Psi}_i \mid \mathbf{y}^{u_i}, \mathbf{X}^{u_i}, \sigma_i^2 \sim \mathcal{N}(\mathbf{m}_{\psi,i,1}, \mathbf{V}_{\psi,i,1}),$$

where $\mathbf{V}_{\psi,i,1} = \big(\mathbf{V}_{\psi,i,0}^{-1} + \sigma_i^{-2}(\mathbf{X}^{u_i})'\mathbf{X}^{u_i}\big)^{-1}$ and $\mathbf{m}_{\psi,i,1} = \mathbf{V}_{\psi,i,1}\big(\mathbf{V}_{\psi,i,0}^{-1}\mathbf{m}_{\psi,i,0} + \sigma_i^{-2}(\mathbf{X}^{u_i})'\mathbf{y}^{u_i}\big)$. Similar to Block 2, we reject draws that imply a nonstationary AR(q_i).

Draw σ_i^2. Let $\mathbf{r}_i = \mathbf{y}^{u_i} - \mathbf{X}^{u_i}\boldsymbol{\Psi}_i$ denote the stacked residuals. Under the conjugate inverse-gamma prior $\sigma_i^2 \sim \mathcal{IG}(a_{i,0}, b_{i,0})$, the conditional posterior is also inverse-gamma:

$$\sigma_i^2 \mid \mathbf{r}_i \sim \mathcal{IG}\left(a_{i,0} + \frac{n_i}{2},\, b_{i,0} + \frac{\mathbf{r}_i'\mathbf{r}_i}{2}\right).$$

where $n_i = T - q_i$.

Block 4: Draw factor loadings. Conditional on $\{f_t\}_{t=1}^T$, the measurement equations imply N separate regressions for the loadings, with innovations that are serially correlated and heteroskedastic. For each indicator i, let $\Psi_i(L) = 1 - \psi_{i,1}L - \ldots - \psi_{i,q_i}L^{q_i}$ denote the lag polynomial. Filtering the ith measurement equation by $e^{-\zeta_{i,t}}\Psi_i(L)$ yields

$$\hat{y}_{i,t} = \lambda_i \hat{x}_{i,t} + \sigma_i \epsilon_{i,t}, \qquad \epsilon_{i,t} \overset{iid}{\sim} \mathcal{N}(0,1), \qquad t = q_i + 1, \ldots, T,$$

where $\hat{y}_{i,t} = e^{-\zeta_{i,t}}\Psi_i(L)y_{i,t}$ and $\hat{x}_{i,t} = e^{-\zeta_{i,t}}\Psi_i(L)f_t$. Thus, conditional on $\{\zeta_{i,t}\}_{t=1}^T$, $\boldsymbol{\Psi}_i$, and σ_i^2, the regression above has homoskedastic innovations. Stacking over $t = q_i + 1, \ldots, T$ gives

$$\hat{\mathbf{y}}_i = \lambda_i \hat{\mathbf{x}}_i + \sigma_i \boldsymbol{\epsilon}_i, \qquad \boldsymbol{\epsilon}_i \sim \mathcal{N}(\mathbf{0}, \mathbf{I}_{T-q_i}),$$

where $\hat{\mathbf{y}}_i = (\hat{y}_{i,q_i+1}, \ldots, \hat{y}_{i,T})'$ and $\hat{\mathbf{x}}_i = (\hat{x}_{i,q_i+1}, \ldots, \hat{x}_{i,T})'$. Next, we drop rows of $(\hat{\mathbf{y}}_i, \hat{\mathbf{x}}_i)$ for which $\hat{y}_{i,t}$ is undefined due to missing $y_{i,t}$ (or lagged values needed to form $\Psi_i(L)y_{i,t}$). Let $\hat{n}_i$ denote the number of remaining observations; the stacked innovation vector $\boldsymbol{\epsilon}_i$ therefore has length $\hat{n}_i \leq T - q_i$. Under the Normal prior $\lambda_i \sim \mathcal{N}(m_{\lambda,i,0}, v_{\lambda,i,0})$, the conditional posterior is

$$\lambda_i \mid \hat{\mathbf{y}}_i, \hat{\mathbf{x}}_i, \sigma_i^2 \sim \mathcal{N}(m_{\lambda,i,1}, v_{\lambda,i,1}),$$

where $v_{\lambda,i,1} = \left(v_{\lambda,i,0}^{-1} + \sigma_i^{-2}\hat{\mathbf{x}}_i'\hat{\mathbf{x}}_i\right)^{-1}$ and $m_{\lambda,i,1} = v_{\lambda,i,1}\left(v_{\lambda,i,0}^{-1}m_{\lambda,i,0} + \sigma_i^{-2}\hat{\mathbf{x}}_i'\hat{\mathbf{y}}_i\right)$. We fix the sign of the factor by requiring the reference loading to be positive; that is, by rejecting draws with $\lambda_{\text{ref}} \leq 0$.[17]

Block 5: Draw log-volatilities $\{\boldsymbol{\zeta}_t\}_{t=1}^T$. For each $j \in \{f, 1, \ldots, N\}$, we draw $\{\zeta_{j,t}\}_{t=1}^T$ following the algorithm of Kim, Shephard and Chib (1998). Define

$$r_{j,t} = \begin{cases} f_t - \sum_{\ell=1}^p \phi_\ell f_{t-\ell}, & j = f, \\ u_{j,t} - \sum_{\ell=1}^{q_j} \psi_{j,\ell} u_{j,t-\ell}, & j \in \{1, \ldots, N\}, \end{cases} \qquad t = \ell_j + 1, \ldots, T,$$

[17] In the empirical application, we use personal income as the reference indicator for each U.S. state.

where $\ell_f = p$ and $\ell_j = q_j$ for $j \in \{1, \dots, N\}$. Note that $r_{j,t} = \sigma_j e^{\zeta_{j,t}} \varepsilon_{j,t}$, with $\varepsilon_{f,t} = v_t$ and $\varepsilon_{j,t} = \epsilon_{j,t}$ for $j \in \{1, \dots, N\}$, thus $\varepsilon_{j,t} \overset{iid}{\sim} \mathcal{N}(0,1)$. Squaring and taking logs yields the measurement equation:

$$z_{j,t} \equiv \log(r_{j,t}^2) - \log(\sigma_j^2) = 2\zeta_{j,t} + \log(\varepsilon_{j,t}^2), \qquad t = \ell_j + 1, \dots, T,$$

where $z_{j,t}$ is missing for $t \le \ell_j$.[18]

Step 1: Draw mixture indicators. We approximate the distribution of $\log(\varepsilon_{j,t}^2)$ by a ten-component Normal mixture following Omori et al. (2007):

$$\log(\varepsilon_{j,t}^2) \mid (s_{j,t} = k) \sim \mathcal{N}(m_k, v_k), \qquad \Pr(s_{j,t} = k) = p_k, \qquad k = 1, \dots, 10.$$

Given current $\zeta_{j,t}$, the mixture indicator $s_{j,t}$ is drawn independently over t with probabilities

$$\Pr(s_{j,t} = k \mid z_{j,t}, \zeta_{j,t}) \propto p_k \, v_k^{-1/2} \exp\left\{ -\frac{(z_{j,t} - 2\zeta_{j,t} - m_k)^2}{2v_k} \right\},$$

whenever $z_{j,t}$ is observed.

Step 2: Draw $\{\zeta_{j,t}\}_{t=1}^T$.[19] Conditional on $\{s_{j,t}\}_{t=1}^T$, the measurement equation can be written as

$$\tilde{y}_{j,t} \equiv z_{j,t} - m_{s_{j,t}} = 2\zeta_{j,t} + \eta_{j,t}, \qquad \eta_{j,t} \sim \mathcal{N}(0, v_{s_{j,t}}),$$

for those t with observed $z_{j,t}$. The state equation is

$$\zeta_{j,t} = \zeta_{j,t-1} + \omega_{j,t}, \qquad \omega_{j,t} \sim \mathcal{N}(0, \sigma_{\omega_j}^2),$$

with $\zeta_{j,0} = 0$. Hence, conditional on $\{s_{j,t}\}_{t=1}^T$, $\{z_{j,t}\}_{t=1}^T$, and $\sigma_{\omega_j}^2$, we draw $\{\zeta_{j,t}\}_{t=1}^T$ using the FFBS algorithm of Carter and Kohn (1994) as in Block 1, and we skip the measurement update whenever $z_{j,t}$ is missing.

Block 6: Draw log-volatility innovation variances. For each $j \in \{f, 1, \dots, N\}$, the random-walk law of motion implies increments $\Delta\zeta_{j,t} \equiv \zeta_{j,t} - \zeta_{j,t-1}$ with $\zeta_{j,0} = 0$. Under the inverse-gamma prior $\sigma_{\omega_j}^2 \sim \mathcal{IG}(a_{\omega,j,0}, b_{\omega,j,0})$, the conditional posterior is

$$\sigma_{\omega_j}^2 \mid \{\Delta\zeta_{j,t}\}_{t=1}^T \sim \mathcal{IG}\left(a_{\omega,j,0} + \frac{\tilde{n}_j}{2}, b_{\omega,j,0} + \frac{1}{2}\sum_{t=1}^{\tilde{n}_j} (\Delta\zeta_{j,t})^2 \right),$$

where $\tilde{n}_j = T$.

[18] In the numerical implementation, we follow Kim, Shephard and Chib (1998) and define $z_{j,t} \approx \log(r_{j,t}^2 + 0.001) - \log(\sigma_j^2)$ to avoid numerical issues when $r_{j,t}^2$ is near zero.

[19] We draw the mixture indicators before the log-volatilities, following the ordering in Del Negro and Primiceri (2015).

MCMC implementation. We run the Gibbs sampler for 7,000 iterations. We discard the first 2,000 iterations and use the remaining 5,000 draws for posterior inference. The sampler is initialized with $\zeta_{j,t} = 0$ for all t and j, which corresponds to constant volatility (i.e., $e^{\zeta_{j,t}} = 1$) at the starting point. The other free parameters are initialized at their prior means. As a robustness check, we re-ran the sampler with all free parameters initialized at 0.001. Posterior summaries are essentially unchanged.

A.3 Baseline Priors

This section describes the prior distributions used in the baseline estimation. To calibrate the prior hyperparameters, we first construct a proxy $\hat{f}_t$ for the common factor by taking the cross-sectional average of standardized growth rates $\{y_{i,t}\}_{i=1}^N$ available in year t. We then use the proxy to compute OLS estimates, which we rely on to inform the location and scale parameters of the baseline priors.

For each $i \in \{1, \ldots, N\}$, we obtain the OLS estimate $\hat{\lambda}_{i,\mathrm{OLS}}$ from the regression $y_{i,t} = \lambda_i \hat{f}_t + e_{i,t}$ using the available observations. Let T_i denote the number of observations used in this regression and define

$$\hat{s}^2_{\lambda,i} = \frac{1}{T_i - 1} \sum_t \left(y_{i,t} - \hat{\lambda}_{i,\mathrm{OLS}} \hat{f}_t \right)^2, \qquad \widehat{\mathrm{Var}}(\hat{\lambda}_{i,\mathrm{OLS}}) = \frac{\hat{s}^2_{\lambda,i}}{\sum_t \hat{f}_t^2},$$

where both summations are taken over the same regression sample. We construct idiosyncratic residuals as $\hat{u}_{i,t} = y_{i,t} - \hat{\lambda}_{i,\mathrm{OLS}} \hat{f}_t$ whenever $y_{i,t}$ is observed. Next, we estimate $\mathbf{\Phi}_{\mathrm{OLS}}$ from an AR(p) regression of $\hat{f}_t$ on the first p lags, and estimate $\mathbf{\Psi}_{i,\mathrm{OLS}}$ from an AR(q_i) regression of $\hat{u}_{i,t}$ on the first q_i lags. Let $\widehat{\mathbf{X}}^f$ denote the $(T-p) \times p$ matrix whose t-th row collects $(\hat{f}_{t-1}, \ldots, \hat{f}_{t-p})$, and let $\widehat{\mathbf{X}}^f_t$ be that row. Then

$$\hat{s}^2_f = \frac{1}{(T-p) - p} \sum_{t=p+1}^{T} \left(\hat{f}_t - \widehat{\mathbf{X}}^f_t \mathbf{\Phi}_{\mathrm{OLS}} \right)^2$$

denotes the associated OLS residual variance. Similarly, let $\widehat{\mathbf{X}}^{u_i}_t$ denote the row vector that collects the q_i lags of $\hat{u}_{i,t}$, and then

$$\hat{s}^2_{u,i} = \frac{1}{|\mathcal{T}_{u,i}| - q_i} \sum_{t \in \mathcal{T}_{u,i}} \left(\hat{u}_{i,t} - \widehat{\mathbf{X}}^{u_i}_t \mathbf{\Psi}_{i,\mathrm{OLS}} \right)^2,$$

where $\mathcal{T}_{u,i}$ collects those $t > q_i$ for which $\hat{u}_{i,t}$ and all required lags are observed.

Factor loadings. For each $i \in \{1, \ldots, N\}$, we specify a Normal prior

$$\lambda_i \sim \mathcal{N}(m_{\lambda,i,0}, v_{\lambda,i,0}), \quad m_{\lambda,i,0} = \hat{\lambda}_{i,\mathrm{OLS}}, \quad v_{\lambda,i,0} = 2\widehat{\mathrm{Var}}(\hat{\lambda}_{i,\mathrm{OLS}}).$$

This prior centers λ_i at the OLS estimate and inflates its variance to avoid overconfidence. Consistent with the sign normalization in the Gibbs sampler, we verify that $\hat{\lambda}_{\text{ref,OLS}} > 0$ for all states.

Autoregressive coefficients. We set Normal priors for the AR coefficients of the common factor,

$$\mathbf{\Phi} \sim \mathcal{N}(\mathbf{m}_{f,0}, \mathbf{V}_{f,0}), \quad \mathbf{m}_{f,0} = \mathbf{\Phi}_{\text{OLS}}, \quad \mathbf{V}_{f,0} = 2\hat{s}_f^2 \Big((\widehat{\mathbf{X}}^f)' \widehat{\mathbf{X}}^f \Big)^{-1},$$

and for each idiosyncratic component,

$$\mathbf{\Psi}_i \sim \mathcal{N}(\mathbf{m}_{\psi,i,0}, \mathbf{V}_{\psi,i,0}), \quad \mathbf{m}_{\psi,i,0} = \mathbf{\Psi}_{i,\text{OLS}}, \quad \mathbf{V}_{\psi,i,0} = 2\hat{s}_{u,i}^2 \Big((\widehat{\mathbf{X}}^{u_i})' \widehat{\mathbf{X}}^{u_i} \Big)^{-1}.$$

Here $\hat{s}_f^2$ and $\hat{s}_{u,i}^2$ are the OLS residual variances from the AR regressions defined above.

Idiosyncratic innovation scale parameters. For each $i \in \{1, \ldots, N\}$, we specify the inverse-gamma prior

$$\sigma_i^2 \sim \mathcal{IG}(a_{i,0}, b_{i,0}), \quad a_{i,0} = 10, \quad b_{i,0} = (a_{i,0} - 1)\hat{s}_{u,i}^2.$$

This choice implies $E(\sigma_i^2) = \hat{s}_{u,i}^2$.

Log-volatility innovation variances. For each $j \in \{f, 1, \ldots, N\}$, we set the prior

$$\sigma_{\omega_j}^2 \sim \mathcal{IG}(a_{\omega,j,0}, b_{\omega,j,0}), \quad a_{\omega,j,0} = \frac{T}{100}, \quad b_{\omega,j,0} = 10^{-4}.$$

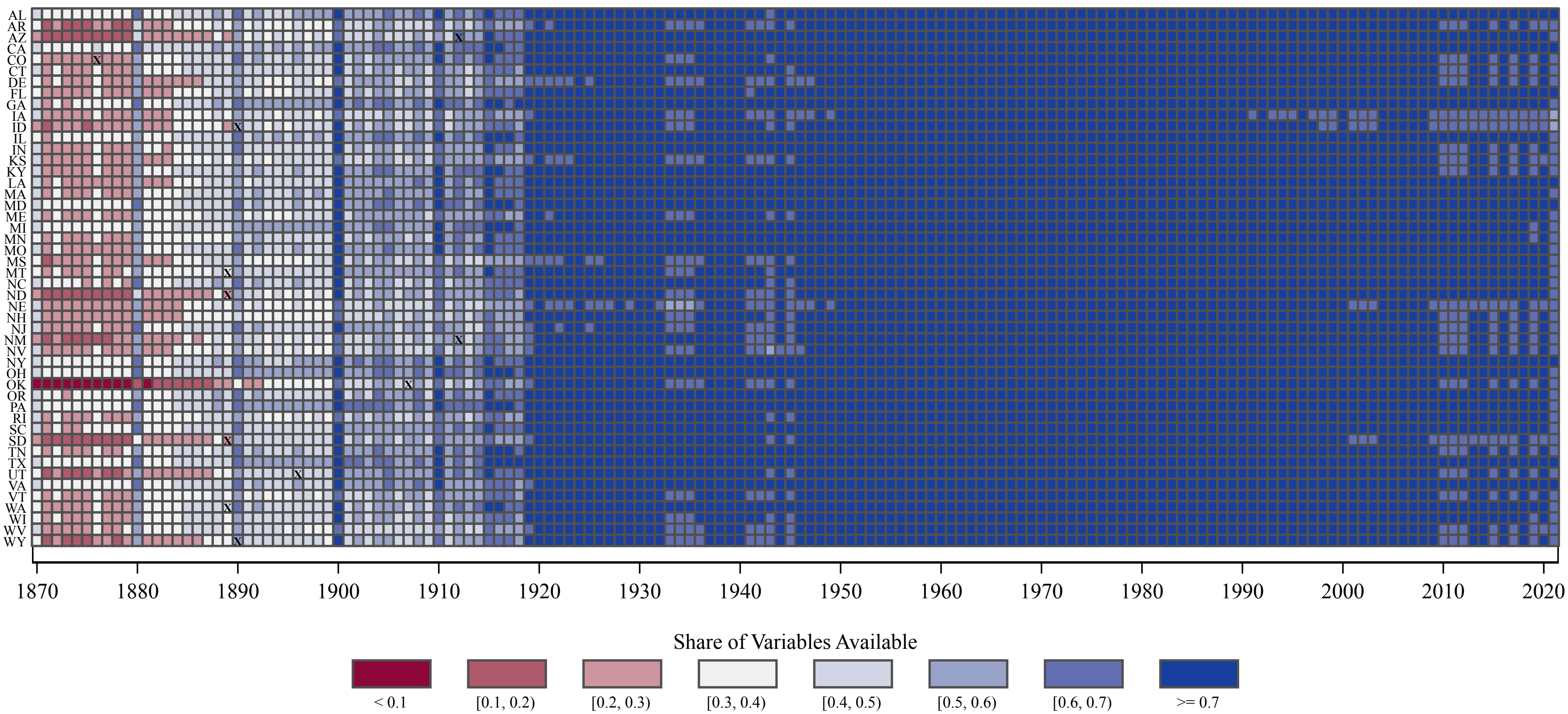
This choice is intentionally conservative: it shrinks $\sigma_{\omega_j}^2$ toward small values and therefore favors slowly evolving log-volatilities, while remaining sufficiently loose for the data to support meaningful time variation when warranted.[20]

B Details on the Dataset

Figure B.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 Hoon et al. (2025).

[20] Since $a_{\omega,j,0} = T/100$, the posterior shape parameter is $a_{\omega,j,0} + T/2$, so the prior contributes $T/100$ versus $T/2$ from the likelihood. This implies a prior-to-data weight of 1-to-50 in the posterior shape. For related discussion of conservative priors in long-sample settings, see, for example, Antolin-Diaz, Drechsel and Petrella (2017, App. F).

Figure B.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. For the purposes of this plot, we exclude the subcomponents of agriculture as their availability is closely linked to the select states which produce the particular major crop or livestock.

C Additional Figures and Tables

C.1 Descriptive Statistics

Table C.1: Descriptive Statistics of the Economic Activity Index (1871–2021)

State	**Average**	**Std. Dev.**	**25th Perc.**	**Median**	**75th Perc.**
Alabama	3.66	6.31	0.63	3.05	6.64
Arizona	5.37	7.20	2.68	5.10	8.47
Arkansas	3.52	6.07	0.87	3.00	5.78
California	4.63	4.76	2.08	4.35	7.20
Colorado	4.84	5.28	2.36	4.65	7.39
Connecticut	3.15	6.36	0.12	3.17	6.79
Delaware	3.32	6.97	−0.45	3.47	6.52
Florida	4.91	4.31	2.31	4.82	7.21
Georgia	4.64	5.12	2.29	4.83	7.66
Idaho	4.38	7.79	1.59	4.48	7.62
Illinois	2.59	5.06	0.34	2.71	4.89
Indiana	3.28	5.92	−0.09	3.43	6.61
Iowa	3.28	5.15	0.36	3.51	6.10
Kansas	3.20	4.55	1.44	2.67	4.22
Kentucky	2.87	4.81	0.56	2.81	5.03
Louisiana	3.37	8.14	−0.62	3.07	7.30
Maine	2.79	3.67	1.04	2.77	4.78
Maryland	4.27	5.69	1.45	4.02	6.27
Massachusetts	3.01	3.73	0.90	3.06	4.99
Michigan	2.84	6.32	−0.27	3.00	5.37
Minnesota	3.66	4.69	1.35	3.72	5.94
Mississippi	3.00	6.86	0.33	2.93	6.27
Missouri	3.19	4.75	0.58	2.80	5.44
Montana	2.50	6.30	0.15	2.80	5.18
Nebraska	3.25	6.96	0.06	2.79	5.70
Nevada	3.98	5.46	0.95	3.61	7.04
New Hampshire	4.00	4.19	2.02	3.95	6.45
New Jersey	3.70	6.25	0.25	3.12	7.01
New Mexico	4.29	6.70	0.90	3.61	8.13
New York	3.09	4.33	0.91	2.87	5.27
North Carolina	3.97	3.93	2.01	4.13	6.60
North Dakota	3.47	8.11	−2.06	4.24	7.49
Ohio	2.59	5.93	−0.54	2.48	5.31
Oklahoma	3.62	4.64	1.31	3.80	5.86
Oregon	4.59	6.38	1.47	4.44	7.66
Pennsylvania	2.72	4.66	0.01	2.63	4.42
Rhode Island	1.92	3.87	0.00	2.12	4.47
South Carolina	3.45	3.91	1.07	3.67	5.88
South Dakota	3.20	5.08	0.44	3.59	6.01
Tennessee	4.18	4.38	2.06	3.90	6.72
Texas	4.79	3.93	2.88	4.88	6.71
Utah	4.13	5.18	2.04	4.57	6.87
Vermont	2.62	6.01	−0.10	2.75	5.31
Virginia	4.16	6.19	1.24	3.51	6.66
Washington	4.58	6.02	1.94	4.20	7.40
West Virginia	2.64	4.36	0.67	2.40	5.03
Wisconsin	3.00	4.43	0.76	2.97	5.21
Wyoming	2.80	4.73	0.77	3.12	5.29

Table C.2: Index Volatility and Correlation with U.S. GDP Growth

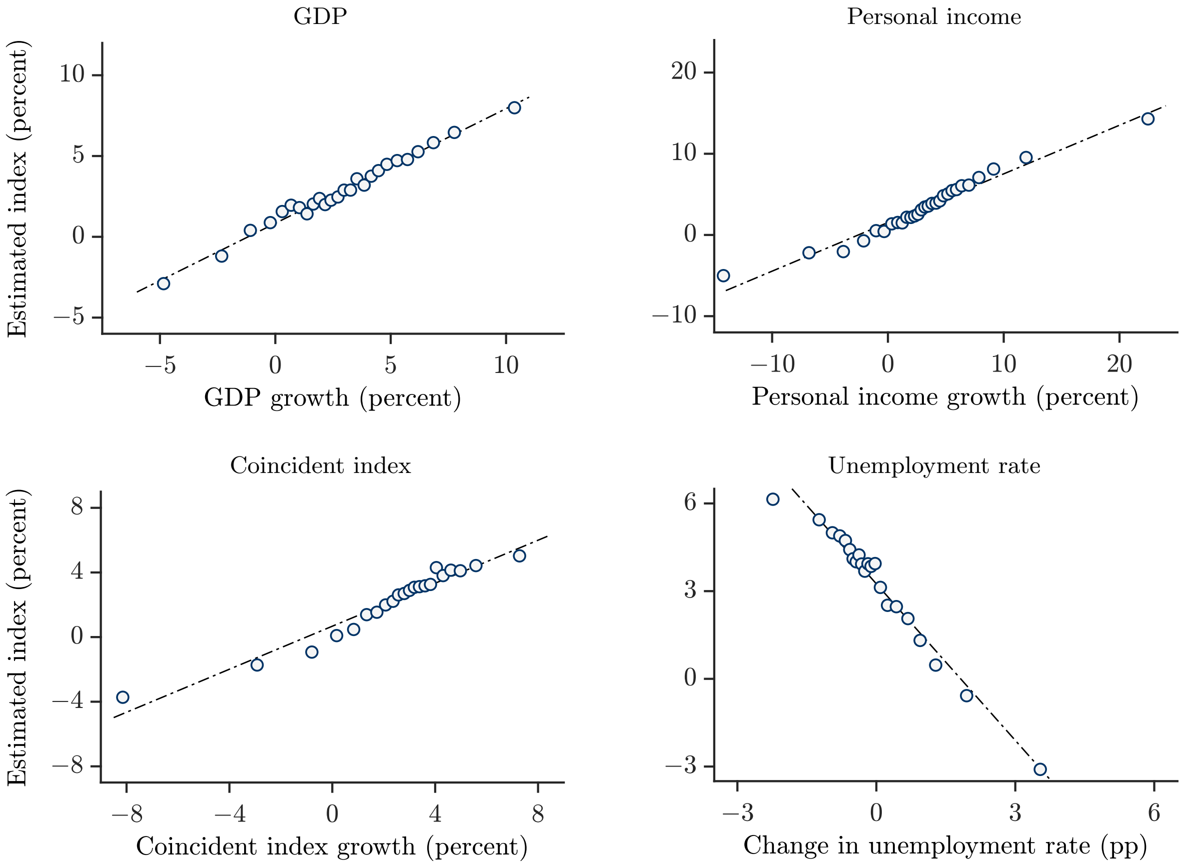
	Index Volatility			**Corr. with U.S. GDP Growth**		
State	1886–1916	1948–1980	1981–2019	1886–1916	1948–1980	1981–2019
Alabama	5.62	3.21	2.34	0.48	0.82	0.80
Arizona	6.79	3.53	3.38	0.27	0.50	0.82
Arkansas	5.09	3.58	2.10	0.39	0.77	0.73
California	4.00	2.99	2.27	0.22	0.71	0.70
Colorado	4.22	2.30	2.41	0.40	0.54	0.51
Connecticut	5.08	4.95	2.45	0.57	0.73	0.61
Delaware	4.35	5.57	3.42	0.13	0.70	0.78
Florida	3.18	3.10	2.65	0.23	0.47	0.80
Georgia	4.95	3.03	2.87	0.14	0.88	0.73
Idaho	7.86	3.13	3.56	0.18	0.55	0.64
Illinois	6.07	2.93	2.36	0.50	0.82	0.72
Indiana	4.92	4.98	3.14	0.38	0.90	0.79
Iowa	4.45	3.20	3.39	0.37	0.67	0.57
Kansas	2.07	3.17	1.96	0.24	0.50	0.69
Kentucky	3.55	2.96	2.61	0.60	0.78	0.70
Louisiana	5.96	3.55	2.93	0.29	0.60	0.18
Maine	1.92	2.63	2.31	0.19	0.65	0.67
Maryland	5.27	3.49	2.20	0.39	0.80	0.79
Massachusetts	1.85	2.78	2.54	0.05	0.77	0.75
Michigan	1.97	6.18	4.07	0.31	0.86	0.74
Minnesota	4.22	2.82	2.57	0.38	0.60	0.76
Mississippi	6.83	4.54	2.08	0.12	0.69	0.63
Missouri	3.96	3.13	2.21	0.50	0.87	0.84
Montana	4.84	2.62	3.09	0.46	0.58	0.63
Nebraska	5.85	2.94	2.54	0.43	0.68	0.66
Nevada	2.57	5.17	3.63	0.03	0.54	0.45
New Hampshire	3.57	3.45	2.95	0.27	0.75	0.67
New Jersey	5.72	3.30	2.25	0.32	0.79	0.71
New Mexico	9.32	3.67	2.99	0.11	0.30	0.55
New York	4.46	2.73	1.99	0.36	0.76	0.66
North Carolina	2.87	2.86	2.45	0.50	0.86	0.82
North Dakota	7.30	4.77	6.25	-0.02	-0.02	0.10
Ohio	6.16	4.17	2.76	0.60	0.89	0.78
Oklahoma	4.70	2.21	2.46	-0.04	0.52	0.21
Oregon	5.44	3.27	3.41	0.03	0.80	0.71
Pennsylvania	4.49	3.13	2.03	0.53	0.85	0.72
Rhode Island	3.72	3.71	2.47	0.09	0.78	0.72
South Carolina	2.91	2.85	2.58	0.27	0.81	0.85
South Dakota	5.79	3.40	4.33	0.40	0.19	0.43
Tennessee	2.51	3.24	2.63	0.55	0.89	0.75
Texas	2.81	2.05	2.24	0.34	0.56	0.42
Utah	4.52	2.74	2.68	0.44	0.54	0.62
Vermont	4.15	4.89	2.71	0.08	0.68	0.68
Virginia	7.38	2.42	2.05	0.01	0.85	0.86
Washington	5.33	3.20	2.43	0.38	0.60	0.57
West Virginia	3.24	3.17	2.00	0.35	0.80	0.55
Wisconsin	2.91	2.99	2.44	0.38	0.86	0.72
Wyoming	4.66	3.13	4.53	0.20	0.05	0.25

Notes: This table reports, for each state, the volatility of the economic activity index and its correlation with U.S. real GDP growth over three sample periods, excluding the war years and the Great Depression years. Volatility is measured as the within-period standard deviation of the index (in percent). U.S. real GDP data are from Williamson (2025), which draws on BEA estimates from 1929–2019.

C.2 Validation Exercise

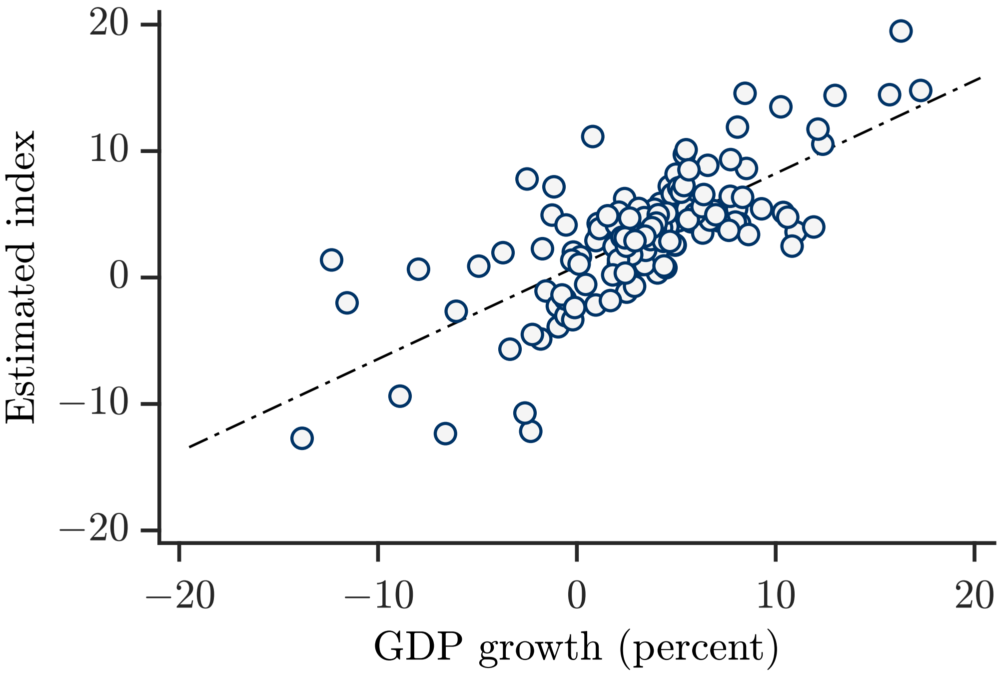
This section provides additional results on the validation exercise for the economic activity indices. Figure C.1 compares the indices with alternative state measures in binscatter plots. Figure C.2 shows that an index estimated at the national level tracks U.S. real GDP growth over 1871–2021. Figure C.3 presents the posterior estimate of the factor against the GDP growth rates for all the states.

Figure C.1: Economic Activity Index and Alternative Activity Measures



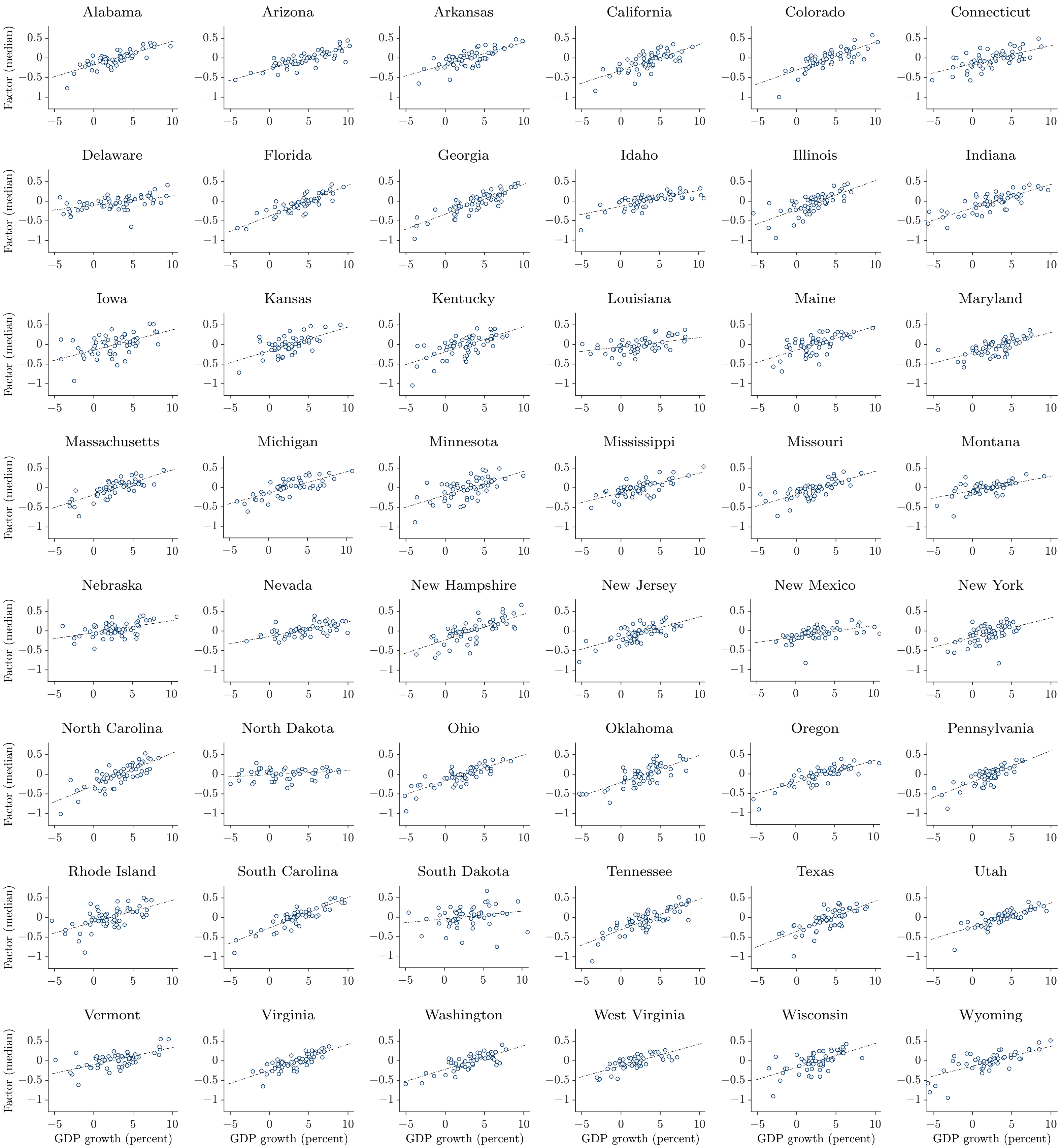
Notes: This figure shows binscatter plots comparing the economic activity index with alternative measures of economic activity across the 48 contiguous US states. The number of bins is chosen using the rule-of-thumb bin selector of Cattaneo et al. (2024). Annual growth rates of state GDP (1964–2021), personal income (1929–2021), and the coincident indexes (1980–2021) are computed as log differences and reported in percent; changes in unemployment rates (1949–2021) are first differences in percentage points. GDP and personal income are from the Bureau of Economic Analysis; coincident indexes are from the Philadelphia Fed; and the seasonally-adjusted fitted claims-based unemployment rates are from Fieldhouse et al. (2022). When the source data are reported at a monthly frequency, we aggregate to annual values by taking simple averages over months.

Figure C.2: Nationwide Economic Activity Index and US GDP Growth



Notes: This figure shows the association between the nationwide economic activity index, estimated using the same approach as for our state-level index, and U.S. real GDP growth over 1871–2021. U.S. GDP data are from Williamson (2025). The R^2 from an OLS regression of GDP growth on the nationwide index is 0.54.

Figure C.3: Posterior Estimate of the Factor vs. GDP Growth



Notes: This figure displays the association between the posterior median of the common factor, $\tilde{f}_t$, and annual GDP growth for the 48 contiguous U.S. states from 1964 to 2021. State GDP data are from the Bureau of Economic Analysis.

C.3 Robustness

We assess the robustness of our state economic activity indices to alternative modeling assumptions and indicator choices. On the modeling side, we (i) impose AR(1) rather than AR(2) dynamics for the common factor and idiosyncratic components, (ii) vary the prior calibration for the log-volatility innovation variances $\sigma^2_{\omega_j}$, and (iii) shut down stochastic volatility altogether. On the indicator side, we (i) add U.S. real GDP growth to the baseline indicator set and (ii) re-estimate the model using data from 1920 onward.

We find that replacing the AR(2) specification with AR(1) dynamics yields indices that closely track the baseline, indicating limited sensitivity to the autoregressive lag order. As shown in Figure C.4, the two series are nearly indistinguishable for a set of representative states. To examine the sensitivity of the prior for $\sigma^2_{\omega_j}$, we re-estimate the model under two alternative calibrations for the inverse-gamma prior. First, holding $a_{\omega,j,0}$ fixed, we vary the scale hyperparameter from its baseline value 10^{-4} to 10^{-5} (tenfold tighter) and 10^{-3} (tenfold looser). Second, holding $b_{\omega,j,0}$ fixed at 10^{-4}, we lower the shape parameter from $a_{\omega,j,0} = T/100$ to $a_{\omega,j,0} = 0.5$ (equivalently, an inverse-χ^2 prior with 1 degree of freedom). This calibration follows Antolin-Diaz, Drechsel and Petrella (2017) and yields an even more diffuse prior with less influence on the posterior. We find that the resulting state indices are essentially unchanged across these alternatives.

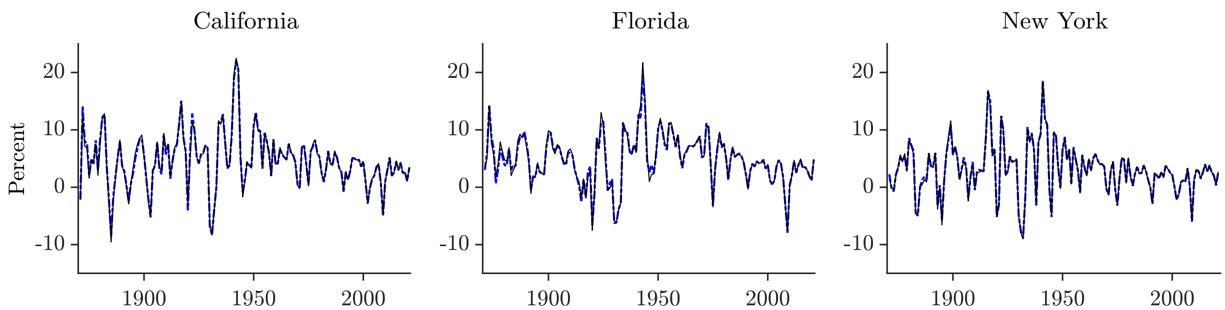
Next, we consider a specification without stochastic volatility in the innovations to the common factor and the idiosyncratic components. Relative to the baseline, this variant can generate large, noticeable spikes in parts of the early sample prior to WWI. This pattern is illustrated in Panel (b) of Figure C.4. A natural interpretation is that stochastic volatility allows the model to underweight episodes in which indicators become temporarily more volatile (i.e., by allowing their idiosyncratic innovation variances to rise), so that the common factor is less likely to track transient series-specific movements.

As an additional robustness check, we augment the baseline indicator set by including U.S. real GDP growth as an aggregate signal. The resulting indices remain broadly similar to the baseline; when differences arise, they are concentrated in the pre-WWI period. Panel (c) of Figure C.4 shows this pattern for a set of representative states. We find that adding national GDP reduces cross-state dispersion in the early sample: average dispersion from 1886 to 1916 falls from 4.24 in the baseline (Table 4) to 2.98 when national GDP is included. This pattern suggests that the aggregate series could serve as a common anchor when state-level coverage is thinner and measurement is noisier. Finally, we re-estimate the model using data from 1920 onward. The resulting state indices closely track the baseline over the post-1920 period, indicating that our post-1920 baseline estimates are robust to excluding the early sample and any pre-WWI idiosyncrasies it may contain. This last result also lends additional credence to our baseline specification, because it shows that perturbations such as including U.S. GDP growth are not decisive for the last 100 years we cover.

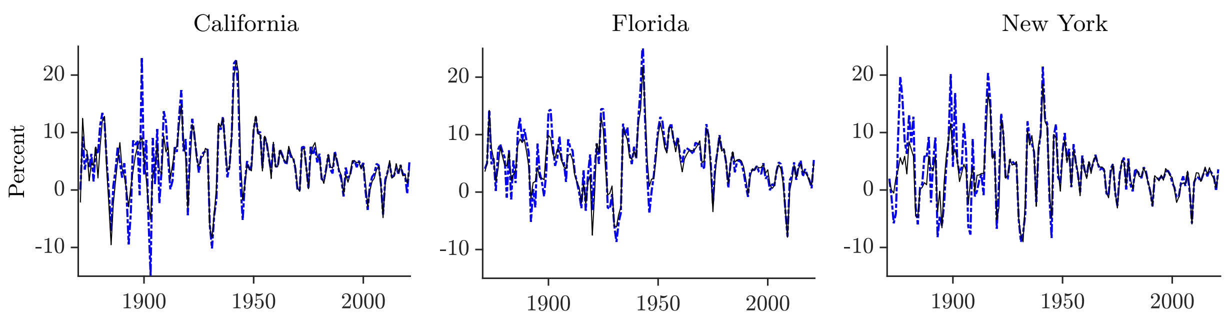
Taken together, these exercises indicate that our qualitative conclusions are robust to a range of plausible modeling assumptions and indicator choices, especially since the interwar period, while highlighting the practical value of incorporating stochastic volatility in a long historical sample.

Figure C.4: Alternative Model and Indicator Specifications

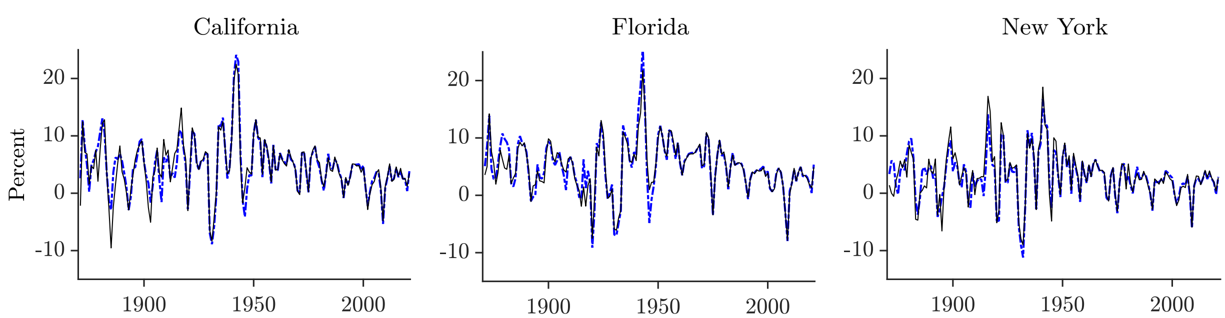
(a) AR(1) laws of motion



(b) Without stochastic volatility



(c) With U.S. real GDP growth



Notes: Each row compares the baseline index with an alternative specification for selected states over 1871–2021: (a) AR(1) dynamics for the common factor and idiosyncratic components; (b) a specification without stochastic volatility; and (c) an expanded indicator set that includes U.S. real GDP growth. In each panel, the baseline is shown as a solid black line and the alternative as a dashed blue line. All series are scaled using the same procedure within each state.

C.4 Synchronization and Dispersion

To assess the evolution of synchronization in state-level business cycles, we compute, for each year, the cross-state standard deviation of our estimated index and a second measure following Kalemli-Özcan, Papaioannou and Peydró (2013). Both metrics are consistent with the patterns described in Section 4.4.

Specifically, we define a synchronization measure for state i in year t as the negative average absolute distance between its economic activity index and the indices of all other states:

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

where $s_{i,t}$ and $s_{i',t}$ denote the scaled economic activity indices for states i and i' in year t, as defined in (8), and S_t is the number of states for which the scaled index is available in year t. By construction, state i is more synchronized with other states as $Synchronization_{i,t}$ approaches zero (i.e., as average pairwise distances shrink). Figure C.5 reports the mean and the 10th and 90th percentiles of $Synchronization_{i,t}$ over time.

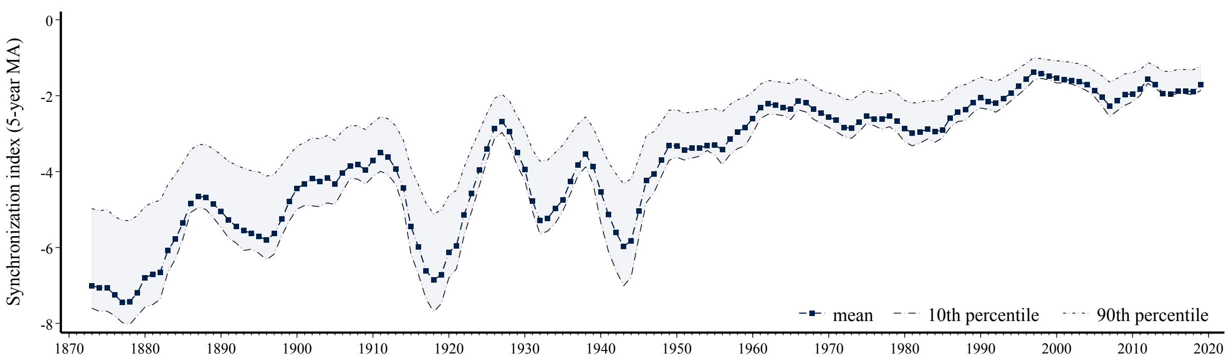
A complementary, "mirror" measure is the cross-sectional standard deviation of the state-level indices: greater dispersion implies lower synchronization. As shown in Figure C.6, cross-state dispersion in economic growth experiences several spikes during the period which encompasses the Great Depression and World Wars, and then declines gradually in the postwar period. Although dispersion fluctuates over time, it remains low from 1990 onward.

Finally, to accompany Table 4, we plot in Figure C.7 the average volatility and correlation with U.S. GDP across states, over a rolling window of 30 years.

We first observe in Figure C.7a a substantial increase in volatility during the period where the rolling window overlaps with the World War I to World War II period, from the early 1920s to the late 1960s. Second, we see an average rolling window volatility which hovers around the mean of 5 both in the pre-war period before 1920, and in the immediate post-war period from 1963 to 1970. Third, we document a steady decline in rolling window volatility starting in the early 1970s and persisting up till an increase in volatility coinciding with the onset of the Great Recession. We interpret these patterns to be broadly consistent with our findings in the first row of Table 4.

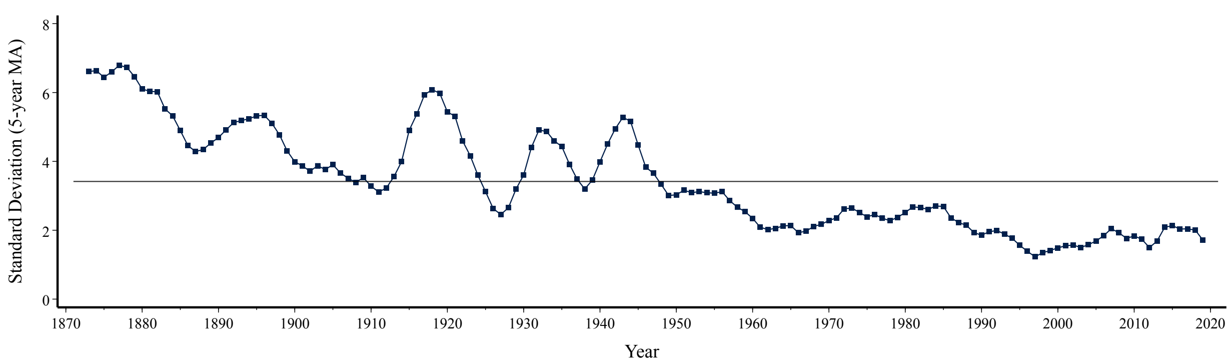
Next, we document in Figure C.7b a rolling window correlation with U.S. GDP which hovers around 0.3 up till the onset of the Great Depression in 1930. We observe a sharp increase in correlation from 1930 up till the mid 1940s, during the period where the rolling window overlaps with the World Wars and Great Depression. From 1950 onward, we observe persistently higher correlations of 0.65 (compared to the pre-1930 period). The rolling window correlation during this period is stable, with the exception of a dip in the mid-1970s and a spike coinciding with the Great Recession. We find these patterns to be broadly consistent with our results in the second row of Table 4.

Figure C.5: Synchronization of State 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 4.2. The solid line denotes the average of the mean index level over time.

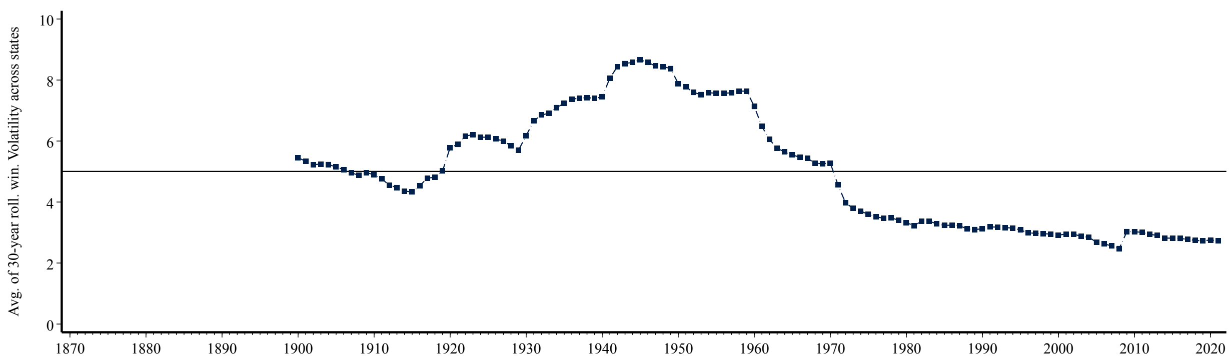
Figure C.6: Dispersion of State Economic Activity Over Time



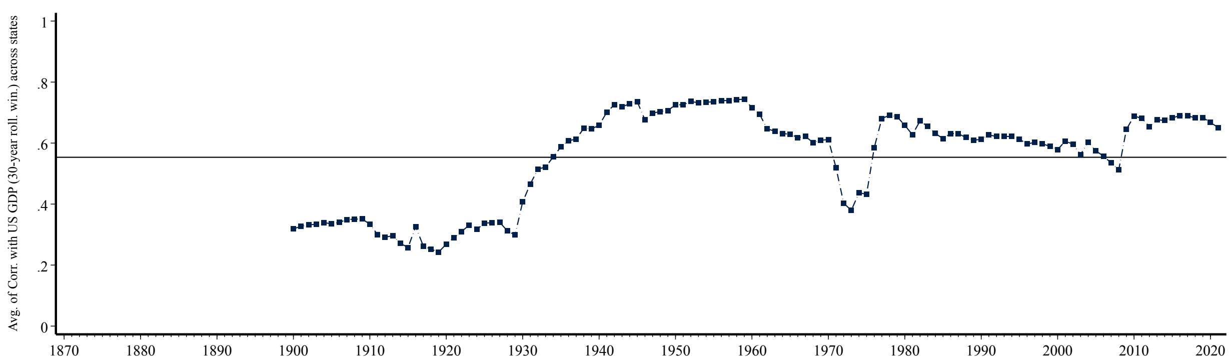
Notes: This figure shows the standard deviation of our estimated economic activity indices across states as a proxy for business cycle synchronization, averaged over a five-year moving window. The horizontal line represents the average value over time.

Figure C.7: Rolling-Window Volatility and Correlation with U.S. GDP Growth

(a) Volatility (30-year Rolling Window)



(b) Correlation with U.S. GDP Growth (30-year Rolling Window)

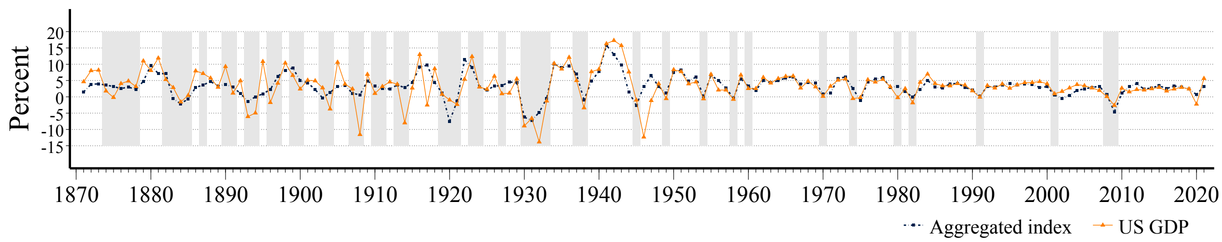


Notes: In Figure C.7a, we report the average across states of rolling window volatility. We compute the volatility for each state as the standard deviation of the SEAI within a 30-year rolling window. Next, we take the average across states for each window. In Figure C.7b, we report the average across states of the correlation of each state with U.S. GDP growth. To do so, we first compute for each individual state the correlation between the SEAI and U.S. GDP growth within a 30-year rolling window. Next, we take the average across states for each window. U.S. GDP data are from Williamson (2025), which draws on BEA estimates from 1929–2019. Within each plot, the horizontal line represents the average value over time.

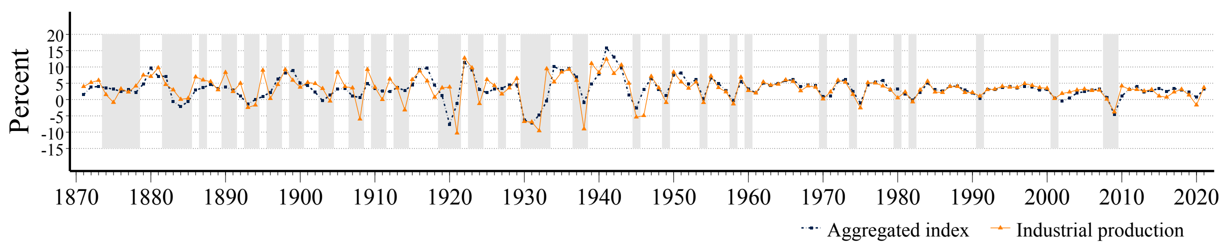
C.5 Aggregated State-Level Index vs U.S. Measures

Figure C.8: Comparison of the Aggregated SEAI and Other US-Wide Measures

(a) Aggregated economic activity index and U.S. GDP



(b) Aggregated economic activity index and U.S. industrial production

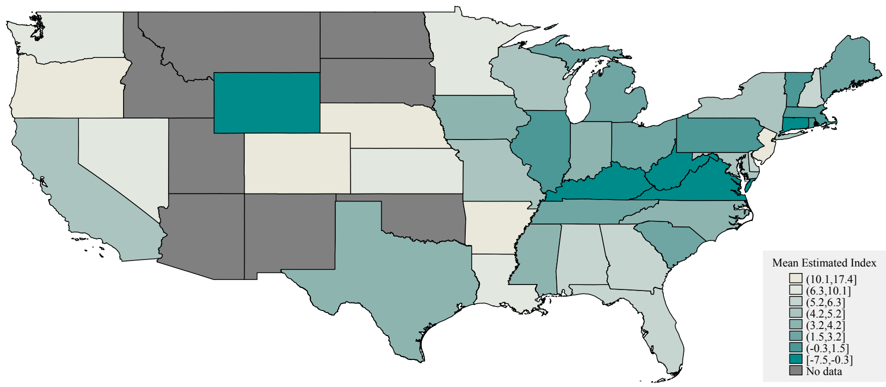


Notes: This figure plots the aggregated economic activity index alongside U.S. GDP and industrial production from 1871 to 2019. The aggregated index is constructed by taking a weighted average of the state-level economic activity indices, with the weights based on the relative size of each state's economy 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 U.S. GDP. U.S. GDP data are from Williamson (2025), which draws on BEA estimates from 1929–2019. The shaded bars indicate recession years. We define national recessions using NBER recession dates.

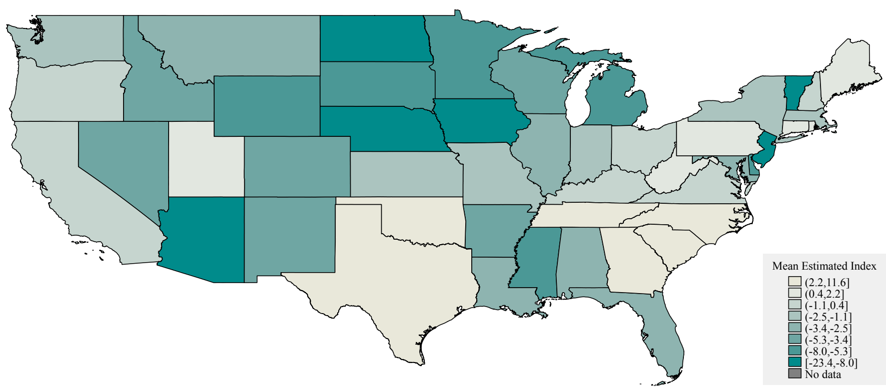
C.6 State-Level Recessions

Figure C.9: Changes in State-Level Economic Activity During US-Wide Recessions

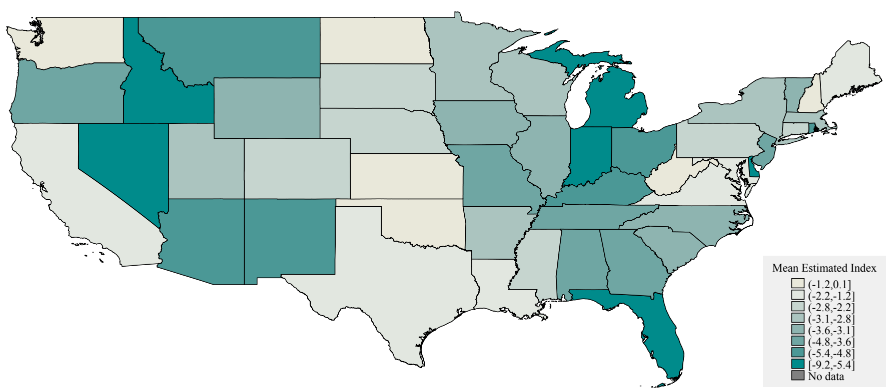
A. 1874-1878 Recession



B. 1930-1933 Recession



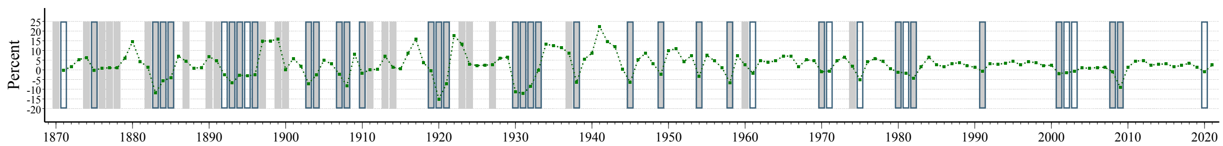
C. 2008-2009 Recession



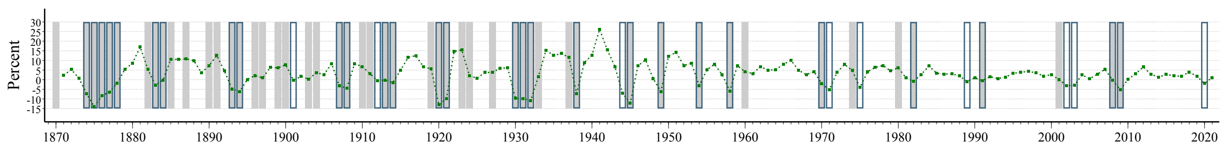
Notes: This figure shows the average percentage changes in economic activity indices during three national recession episodes: the 1874–78 Recession, the Great Depression (1930–33), and the Great Recession (2008-09). We define national recessions using NBER recession dates.

Figure C.10: Recession Dates for Selected States: 1871–2021

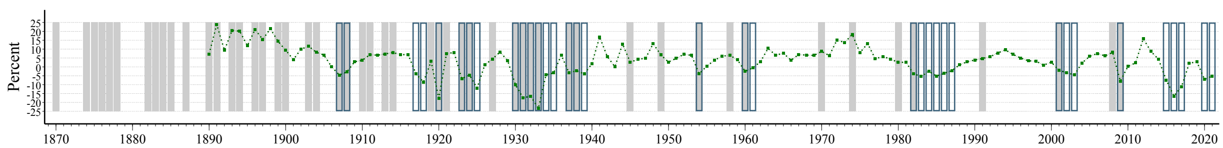
(a) Ohio



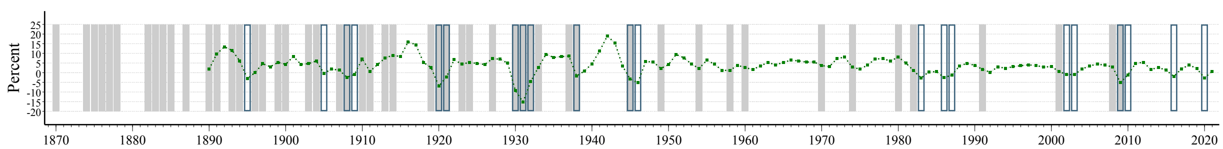
(b) Connecticut



(c) North Dakota

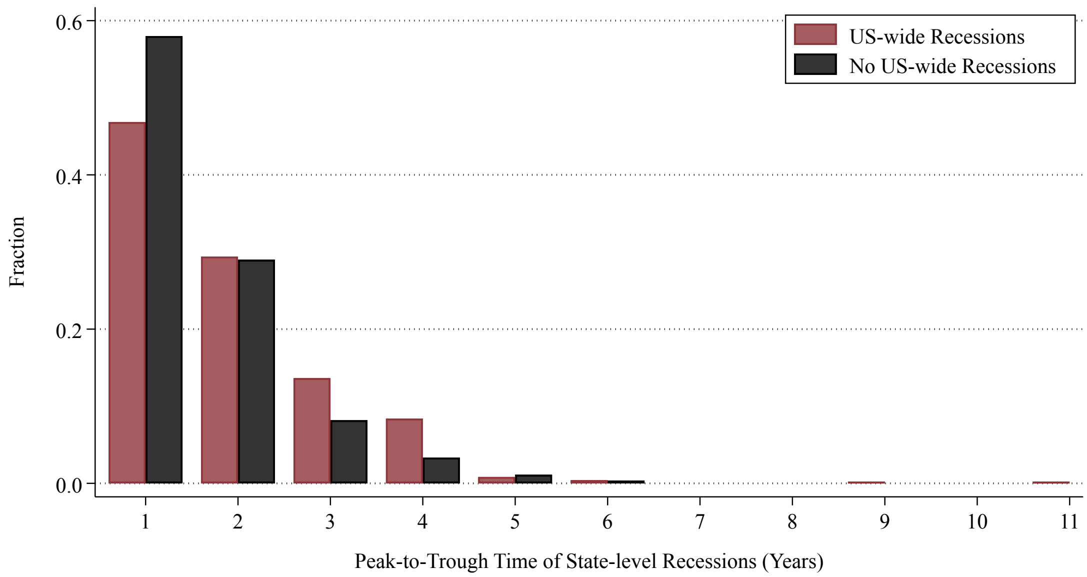


(d) Oklahoma



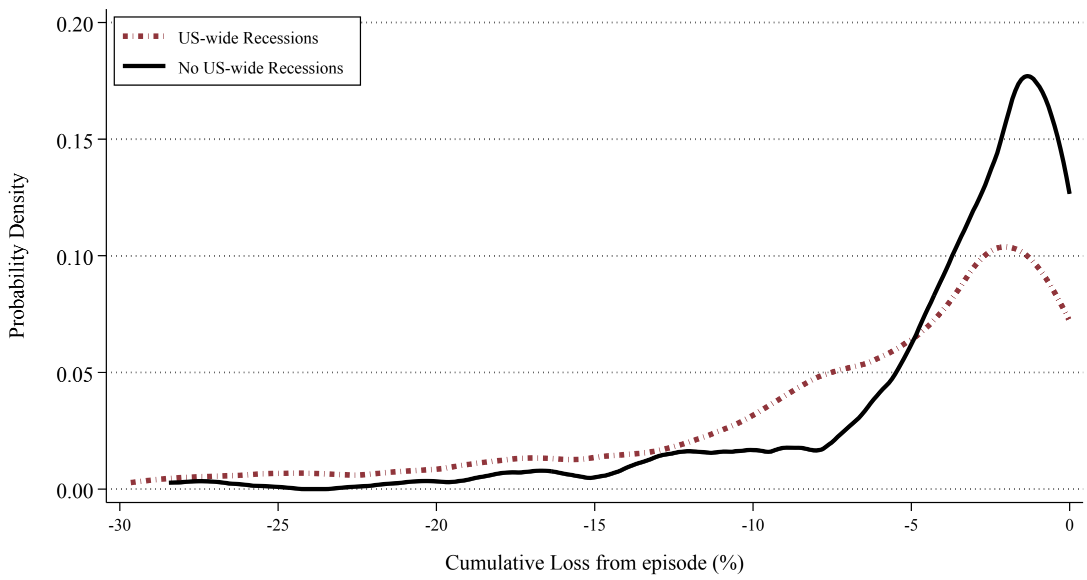
Notes: Recession dates for the states are identified by applying the Bry and Boschan algorithm (1971) to the economic condition indices (scaled to levels). State recession dates are presented as blue boxes; the gray bars correspond to US NBER recession dates; and the dashed lines plot the SEAI.

Figure C.11: Peak-to-trough years of state recessions within and outside of US-wide Recessions



Notes: This figure plots a histogram of peak-to-trough time for state recessions which coincide with US-wide Recessions, in red, and those that do not, in black. We define state-level recessions with the Bry and Boschan (1971) algorithm applied to our state economic activity index (rescaled to levels). We define national recessions using NBER recession dates. We define a state recession as coinciding with a US-wide recession if start year of the state recession, i.e. the first year after the peak, happens during a US-wide recession year.

Figure C.12: Cumulative loss of state recessions within and outside of US-wide Recessions



Notes: This figure presents a density plot showing the distribution of the cumulative loss of state recession episodes, which coincide with US-wide Recessions, in red, and those that do not, in black. We define state-level recessions with the Bry and Boschan (1971) algorithm applied to our state economic activity index (rescaled to levels). We compute the cumulative loss of each state recession episode by computing the sum of our state economic activity index (in growth rates) over the years for which the state is experiencing the particular recession episode. We define national recessions using NBER recession dates. We define a state recession as coinciding with a US-wide recession if start year of the state recession, i.e. the first year after the peak, happens during a US-wide recession year.

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