The Dynamics of Labor Force Participation: All Quiet on the Appalachian Front?

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Abstract

National and local economic shocks have dynamic effects on labor force participation rates (LFPR) dependent on a given regions and time. This is especially true for the areas such as Appalchia given the direct connection between historic regional characteristics and LFPR. As such, we focus on comparing LFPR in this region to non-Appalachian states in this study. To understand the heterogenous LFPR across the United States, we use a dynamic factor model with time-varying loading parameters and stochastic volatility to explore the synchronicity and divergence between state LFPRs. We decompose the change in state LFPR at each point in time into national, regional, and state-specific factors and find that the national (between 35 – 55%) and state-specific factors (between 27 – 55%) are the dominant contributors to the observed variations. Interestingly, West Virginia displayed the strongest connection to our regional/Appalachian factor (on average 22%). Our results suggest that a one-size-fits-all prescription may not be as efficient as more targeted labor policy. Additionally, economically distressed areas may experience increased labor force participation and economic growth by varying the level of policy interventions during different stages of the business cycle.

1 Introduction

Not all shocks to labor force participation rates are created equal. Before the 2008-2009 Great recession, most studies posited that the national labor force participation rate, the percentage of the working-age population who are either employed or actively searching for work, was mildly procyclical, or relatively stable (Van Zandweghe, 2012; Veracierto, 2008). However, several studies since then have determined that the 2008-2009 recession adversely affected the labor force participation rate in the U.S. (Aaronson et al., 2014; Council of Economic Advisors, 2014; Erceg and Levin, 2014; Hotchkiss and Rios-Avila, 2013; Van Zandweghe, 2012). While a substantial national recession like the Great Recession is far-reaching, other exogenous shocks to labor force participation rates may only affect specific regions or states within the U.S. For example, regulatory changes and the OPEC oil embargo in the 1970s caused the price of coal to sharply increase (Van Zandweghe et al., 2017). As a result, employment, labor force participation, and earnings soared in the Appalachian region due to its heavy reliance on the coal industry, while other areas around the U.S. experienced declines in economic activity (Black, Daniel, and Sanders, 2002; Juhn, 1992). Later, in the 1980s, these economic experiences were reversed due to a subsequent bust in the coal market. Figure 1 shows the dynamics and differing responses of the change in U.S. state LFPR to such socks. The divergence of state LFPR and different economic shocks demonstrates the importance of understanding how national, regional, and state-level forces influence the change in labor force participation rates across time.

Determining the role and relative importance of national, regional, and state-level forces on the change in labor force participation rates has important policy implications. Empirical studies show that increases in LFP have large, positive effects on employment growth and national GDP (see Bryant et al., 2004; Bustelo et al., 2019; Cai and Lu, 2013; Juhn and Potter, 2006; Shoven, 2007, for example). At the peak of U.S. national labor force participation (LFP) from 1990 to 2000, labor contributed 1.34 percentage points to national economic growth in terms of output per hour (Bureau of Labor Statistics, 2021). However, from 2000

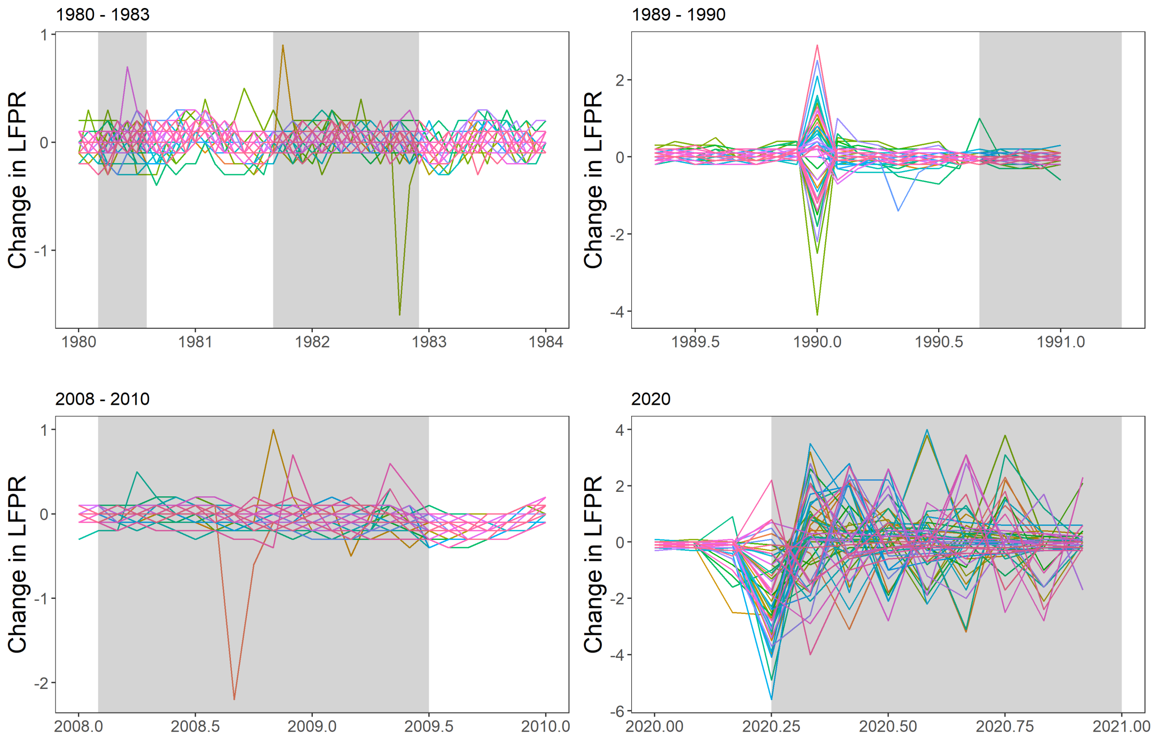

Figure 1: **Change in LFPR for Select Periods**

Note: (Top Left): Change in state LFPR over the years 1980 - 1983. These dates correspond with the Second Energy Crisis/Inflation and "Double Dip Recessions. (Top Right): Change in state LFPR over the years 1989 - 1991. These dates correspond to the S&L Crisis and Gulf War Recession. (Bottom Right):Change in state LFPR over the years 2008 - 2009. These dates correspond with the Great Recession. (Bottom Right): Change in state LFPR over the year 2020. These dates correspond with the COVID-19 pandemic and Recession. NBER-dated recessions are in gray.
Source: Bureau of Labor Statistics (BLS)

to 2007, simultaneous with the decline in U.S. LFPR, labor contributed only 0.23 percentage points to output growth. As of 2019, labor contribution to output growth in the U.S. only recovered to 0.49 percentage points. Taylor (2016) suggests that with low unemployment rates, future growth must come primarily through increased labor force participation. Fostering labor force participation and subsequently experiencing economic growth requires improving our understanding of how driving forces at different geographic levels influence changes in labor force participation rates over time.

In this study, we examine the role and relative importance of geographic levels on the change in state labor force participation rates. We investigate the extent to which state labor force participation rates move together. Specifically, we decompose state LFPR into a national (also referred to as a common component), a regional (Appalachia or Non-Appalachia), and a state-specific (idiosyncratic) factor using a Dynamic Factor Model with time-varying and stochastic volatility. To best capture dynamics in U.S. LFPR, we solely use state, monthly, time-series labor force participation rates for all U.S. states and Washington D.C. over the 1976-2020 sample period.. We, therefore, analyze the overall synchronicity and divergence of state-level LFPR data over time. We stipulate the national, regional, and state geographic levels since, arguably, influences on the change in state-level LFPR will primarily derive from an individual or joint shocks at these levels. We specifically designate the Appalachian region, which is shown in Figure 2, as our main region of focus due to the documented evidence for a strong and unique relationship between the LFPR and the geographic region itself. While the U.S. defines other geographic regions within its borders, we find none with a geographic relationship to LFP that is steeped in so much historical rhetoric and culture as we find with the Appalachian region. We discuss the empirical evidence and other support for this unique connection in Section 2.

Our results demonstrate that the choice of year and state is crucial to the relative importance of each factor's contribution to the LFPR. For example, in West Virginia, around 97% of variation in the change in state LFPR is explained by the Appalachian region factor in 1982, but less than 1% in 2010. In addition, our findings suggest that policy created at state or regional levels to increase labor participation and induce GDP growth may be more effective if enacted when the LFPRs are less synchronized (e.g. - where LFPR diverge). We find that that this may occur during or after a local or federal shock to LFPR. Broader or more national policies may be appropriate during business cycle expansions or periods of economic recovery which coincide with stronger synchronization of LFPR and when the variance of the change in LFPR is explained more by the state and regional factors. For example, in 1999, a period characterized by growth and expansion, we see more national synchronization of LFPR and only about 21% of variation in the change in state LFPR is explained by

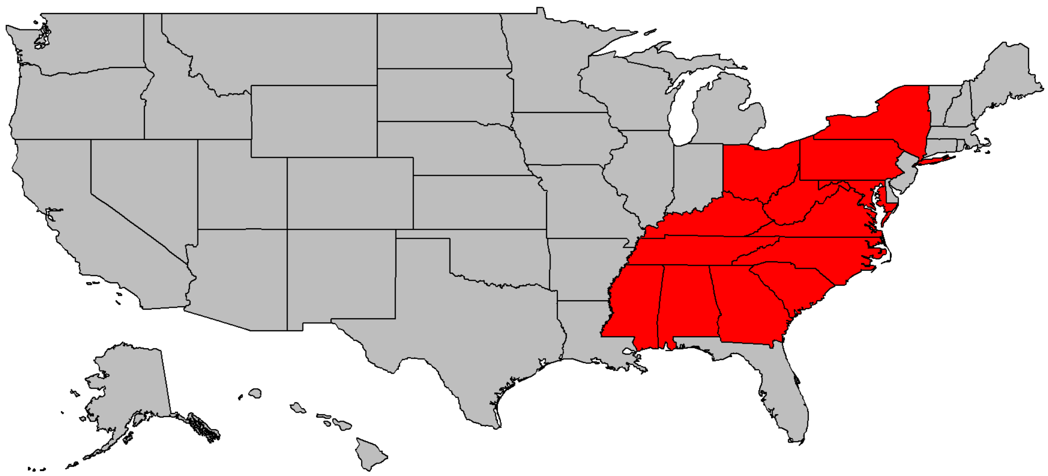

Figure 2: **The Appalachian Region**

Note: The region is officially defined by 420 counties across 13 states including Alabama, Georgia, Kentucky, Maryland, Mississippi, New York, North Carolina, Ohio, Pennsylvania, South Carolina, Tennessee, Virginia and West Virginia. Since our analysis is at the state level, we include all states with at least one Appalachian county depicted above (in red) as our definition of the Appalachian region.
Source: Appalachian Regional Commission

the national factor while 62% of variation is explained by state-idiosyncratic factors. The Appalachian region plays an important role in LFPR dynamics at specific points over the sample period, but when we exclude West Virginia, the influence of the Appalachian region gets progressively weaker.

This study bridges multiple fields and contributes to several strands of literature. From the microeconomics and regional development perspective, there is a growing interest and a burgeoning literature centered on determining how labor force participation (and general labor market dynamics) within Appalachia has changed and whether there is a structural difference in the region (see Bradley, Herzenberg, and Wial, 2001; Dorsey, 1991; Isserman and Rephann, 1993; Stephens and Deskins, 2018). However, these previous studies use data before the most recent economic downturns and analyze only one or two years at a time. Previous research suggests that the role of the Appalachian region in explaining LFP may change over time given local and national economic conditions (Isserman and Rephann, 1993). However, previous empirical approaches do not simultaneously capture longer horizons and the second moment of LFPR. Instead, they often assess the level and short-term trends. In addition, these studies focus on drivers of LFP through cross-sectional analysis, rather than through time-varying parameters and potential intertemporal and spatial differences. Therefore, we seek to fill the gap in the literature with the innovation that we use macroeconomic models to ensure our results are not driven by the choice of year and the state of the business cycle. Given the interest in the Appalachian region, we add to this strand by assessing the synchronicity of LFPR within the region, and emphasize that this carries important implications for the region's labor and economic growth potential.

The rest of this paper is organized as follows. Section 2, provides a discussion of the Appalachian region and the challenges related to labor force participation. Section 3, presents a description of the data and summary statistics. A discussion of the empirical methodology is found in Section 4. Discussion of our results is outlined in Section 5 and Section 6 concludes and offers potential policy recommendations.

2 Background on Appalachian Labor Force

The Appalachian region is often characterized by its economic disparity, persistent poverty, and historically low levels of skilled labor (Appalachian Regional Commission, 2020; Bollinger, Ziliak, and Troske, 2011; Grossman and Levin, 1961; Partridge, Betz, and Lobao, 2013; Rogers, Mencken, and Mencken, 1997; Stephens and Deskins, 2018). Labor force participation rates in Appalachia have also been consistently lower than in the rest of the U.S. over the past 45 years. However, while Appalachia performs poorly in LFP relative to the rest of the U.S., the region still accounts for approximately 31% of national GDP[1] (Bureau of Economic Analysis, 2021). This illuminates the Appalachian region's importance in terms of macroeconomic activity. As such, even small improvements in the region's LFP could have

[1]State-level GDP is aggregated for all 13 states with at least some counties in the Appalachian region. A breakdown of the percentage of each state in the Appalachian region can be found in Table A.2 of the Appendix.

substantial impacts on national growth.

This Appalachian labor force participation gap and the potential growth for the region has received some attention from media, policymakers, government agencies, and researchers (Brainard et al., 2017; Jones, 2020). Efforts to raise levels of education and income in the area began in 1960 with a visit from then, presidential candidate John F. Kennedy (Schmitt, 2009). Later, the Appalachian Region Development Act of 1965 created the Appalachian Region and paved the way for additional legislation for economic development which was aptly nicknamed, the War on Poverty. However, despite efforts for improvements, Appalachia remains one of the most economically depressed regions in the U.S. (Bollinger, Ziliak, and Troske, 2011)

Encompassing the central and southern portions of the Appalachian Mountain range, the Appalachia region consists predominantly of rural areas covered by forests and crops (National Land Cover Dataset, 2000). Some authors have characterized the region as remote or even geographically isolated, and studies show that rurality does influence labor force participation, other labor market outcomes, and the economy (Brainard et al., 2017; Stephens and Deskins, 2018; Weingarden et al., 2017). With an abundant natural resource endowment in terms of coal and natural gas, many parts of the region have historically been reliant on the timber, gas, and coal mining industries as the main source of employment. This strong reliance on natural resource industries creates a regional connection to the LFPR that is susceptible to regional shocks and policy changes that other regions do not experience.

A few empirical studies have examined whether a unique Appalachian culture or behavior drives labor force participation, but no consensus has been reached. Dorsey (1991) suggests that an "Appalachian effect" or unique Appalachian culture does persistently decrease the LFPR for the region. West Virginia is of particular interest to Dorsey (1991) as it is the only state entirely encompassed by the Appalachian region. West Virginia stands out relative to the other Appalachian region states as it exhibits persistently lower labor force participation rates (Dorsey, 1991) and ranks higher in negative health indicators (Raghupathi and

Raghupathi, 2018). Using state-level data for 1987, Dorsey finds that traditional economic and demographic variables have little explanatory power and contends that cultural differences explain most of the variation in LFP. However, Isserman and Rephann (1993) criticize Dorsey (1991) for using only one year of data as it may produce misleading conclusions.

To expand the methodological rigor, Isserman and Rephann (1993) utilize multiple model specifications (including the one used in Dorsey (1991)) separately on 1980, 1987, and 1991 county-level data. Isserman and Rephann (1993) find a small, negative Appalachian effect for male and female workers in 1980 in only one specification. Other specifications revealed small negative Appalachian effects for 1980, 1987, and 1991 for female workers but only for male workers in 1987. While the authors conclude that their results depend greatly on the year of data chosen for analysis, they also only use one year of data for each of their specifications. The authors posit that the choice of year may explain the contrasting results with Dorsey (1991) even given the different geographical scales between the two studies.

Stephens and Deskins (2018) use county-level data to investigate the drivers of LFP and the differences between rural and urban areas and between the Appalachian and Non-Appalachian regions. The authors first find LFPR in rural counties in the Appalachian region to be about 1.5 percentage points lower than rural counties outside the region. They also find that the factors accounted for in the analysis, via an Oaxaca-Blinder decomposition, explain much of the variation between rural and urban areas. They attribute the variation unexplained by the known factors, 1.1 percentage points, to be a potential "Appalachian Effect" on LFP.

The connection to LFPR through the regional characteristics and debate described in this section motivate our use of Appalachia as our region of interest. With this strong connection between the LFPR and the regional economy, previous research suggests that the role of the Appalachian region in explaining LFP may change over time given local and national economic conditions (Isserman and Rephann, 1993). By including the Appalachian region in our analysis, we can measure the influence of the regional shocks on Appalachian state LFPR and if comovement of LFPR in these states persists over time.

We add to the debate above by contending, along with Isserman and Rephann (1993), that the year chosen for analysis may influence results regarding an "Appalachian Effect" on LFPR. We suggest that regional and national shocks may exacerbate the region's already poor performance in LFPR and other indicators disproportionally compared to other areas in the U.S. and may explain the "Appalachian Effect" for these points in time. In this paper, we demonstrate that the comovement or divergence in the change in state LFPR varies over time, geographical level, and shock. We also show that the years of data and subsequent conclusions in previous studies align with periods of stronger regional and national synchronization of change in state LFPR due to regional or national shocks.

3 Data

To investigate the synchronicity and response of the Appalachian region labor force to changing economic environments, we use monthly labor force participation rates for the 50 U.S. states and Washington D.C. over the period January 1976– December 2020.[2] We estimated our model using the first difference of the LFPRs and the differenced data can be seen in Figure 3.[3] This data is collected from the Bureau of Labor Statistics (BLS)[4]. There is a notable difference in each state's response during periods of recessions, financial crises, and the COVID-19 pandemic. For example, Maryland and Virginia exhibited relatively large negative changes around the 1990/91 and 2007/2009 recessions. However, Mississippi and Alabama show positive changes in the LFPR during the same periods. As expected, most of the states exhibit significant declines in the LFPR during the pandemic period.

While the unemployment rate is popular for empirical analysis and economic policies, we

[2] All Augmented Dickey-Fuller tests supported the conclusion of a unit root process and high persistence.

[3] In Section 5, we present the estimation results from our DFM-TV-SV model with the 1976-2020 data. Given the visible and large decreases in the labor force participation rates (Figure 3) during the COVID-19 period, we also re-estimated the model excluding data for 2020. The results were quantitatively similar and are available upon request.

[4] Retrieved at: https://download.bls.gov/pub/time.series/la/

use the LFPR as it provides a truer representation of labor market conditions (Juhn and Potter, 2006). That is, the unemployment rate does not always reflect that people have dropped out of the labor force (Hotchkiss and Rios-Avila, 2013; Juhn and Potter, 2006; Stephens and Deskins, 2018). An economy might simultaneously experience a high level of discouraged workers (individuals who give up looking for a job and fall out of the labor force) and a low unemployment rate (Hotchkiss and Rios-Avila, 2013).[5] At face value, this would signal improving economic conditions and a thriving labor market. Consequently, unemployment rates in distressed areas can be comparable to the national average when labor force participation remains low. For example, since 2000, West Virginia reported an average rate of unemployment of 6.2% compared to the national average of 6%[6]. Yet, as discussed earlier, West Virginia has persistently lower LFPR as compared to the rest of the country.

The LFPR represents the percentage of the civilian and noninstitutional working-age population that is either working or actively looking for work. Table A.1 highlights that the LFPR varies within the Appalachian region and across all states. Over the sample period, West Virginia has the lowest rates in the country. Within the Non-Appalachian region, New Mexico and Oklahoma exhibit the lowest labor force participation rates, while Alaska and Minnesota have the highest. It should be noted that within the Appalachian region, South Carolina and Maryland exhibit higher labor force participation rates but also make up the smallest percentages (in terms of the number of counties) of the Appalachian region[7].

Given the conflicting results of previous literature and the different choices in the years studied, we acknowledge that the labor force dynamics of the Appalachian region may change over time with economic conditions. Moreover, (counter)cyclical factors play a large role in national and sector-specific labor markets. The global COVID-19 pandemic and Great

[5] In addition, unemployment does not gauge the size of the underground or "informal" economy – as evidenced by the fact that some developing countries have low official unemployment rates (Bradley, Herzenberg, and Wial, 2001).

[6] Visualizations of unemployment rate data are available upon request.

[7] (See Table A.2 in the Appendix)

Recession were felt worldwide. The U.S. dropped 31 places in international LFPR rankings between 2000 and 2020 (World Bank, 2021). Utilizing monthly LFPR data over 45 years allows us to account for long-term trends, major economic events, and measure the evolution and relative importance of the Appalachian region. While more granular data is arguably better, we use state-level LFPR data given the unavailability of monthly county-level data for a similar sample period. This aggregation reflects a potential drawback to our choice of analysis at the state level. However, given the large number of counties and equivalents across the U.S. (3143) and the computational burden of our model estimation, we are restrained to a state-level analysis. Regardless, research at this level helps fill the gap in the analysis of statewide participation rates as many studies on individual labor force participation decisions already exist. Additionally, using aggregate state participation rates allows for a focus on regional differences and on actionable policy at the state level, since potentially, only a few metropolitan areas may be able to implement local policy.

4 Structural Model

We consider a Dynamic factor model with Time-Varying Stochastic Volatility (DFM-TV-SV) in the spirit of Del Negro and Otrok (2008). In general, the dynamic factor model is a dimension reducing technique which models the co-movements of a high-dimensional vector of time series variables (the LFPR) as a function of a few latent dynamic factors (Stock and Watson, 2011).

Using a similar state space analysis, Stock and Watson (2016) posit that comovements of many macroeconomic variables can be described by a unobserved single index or dynamic factor. We build off this premise and model changes in state LFPR as functions of a national, regional, and idiosyncratic (state-specific) factors. Restricting our latent factors of LFPR to a small number in our dynamic factor analysis is consistent with standard dynamic equilibrium macroeconomic theory (Stock and Watson, 2016). To this end, we employ the MCMC

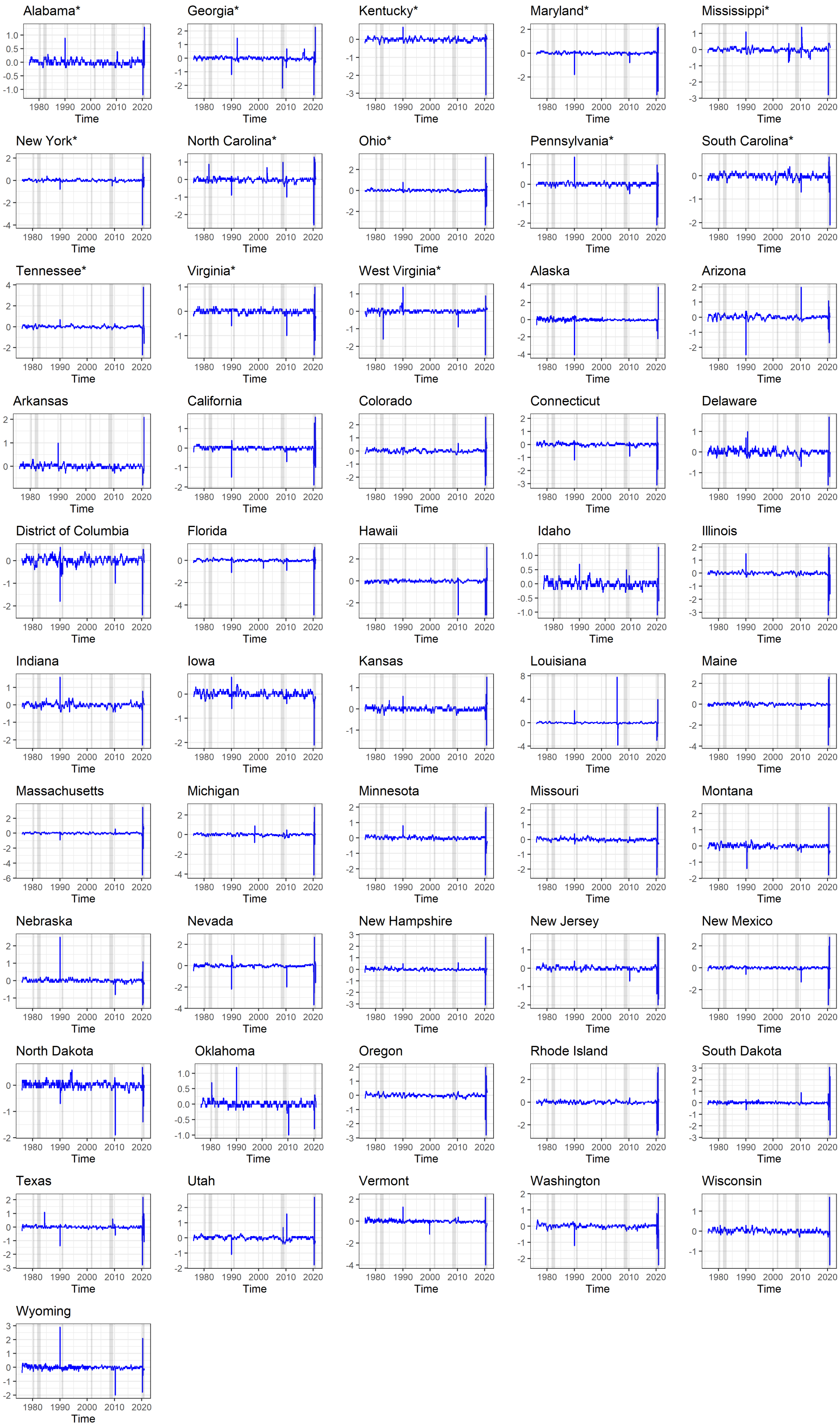

Figure 3: **Change in U.S. State Labor Force Participation Rates**

Note:Shaded regions are the NBER-dated recessions.

estimation method to estimate this general model using a panel of state LFPR data in the U.S. for the past few decades.

To our knowledge, ours is the first study to apply the DFM framework to regional U.S. labor force participation. Other studies have used this methodology to investigate variables such as output growth (Bian et al., 2020), bond yield (Bhatt, Kishor, and Ma, 2017), changes in business cycles (Del Negro and Otrok, 2008), labor market conditions (Chung et al., 2014), inflation (Mumtaz and Surico, 2012), equity market valuations (Ma, Vivian, and Wohar, 2018), commodities (West and Wong, 2014), oil (Aastveit, Bjørnland, and Thorsrud, 2015), and cattle prices (Foster, Havenner, and Walburger, 1995; Walburger and Foster, 1998).

4.1 Standard Dynamic Factor Model

We consider the following specification for our measurement equation:

$$y_{i,t} = \omega_{i,t}\mathcal{C}_t + \widetilde{\beta}_{i,t}\mathcal{R}_t + \xi_{i,t} \tag{1}$$

where $y_{i,t}$ is the change in labor force participation rate for state (and Washington, D.C.) i = 1,2,...51 at month t. $\mathcal{C}_t$ is the national or common factor that affects $y_{i,t}$. $\mathcal{R}_t$ is a vector that contains the two regional factors, $r_{j,t}$, $j = 1, 2$ corresponding to the Appalachian and Non-Appalachian regions, respectively.[8] $\xi_{i,t}$ is the idiosyncratic or state-specific factors. The idiosyncratic factors account for movement by each state after the national and regional factors are removed. Since the geographical characteristics of the comovements are unobserved, we infer them from factor loadings which are the coefficients of the vectors of the lagged factors.

The national factor's loading parameter, $\omega_{i,t}$, captures the exposure to a national (common) factor. The row vector $\widetilde{\beta}_{i,t}$ has a non-zero time-varying regional loading parameter $\beta_{i,t}$

[8]Thirteen (13) states with counties within the Appalachian region are included in the Appalachian region factor and the 38 other states (including Washington D.C.) for the Non-Appalachian region factor. For brevity, we report only the results for the Appalachian region. The full results will be made available upon request.

for the position corresponding to the region for state i and zeros for all other elements. Accordingly, each regional factor, $r_{j,t}$, captures changes in the LFPR specific to each region and is separately identified by setting Appalachian region loadings to zero for Non-Appalachian region states and Non-Appalachian region loadings to zero for Appalachian states. We capture the dynamics of each factor by including time-varying factor loading parameters.

The transition equations for each factor evolve as stationary processes:

$$\mathcal{C}_t = \sum_{p=1}^{P} \phi_p^{\mathcal{C}} \mathcal{C}_{t-p} + e^{h_t^{\mathcal{C}}} \cdot \nu_t^{\mathcal{C}}; \quad \nu_t^{\mathcal{C}} \sim i.i.d.\mathcal{N}(0, \sigma_{\mathcal{C}}^2) \tag{2}$$

where $\phi_p^{\mathcal{C}}$ is the autoregressive coefficient for the national factor, $P = 2$. $e^{h_t^{\mathcal{C}}}$ represents the stochastic volatility components, and $\nu_t^{\mathcal{C}}$ the innovation to the law of motion for the national or common factor.

$$r_{j,t} = \sum_{l=1}^{L} \phi_{j,t}^{\mathcal{R}} r_{t-l} + e^{h_{j,t}^{\mathcal{R}}} \cdot \nu_{j,t}^{\mathcal{R}}; \quad \nu_{j,t}^{\mathcal{R}} \sim i.i.d.\mathcal{N}(0, \sigma_{j,s}^2) \tag{3}$$

where $\phi_{j,t}^{\mathcal{R}}$ is the autoregressive coefficient for each regional factor, $L = 2$, $e^{h_{j,t}^{\mathcal{R}}}$, the stochastic volatility components, and $\nu_{j,t}^{R}$ the innovation to the law of motion for the regional factor.

$$\xi_{i,t} = \sum_{q=1}^{Q} \phi_q \xi_{t-q} + e^{h_{i,t}^{\mathcal{S}}} \cdot \nu_{i,t}^{\mathcal{S}}; \quad \nu_{i,t}^{s} \sim i.i.d.\mathcal{N}(0, \sigma_i^2) \tag{4}$$

where ϕ_q is the autoregressive coefficient for the idiosyncratic shock, $Q = P = L = 2$, $e^{h_{j,t}^{r}}$, the stochastic volatility components, and $\nu_{i,t}^{s}$ the innovation to the law of motion for the idiosyncratic factor. For proper identification, we follow the literature and assume that $\nu_t^{\mathcal{C}}, \nu_{j,t}^{\mathcal{R}}$, and $\nu_{i,t}^{\mathcal{S}}$ are orthogonal to each other.

4.2 Dynamic Factor Model with Time-Varying Stochastic volatility

To capture the dynamics in the volatility over time, we expand the standard DFM to include stochastic volatility in the laws of motion of the national, regional, and idiosyncratic factors (Equations 2 – 4). This extension assumes random, rather than constant, innovations (error terms) of each factor.[9] In particular, we observe differential volatility across time and economic conditions. Importantly, this assumption and specification allows us to capture changes in the sensitivity of our factors to labor conditions over our sample. To this extent, we are able to capture potential volatility changes due to new or amended labor policy and major shocks to the local economies like the COVID-19 pandemic and natural disasters.

Formally, the innovations, $e^{\bullet}$, vary over time and each stochastic volatility term, $h_{\bullet}$, evolve according to a random walk process without drift such that:[10]

$$h_t^{\mathcal{C}} = h_{t-1}^{\mathcal{C}} + \sigma_{\mathcal{C}}^h \cdot \eta_t^{\mathcal{C}}; \quad \eta_t^{\mathcal{C}} \sim i.i.d.\mathcal{N}(0,1) \tag{5}$$

$$h_{j,t}^{\mathcal{R}} = h_{j,t-1}^{\mathcal{R}} + \sigma_{j,\mathcal{R}}^h \cdot \eta_{j,t}^{\mathcal{R}}; \quad \eta_{j,t}^{\mathcal{R}} \sim i.i.d.\mathcal{N}(0,1) \tag{6}$$

$$h_{i,t}^{\mathcal{S}} = h_{i,t-1}^{\mathcal{S}} + \sigma_i^h \cdot \eta_{i,t}^{\mathcal{S}}; \quad \eta_{i,t}^{\mathcal{S}} \sim i.i.d.\ \mathcal{N}(0,1) \tag{7}$$

where $\sigma_{\mathcal{C}}^h, \sigma_{j,\mathcal{R}}^h, \sigma_i^h$ are the standard deviations of the innovation to each law of motion respectively and $\eta_t^{\mathcal{C}}, \eta_{j,t}^{\mathcal{R}}$, and $\eta_{i,t}^{\mathcal{S}}$ are the volatility shocks. We also assume that, $\eta_t^{\mathcal{C}}, \eta_{j,t}^{\mathcal{R}}$, and $\eta_{i,t}^{\mathcal{S}}$ are orthogonal to each other.

Lastly, for identification, we follow the standard normalization procedures used in the

[9]Formally, the stochastic volatility model assumes that the variance of the error term is itself normally distributed.

[10]Del Negro and Otrok (2008) opines that policy or structural changes occurring over time are permanent and not transitory. We, therefore, model the time-variation as a drift rather than a stationary process. This is a departure from previous studies on Appalachia's LFPR (Dorsey, 1991; Isserman and Rephann, 1993; Stephens and Deskins, 2018) as they often do not account for long term trends, or changes in national- and state-level labor force conditions. We contend that our approach is more flexible and better accounts for potential long term trends and structural changes in LFP conditions. This DFM-TV-SV model approach therefore fill the gaps in the previous literature.

macroeconomics literature (See Bhatt, Kishor, and Ma, 2017; Del Negro and Otrok, 2008, for example). First, given that the scale of the factor loadings and the standard deviations for each factor cannot be separately identified, we restrict the shocks of the national and regional factors $\sigma^2_{\mathcal{C}} = \sigma^2_{1,\mathcal{R}} = \sigma^2_{2,\mathcal{R}} = 1$. Second, since the scale of stochastic volatility term $h_\bullet$ is determined by the initial condition, we constrain each h in the stochastic volatility equations (5 – 7) to a starting value of zero. That is, $h^{\mathcal{C}}_0 = h^{\mathcal{R}}_{j,0} = h^{\mathcal{S}}_{i,0} = 0$. This assumes no stochastic volatility before the sample period but allows for derivation of an ergodic distribution for the initial conditions (Del Negro and Otrok, 2008).

4.3 Gibbs-Sampling Algorithm

Following Bhatt, Kishor, and Ma (2017); Bian et al. (2020); Del Negro and Otrok (2008), we estimate our model via a Monte Carlo Markov Chain (MCMC) Bayesian estimation utilizing the Gibb-Sampling Algorithm a lá Kim, Nelson et al. (1999). Below, we provide a brief description of our model estimation. For additional information about our execution of the procedure and the Gibb Sampler, the interested reader is directed to the technical appendix of Bhatt, Kishor, and Ma (2017).

For notational ease, let Ξ be the collection of time-varying coefficients and hyperparameters such that

$$\Xi = \left(\omega^{T\prime}, \beta^{T\prime}, \varphi'_{\mathcal{C}}, \varphi'_{\mathcal{R}}, \varphi'_{\mathcal{S}}, g^2, \{h^{\mathcal{C}}_{1,t}\}^T_{t=1}, \{h^{\mathcal{R}}_{1,t}\}^T_{t=1}, \{h^{\mathcal{R}}_{2,t}\}^T_{t=1}, \{\{h^{\mathcal{S}}_{1,t}\}^T_{t=1}\}^{51}_{i=1}{}'\right),$$

where $\omega^T = \{(\omega_1, \omega_2, \ldots, \omega_{51})'\}^T_{i=1}$ and $\beta^T = \{(\widetilde{\beta_1}, \widetilde{\beta_2}, \ldots, \widetilde{\beta_{51}})'\}^T_{t=1}$ denote our time-varying coefficients. $\varphi_{\mathcal{C}} = (\phi^{\mathcal{C}}_1, \phi^{\mathcal{C}}_2)$, $\varphi_{\mathcal{R}} = (\phi^{\mathcal{R}}_{1,1}, \phi^{\mathcal{R}}_{1,2}, \phi^{\mathcal{R}}_{2,1}, \phi^{\mathcal{R}}_{2,2})$, $\varphi_{\mathcal{S}} = (\phi_{1,1}, \phi_{1,2}, \phi_{2,1}, \phi_{2,2}, \ldots, \phi_{51,1}, \phi_{51,2})$, and $g^2 = \{\sigma^2_i\}^{51}_{i=1})$ are the time invariant variances. Lastly, the $h_\bullet$ represent the latent stochastic volatilities.

1. Draw the common and regional factors conditioned on the time-varying factor loadings, the autoregressive coefficients of the national and idiosyncratic components, the time

invariant variance, and the stochastic volatilities.

$$f\left(\{\mathcal{C}_t\}_{t=1}^{T}, \{\mathcal{R}_{1,t}\}_{t=1}^{T}, \{\mathcal{R}_{2,t}\}_{t=1}^{T} \middle| \; \Xi\right)$$

Given the presence of stochastic volatility, this process requires modification from the original procedure outlined in Chib and Greenberg (1994). This modification is described in detail in Del Negro and Otrok (2008).

2. Take a random draw of the AR(Q) and variance parameters for the idiosyncratic factor conditioned on the national factor, regional factors, time-varying factor loadings, and the idiosyncratic stochastic volatility.

$$f\left(\varphi_S, g^2 \middle| \; \{\mathcal{C}_t\}_{t=1}^{T}, \{\mathcal{R}_{1,t}\}_{t=1}^{T}, \{\mathcal{R}_{2,t}\}_{t=1}^{T}, \omega, \widetilde{\beta}, \{h_{i,t}\}_{t=1}^{T}\right)$$

3. Get a random draw of the time-varying loadings parameters, conditioned on the national factor, regional factors, the autoregressive coefficients of the national factor, the time invariant variances, and idiosyncratic stochastic volatility.

$$f\left(\omega, \widetilde{\beta} \middle| \; \{\mathcal{C}_t\}_{t=1}^{T}, \{\mathcal{R}_{1,t}\}_{t=1}^{T}, \{\mathcal{R}_{2,t}\}_{t=1}^{T}, \varphi_c, \sigma^2, \{h_{i,t}\}_{t=1}^{T}\right)$$

Since we assume the errors, conditional on the factors in Equation 1, and the innovations in the factor loadings are independent across i, we can draw the time-varying loadings one at a time. This diminishes the effect of dimensionality and aid in efficiency.

4. Take a random draw of the AR parameters of the national and regional factors, conditioned on their respective loading factor and stochastic volatilities.

$$f\left(\varphi_{\mathcal{C}} \middle| \; \{\mathcal{C}_t\}_{t=1}^{T}, \{h_{1,t}^{\mathcal{C}}\}_{t=1}^{T}\right)$$
$$f\left(\varphi_{\mathcal{R}} \middle| \; \{\mathcal{R}_{1,t}\}_{t=1}^{T}, \{\mathcal{R}_{2,t}\}_{t=1}^{T}, \{h_{1,t}^{\mathcal{R}}\}_{t=1}^{T}, \{h_{2,t}^{\mathcal{R}}\}_{t=1}^{T}\right)$$

5. Get a random draw of the time invariant and time-varying stochastic volatility for the national, regional and idiosyncratic components, conditioned on the factor loadings and autoregressive parameters. This step follows the algorithm from Kim, Shephard, and Chib (1998)

$$f\left(\{h_{1,t}^{\mathcal{C}}\}_{t=1}^{T}, \sigma_{\mathcal{C}}^{h} \middle| \{\mathcal{C}_t\}_{t=1}^{T}, \varphi_{\mathcal{C}}\right)$$
$$f\left(\{h_{1,t}^{\mathcal{R}}\}_{t=1}^{T}, \{h_{2,t}^{\mathcal{R}}\}_{t=1}^{T}, \sigma_1^{h}, \sigma_2^{h} \middle| \{\mathcal{R}_{1,t}\}_{t=1}^{T}, \{\mathcal{R}_{2,t}\}_{t=1}^{T}, \varphi_{\mathcal{R}}\right)$$
$$f\left(\{h_{1,t}^{\mathcal{S}}\}_{t=1}^{T}, \sigma_i^{h} \middle| \{\mathcal{C}_t\}_{t=1}^{T}, \{\mathcal{R}_{1,t}\}_{t=1}^{T}, \{\mathcal{R}_{2,t}\}_{t=1}^{T}, \omega, \widetilde{\beta}, \varphi_{\mathcal{S}}\right)$$

6. **Repeat steps 1 - 5**: $(B + K)$ number of times where B is the number of burn-ins or draws discarded in order to reach confidence in the initial conditions imposed. K is the number of keepers or draws that are saved after the allotted burn-in values have been reached. We use B = 10,000 and K = 40,000 draws respectively.

5 Results

Over time, we find that the economic structure of a state and its connection to the national and regional economies have different sensitivities. This provides a strong justification for using a model with time-varying loading parameters and stochastic volatility. In Figures 4 and 5, we plot the time-varying loading parameters (posterior medians) of an unobserved national/common factor, for the Appalachian region and selected Non-Appalachian states together with their 90% confidence intervals.[11] These national factor loadings reflect changes in the sensitivity or a measure of synchronization of each state with the national factor. The tight confidence intervals around our median estimates indicate a fairly low level of parameter uncertainty. In Figure 6, we plot the time-varying loading parameters (posterior medians)

[11]For the sake of brevity, we have suppressed the results for the rest of the non-Appalachian states. The full results are available from the authors upon request.

for an unobserved Appalachian regional factor for the Appalachian states, together with their 90% confidence intervals[12] The Appalachian regional factor loadings reflect changes in the sensitivity or a measure of synchronization of each Appalachian state with the regional factor.

5.1 National and Regional Factors Loadings

We observe considerable time variations in the national factor loading parameters across states. We see that the lower bound of the 90% confidence bands in the latter part of the sample period is above the upper bound of the confidence bands in the early part of the sample period. Not only does this provide further justification for using a general approach for modeling comovement among state LFPR, it also justifies our extension of the standard DFM with time-varying parameters.

Additionally, despite the substantial time variations, the dynamics and overall shape of the national factor loadings over time are similar across states and are mostly positive. The negative loading parameters at the beginning of the sample period indicate that each state's LFPR had a relatively sensitive and negative correlation with the national factor. Noticeably, there is a change in sign of the factor loadings near 1990. Most states exhibit near-zero correlation with the national factor in 1990 which is supported by the divergence in the change in state LFPR time series seen in Figure 1. After the 1990 recession, the loading parameters are mostly positive indicating that change in LFPR for each state is relatively sensitive and positively correlated with the national factor. Around the Great Recession (2008 – 2009), we observed a mixed response across states. In general, most states decrease in sensitivity, indicating a divergence of state LFPR from the national factor. The responses in Appalachian states such as Alabama, Georgia, and Kentucky were a bit more extreme than their counterparts. Interestingly, for Georgia, the positive correlation with the national factor becomes negative and for Pennsylvania, the sensitivity to the common factor increased

[12] Results for Non-Appalachian regional factor loadings are available upon request.

significantly at the onset of the crisis and quickly decreased thereafter. The sensitivity or correlation to the common factor for other states such as California and Iowa, seen in Figure 5, increased through the recession, and for Oregon remained the same.

Turning our attention to the loading parameters of the Appalachian regional factors. Figure 6 reveals that the sensitivity of statewide LFPRs is much more heterogeneous (than their national factor counterpart). Although the median estimates are, by and large, near-zero, we observe a large degree of parameter uncertainty. This was especially true during the COVID-19 pandemic period when the range of the upper and lower bounds widened most.

West Virginia is a notable exception here. The confidence bounds are much tighter around that state's median estimates during the early and late 1980s. Moreover, during theses periods West Virginia has a much larger connection to the regional economy, compared to other states – the estimates ranged from ± 0.4. In the early 1980s, West Virginia exhibits strong and negative regional factor loadings. This would indicate a strong sensitivity or synchronization and a negative relationship with the regional economy. West Virginia and the Appalachian region experienced a coal bust in this period which precipitated a high level of unemployment (Black, McKinnish, and Sanders, 2005). This was further exacerbated by the national recessions in the early 1980s. Our model not only distinguishes the national sensitivity from the regional, but our results also indicate that while the connection to the national economy was relatively strong during this time, the connection or influence of the regional economy was stronger.

Approaching the end of the 1980s, the regional factor loadings for West Virginia gradually increased. This strong comovement between the that state's LFPR and the Appalachian factor coincides with the labor growth and expansion in 1987-1988 (Howe and Parks, 1989) and the Pittston Coal Strike of 1989 (Birecree, 1996). Moreover, much of the regional economy shifted away from the reliance on coal and restructured the West Virginia labor market into other industries (Stevens, 1986). Together with the decline in the sensitivity to the national factor (Figure 4) for West Virginia during this time, our results point to a

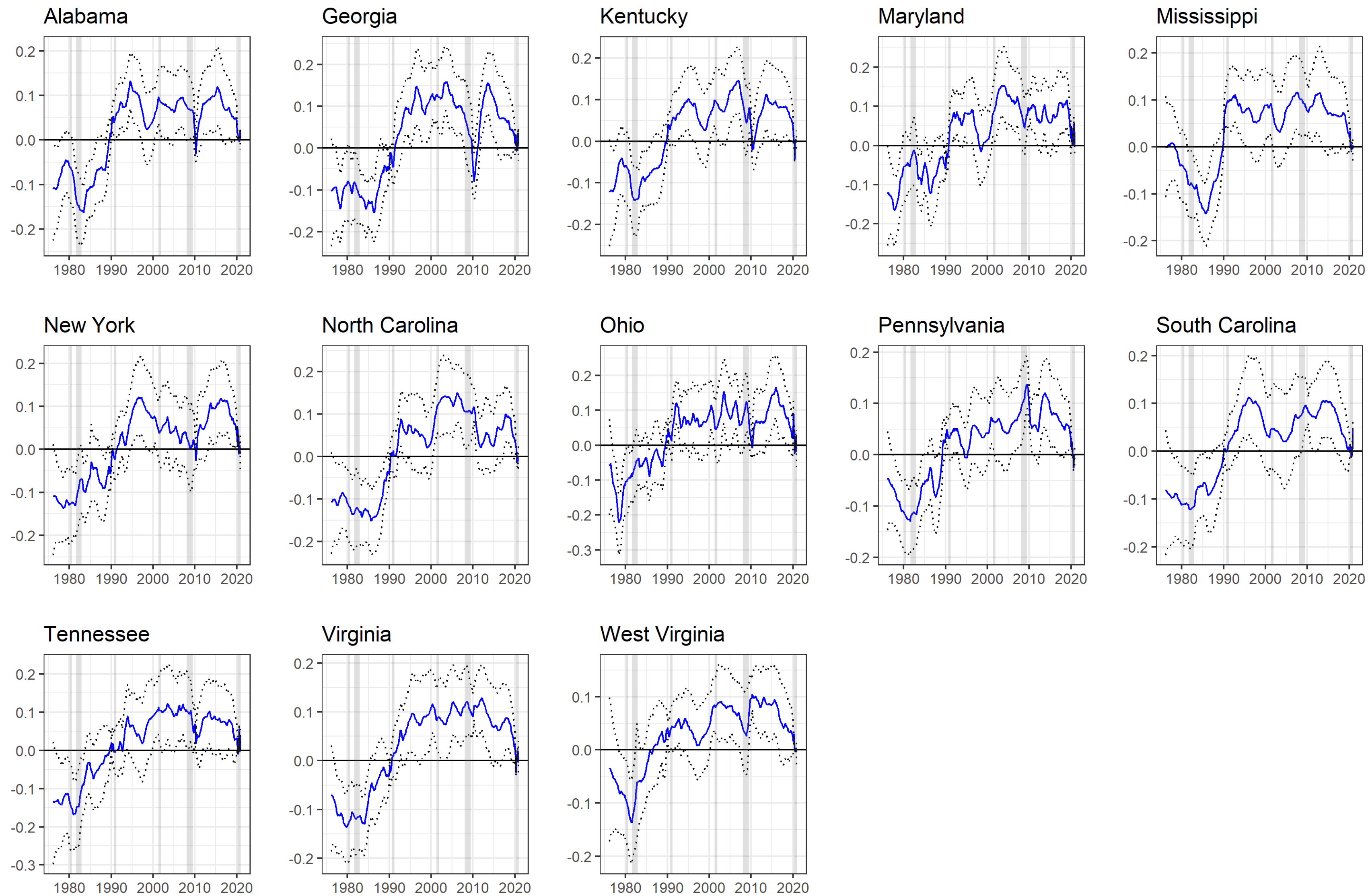

Figure 4: **National Factor Loadings by States in the Appalachian Region**

Note: Shaded regions are the NBER-dated recessions. The blue solid lines represent the median of the posterior distribution. Dashed lines represent the 5th and 95th percentiles.

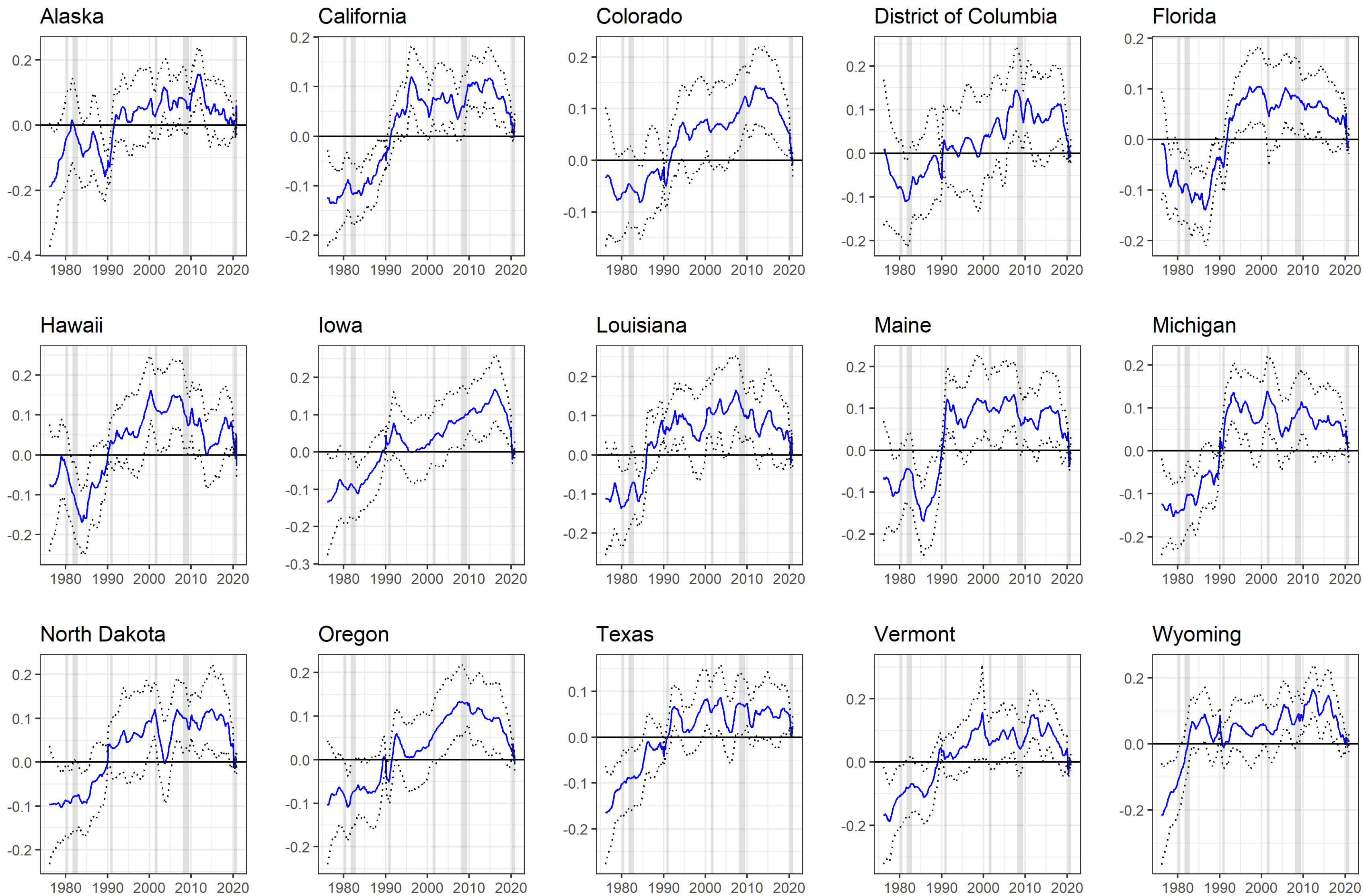

Figure 5: **National Factor Loadings by States Not in the Appalachian Region**

Note: Shaded regions are the NBER-dated recessions. The blue solid lines represent the median of the posterior distribution. Dashed lines represent the 5th and 95th percentiles.

potentially more insulated West Virginian economy. In short, given its state-specific labor market characteristics, West Virginia displayed a strong connection to the regional economy making West Virginia susceptible to regional shocks.

5.2 Variance Decompositions

From Equation 1, our model implies the following variance decomposition structure:

$$\mathrm{Var}(y_{i,t}) = \omega_{i,t}^2 \ \mathrm{Var}(\mathcal{C}_t) + \widetilde{\beta}_{i,t} \ \mathrm{Var}(\mathcal{R}_t)\widetilde{\beta}'_{i,t} + \ \mathrm{Var}(\xi_{i,t}) \tag{8}$$

The fraction of volatility due to say, the national factor, $\mathcal{C}$, would be:

$$\frac{\omega_{i,t}^2 \ \mathrm{Var}(\mathcal{C}_t)}{\mathrm{Var}(y_{i,t})}$$

Below, we discuss the contribution of each of the three components (of Equation 8) to the state LFPR.

Figures 7 and 8 plot the percentage contributions of the national, regional, and state factors to the total change in LFPR variations for all states within Appalachian and selected, non-Appalachian states [13]. These plots allow us to ascertain the relative importance of each factor in explaining labor market dynamics. Despite an obvious heterogeneity across space and time, we observe that the national and idiosyncratic factors are consistently the dominant contributors. This implies that much of the variations in the state LFPRs is explained by either national labor market trends or individual state circumstances.

Interestingly, concerning time, the contribution of the national factor was most pronounced during periods of recessions, financial crises, or the COVID-19 pandemic. The national factor dominated during the early 1980s, 1990, early 2000s, 2009-2010 and 2020 for most states in and out of the Appalachian region. At times, close to 100% of the vari-

[13] Our estimation algorithm included all 50 states (plus Washington D.C.). The full results are available upon request.

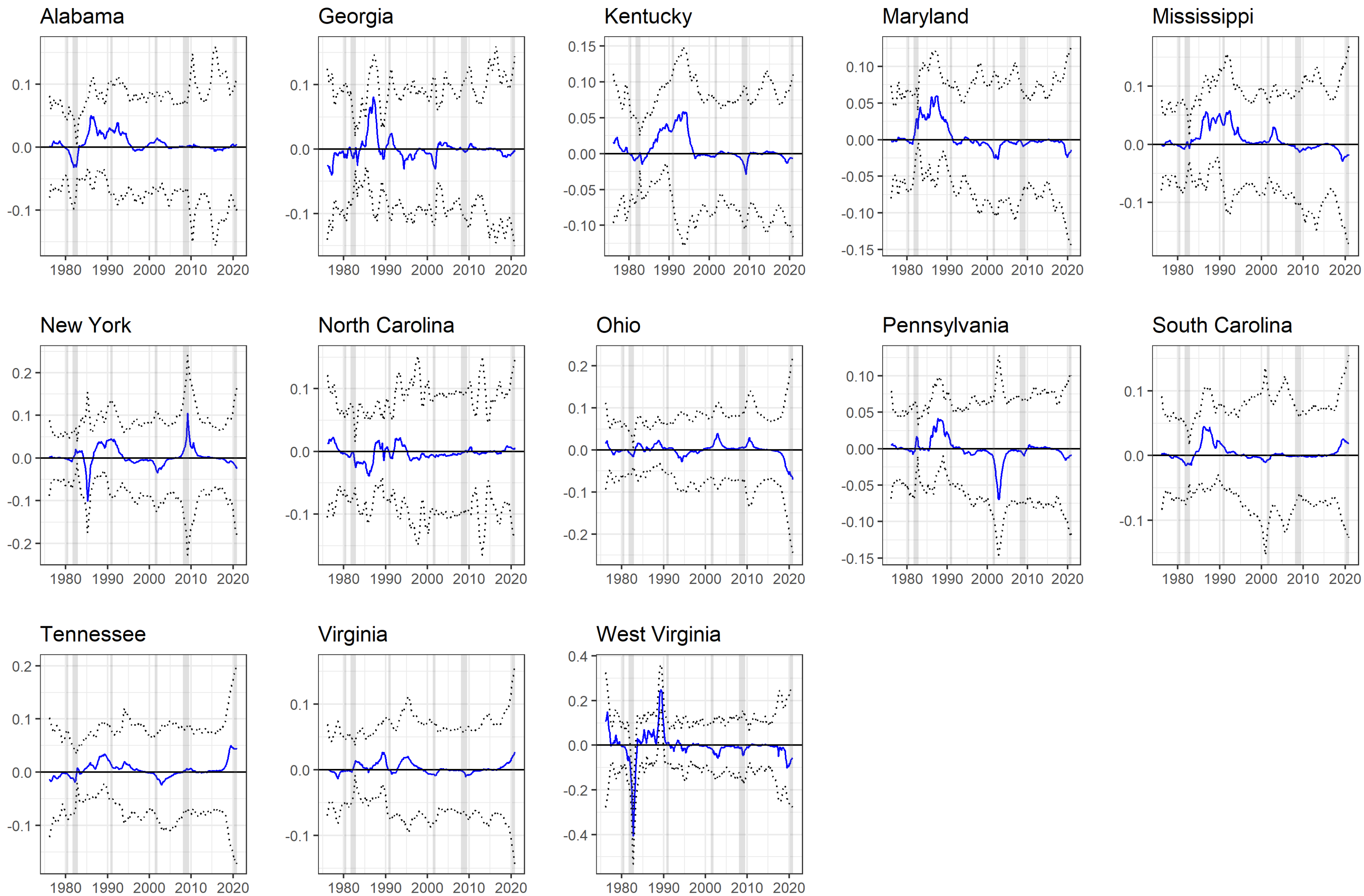

Figure 6: **Regional Factor Loadings by State in the Appalachian Region**

Note: Shaded regions are the NBER-dated recessions. The blue solid lines represent the median of the posterior distribution. Dashed lines represent the 5th and 95th percentiles.

ations in the LFPRs variation was explained by the national factor which corresponds to the zero correlation of the state changes in LFPR with national factor seen in Figures 4 and 5. This indicated the national shock led to divergence in the change in LFPR across states. However, outside these periods, the idiosyncratic factor is more important. In other periods, states appear to be more insulated and more susceptible to state-specific labor and economic shocks.

Additionally, concerning location, we see the idiosyncratic factor is more important in states such as Alaska, Colorado, Iowa, Oregon, and Washington D.C in Figure 8. These states are either far away from the rest of the county or have a unique economic structure that seems to drive these results. Conceivably, geographic isolation at the outskirts or rural center of the U.S. leads to a smaller connection with national trends and more susceptibility to idiosyncratic shock. We found the case of West Virginia to be rather curious as well. Unlike its Appalachian counterparts, the state appeared to be much more insulated outside of national crises windows. In fact, over the sample period, West Virginia again exhibited the closest connection to the Appalachian factor. Figure 9 reveals significant heterogeneity across the states in Appalachian region, but the Appalachian factor explains a large portion of West Virginia LFPR dynamics compared to the other states. On several occasions, the computed contribution surpassed 75%. In the mid-1980s, the Appalachian factor explained almost 100% of the change in LFPR for West Virginia. Most other states, barring New York, experienced much smaller contributions from the Appalachian factor.[14] For the remaining states, incidents of increases in the relative importance of the Appalachian factor appear to coincide with periods of economic recovery and booms.

Additionally, Figure 9 indicates that most states in the Appalachian region exhibit a slightly decreasing trend in the overall importance of the Appalachian region factor throughout the sample period. This indicates that state labor force participation is becoming less

[14]In 1985 and 2009 around 60% of the variation in New York's LFPR was explained by the Appalachian Factor. These peaks appear to coincide more with recessionary periods in the early 1990s, 2000s and the Great Recession in 2008-2009.

influenced by regional shocks or trends (and more influenced by increasingly important national shocks and trends). We conclude, therefore, that changes in the LFPRs are more largely attributable to a state's connection to the national LFPR dynamics and its local labor market during times of economic prosperity. In periods of national turmoil, however, the national factor clearly explains much of the variation but state LFPRs respond more in connection to the idiosyncratic factors. In the discussion that follows, we attempt to place our findings in the context of the extant literature.

Existing studies pose the open-ended question about whether an "Appalachian Effect" and/or cultural factors contribute to lower LFPR in the long run for the Appalachian region. As we briefly discussed in Section 2, a consensus has yet to be reached and the question remains unanswered. Since our model and results do not attempt to measure a cultural effect, we focus instead on the temporal aspect of the question. Isserman and Rephann (1993) argue that a cultural effect would be persistent and not "ebb and flow" over time. The authors conclude that if empirical results depend on the choice of year, then the gap in LFPR between the Appalachian region and the rest of the U.S. cannot be caused by an Appalachian culture. The results for the portion of the variance explained by our Appalachian region factor support this conclusion. For example, the Appalachian region factor explains a relatively larger portion of the variance for most of the states in the Appalachian region in the mid-1980s, as seen in Figure 9. This coincides with the strongest Appalachian region effects found by Isserman and Rephann (1993) and Dorsey (1991) with 1987 data. We argue that the gap in LFPR captured by these previous studies in 1987 are potentially driven by a regional shock, such as the coal bust during the late 1980s. Again, this highlights the fact that the choice of year is a critical driver of the postulation in the current literature.

Comparing our findings with more recent studies, Stephens and Deskins (2018) determine that Appalachian counties are 7.1 percentage points lower in LFPR than similar non-Appalachian counties. Through a Blinder-Oaxaca decomposition, the authors determine that of the 7.1 percent difference, 1.1 percentage points remained unexplained by their model.

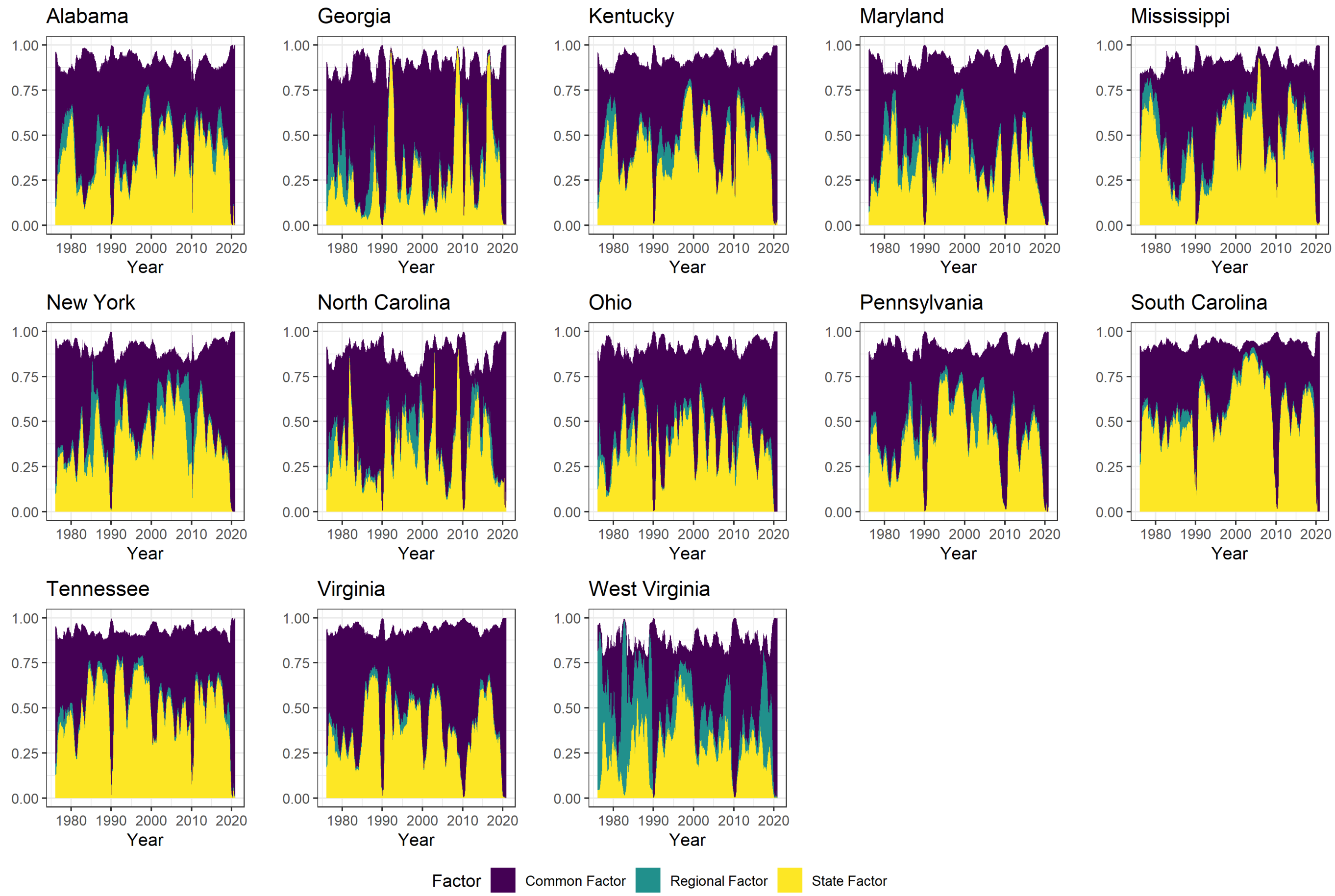

Figure 7: **Variance Contribution of Factor by State in the Appalachian Region**

Note: Colored areas represent the percent contribution of each factor to observed variation in the change in LFPR. Percent contributions are respective medians of the posterior distribution.

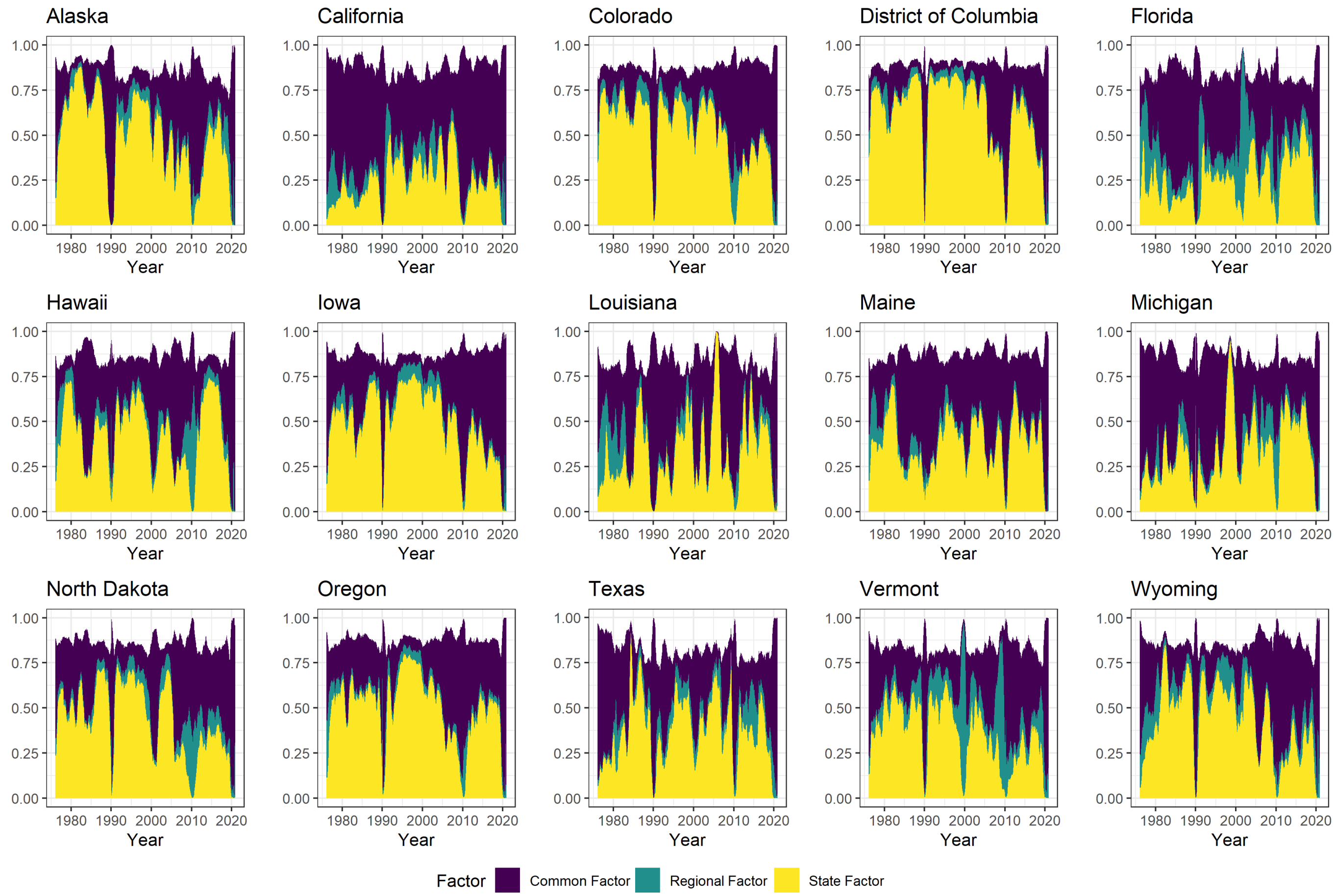

Figure 8: **Variance Contribution of Factor by State**

Note: Colored areas represent the percent contribution of each factor to observed variation in the change in LFPR. Percent contributions are respective medians of the posterior distribution.

They posit this as evidence supporting an "Appalachian Effect". However, our results show a weak relationship between change in state LFPR and the regional economy in 2000 and 2010. Figure 6 shows that for these years the regional factor contributes little to the variance in the change of LFPR. Moreover, we find a stronger relationship with the national economy over these years. For example, on average across the Appalachian states, the national factor explains over 88% of the variation in the change in LFPR in April of 2010. This may be explained by national economic trends and events such as decreases in unemployment and layoffs throughout 2010 and the signing of the Jobs Bill (HIRE) and the Affordable Care Act (ACA) in March 2010, by President Obama. Figure 7 shows that for Maryland, North Carolina, Pennsylvania, South Carolina, Virginia, and West Virginia, the variation explained by the national factor exceed 98% for the middle part of 2010. Again, since our methodology centers around changes in LFPR, the weaker influence of the Appalachian region factor for 2000 and 2010 for most of the states in the region may simply reflect the lack of major regional economic or labor market events during these years. However, given our results, we suggest that the unexplained variation in Stephens and Deskins (2018) may be related to a disproportionate effect of national economic shocks or events during this time on an already economically distressed Appalachian region.

Figure 10 presents the average cross-state time-varying correlation. There is a general upward trend in the median correlation statistic over the sample period. In congruence with our results from Figures 4 and 5, we especially see evidence of the divergence in the change in state LFPR across states in 1990 and 2020. In Figure 10 there is an asymmetric response in the correlation during periods of crisis. During the recession of the late 1990s and the Great Recession (2008-2009), the average cross-state correlation increased. This indicates that during and immediately following these episodes, the LFPRs across states were becoming more synchronized. To this effect, policies aimed at dampening labor market shocks and encouraging recovery could prove more effective as a one-size-fits-all approach becomes more useful. Figure 10 also show that over time cross-state correlation is increasing

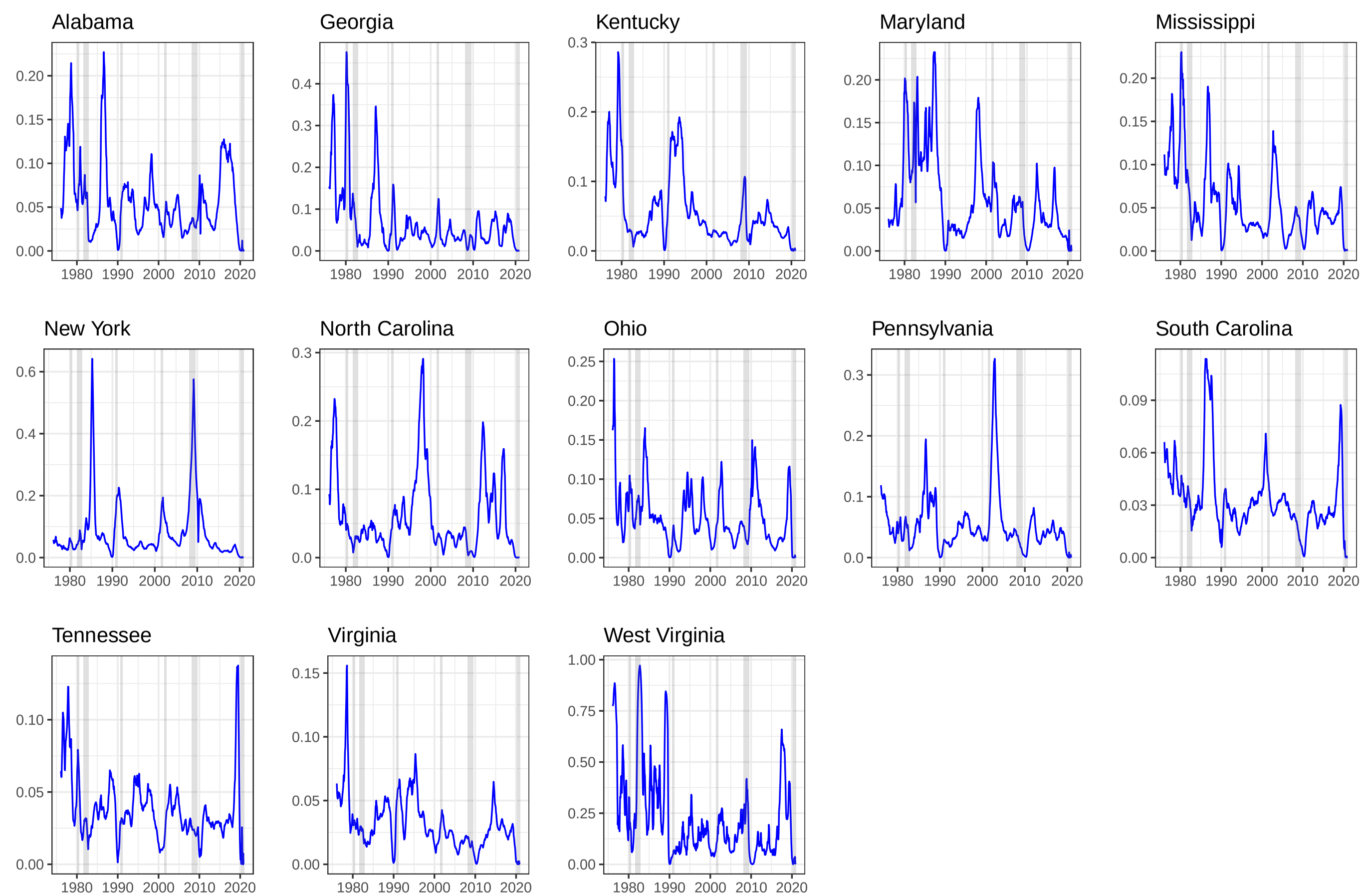

Figure 9: **Variance Contribution of the Appalachian Regional Factor by State**

Note: Shaded regions are the NBER-dated recessions. The blue solid lines represent the median of the posterior distribution.

in general. Together with our previous results from the variance contribution and factor loadings, we can then conclude that changes in state LFPRs are becoming more connected with the national factor over time.[15]

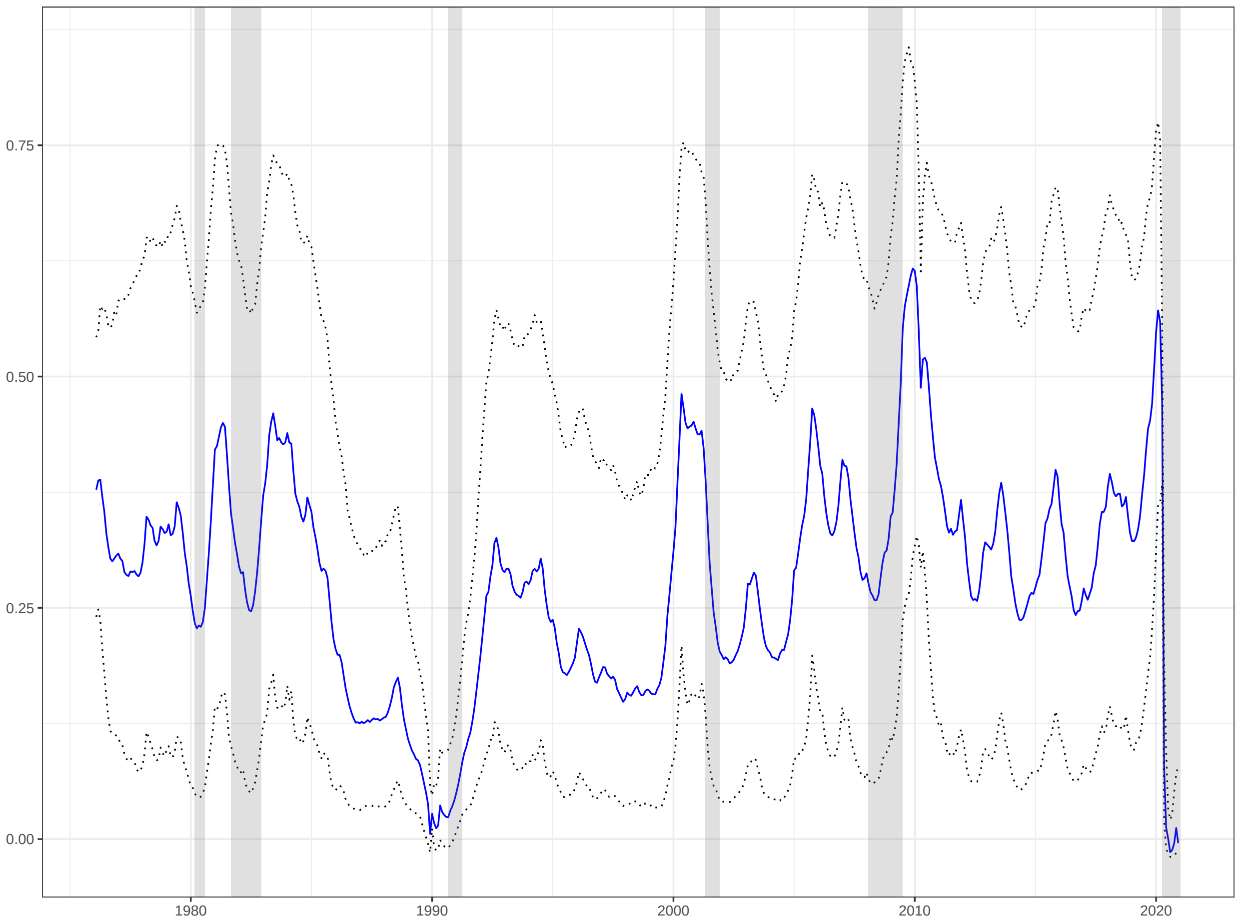

Figure 10: **Average Cross State Correlation (All States)**

Note: Shaded regions are the NBER-dated recessions. The blue solid lines represent the median of the posterior distribution. Dashed lines represent the 5th and 95th percentiles.

For robustness, we replicate our results with 2020 omitted from our sample. Since we are assessing volatility and relative contributions of our data over time we expect excluding

[15]Since LFPs were unusually low in 2020, we checked the robustness of our result re-estimated our model results to be at least partially driven by the outlying market conditions during that time. Our results excluding 2020 and the sensitivity of our model and findings to the 2020 data are presented and discussed in Section **??** of the Appendix.

2020, as an unusually low LFP year and major economic shock, to impact the results[16]. We find that the results for the average cross-state correlation and variance contributions across samples are very similar. The main differences reside in the national and regional factor loadings. As previously mentioned, the national factor loadings in the sample including 2020 move from negative to positive after about 1990. However, this transition is absent for the 1976-2019 sample. In this case, the national factor loadings are positive from 1976 to 1990. We also find a reversal in relationship across the samples in the regional factor loadings for West Virginia. As discussed earlier, West Virginia exhibits strong and negative regional factor loadings in the early 1980s for the 1976-2020 sample. However, the regional factor loadings for West Virginia during this same time in the 1976-2019 sample are also strong but in this case positive. These results indicate that the direction of correlation between the factors and the change in state LFPR is inconsistent across samples. While knowing whether changes in state LFPR are increasing or decreasing with the national and regional factors may be beneficial, we focus on the strength of the relationship in this paper and find the results to be robust across samples.

6 Conclusion

In this paper, we demonstrate that comovement or divergence of the change in state LFPR varies over time, geographic level, and economic and labor market fluctuations. In particular, we examine the relative contribution of a latent regional factor to the labor force dynamics of states in Appalachia over time. Using a dynamic factor model with time-varying parameters and stochastic volatility, we show that the choice of year and state together with the economic conditions are crucial to the relative importance of each factor's contribution to the LFPR.

We determine that national and state-specific factors play a dominant role in explaining the change in LFPR variations for most U.S. states during periods of recessions and general economic downturns. During large national recessions, we find divergence in the change in

[16]Visualizations for our results excluding 2020 can be found in Section **??** of the Appendix

U.S. state LFPR. However, during times of recovery and expansion, change in state LFPR is more synchronized with the national factor. We determine that the influence of the Appalachian factor increases during economic expansions or recoveries, albeit still smaller in magnitude than the common and idiosyncratic components. We conclude that these findings may influence the results of cross-sectional studies using LFPR given the years and economic and labor market conditions over which the data covers.

Consistent with other studies, we find that West Virginia displays the strongest connection to the Appalachian region factor. The regional factor persistently contributes more than 1/2 of the volatility observed in that state's change in LFPR. This is far higher than any of the other 12 states. Additionally, the change in LFPR for West Virginia synchronizes greatly with the Appalachian region factor during two periods of regional labor market shifts (Coal Boom and Bust). This curious observation offers an avenue for further investigation. Our approach and results highlight the need for policies that accommodate both the state of the economy and state-specific characteristics.

6.1 Policy Implications

Our results are important for policymakers and potential improvements in regional and national output growth. Federal labor policy is more effective when LFP is highly synchronized across the nation. However, when regions of the U.S. exhibit distinct behavior or if states themselves exhibit more individual behavior, then more localized and targeted labor policies would be more efficient.

In short, given the relationship between LFP and output, increasing regional and local participation would stimulate output growth. However, our results point to the need for disparate government responses during crises and booms. There is a need for a federal response during periods of economic growth and economic recovery as states become more homogeneous and connected to the national factor. During periods of economic crisis and pandemics, there is a greater need for state and region-specific policies. By varying the level of policy interventions during different stages of the business cycle, economically distressed areas would experience more targeted labor market policies than a one-size-fits-all prescription. It is also important to note that state LFPRs are gradually growing more synchronized and connected to the national factor. While this presents opportunities to implement more effective federal-level policies to assist depressed labor markets, it also reduces the nation's ability to absorb labor market shocks. This has important long-term implications for the Appalachian region since economically distressed areas are already more vulnerable to economic shocks.

It is also important to note that while the Appalachian region factor explains significant portions of the variance in West Virginia throughout the sample period, we find that the connection or synchronization with the Appalachian region factor is near-zero. Zero correlation with the Appalachian region factor is most likely due to the lack of regional shocks induced by a gradual shift from dependence on natural resource employment to other industries. However, given the level of contributions of the Appalachian region to the observed variance in the change in LFPR in recent years (Figure 9), we expect that West Virginia is not completely impervious to regional economic shocks.

6.2 Limitations and Avenues for Future Work

Given that this study is limited to state-level data we do not address concerns in Isserman and Rephann (1993) related to the idea that the geographic level of the data may significantly contribute to certain findings.[17] A future avenue for research could focus on a more disaggregated analysis to account for differences across the rural-urban spectrum and county inclusion/exclusion within Appalachia. While we specifically emphasize the macroeconomic nature of state-level LFPR, further investigation into the impact on the rural/urban divide of these results may be warranted. This is buoyed by the fact that West Virginia appears to

[17]Due to the high computational burden of our model and the curse of dimensionality, we were not able to explore this avenue. We would expect to see more diversity within and between states and counties and a potentially more pronounced Appalachian factor.

be structurally different– as evidenced by the persistently low labor force participation and relatively large variance contributions of the Appalachian region factor. While it is “all is quiet on the Appalachian front” regarding regional results for most Appalachian states, West Virginia stands out. Since West Virginia is the only state with all counties designated in the Appalachian Region, further research may provide insight into narrowing down problematic sub-regions and why certain areas remain economically distressed. Moreover, this will allow for direct comparability with the extant literature.

Lastly, our results prompt questions about the relationship between the national, regional, and state factors and known drivers of labor force participation. Some examples pertain to when and how West Virginia adjusts to shocks in LFP, and how much of the variation and error realization of the latent factors are explained by unexpected changes in other factors and included variables. More research is needed to ameliorate decades of low labor force participation and maximize the growth potential for West Virginia and the rest of the Appalachian region.

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7 Appendix

Table A.1: **State LFP Descriptive Statistics**

States	Mean	Median	Min	Max	S.D.
Alabama	60.50	60.90	55.90	64.50	2.29
Alaska	70.87	71.90	61.10	75.30	2.72
Arizona	63.16	63.50	59.10	67.10	2.00
Arkansas	60.98	61.15	56.20	64.20	2.02
California	65.12	65.70	59.20	68.00	1.77
Colorado	70.54	70.60	64.90	74.30	2.06
Connecticut	67.64	67.60	63.30	71.30	1.71
Delaware	65.95	66.60	60.10	70.90	3.00
District of Columbia	67.50	67.40	63.00	72.10	2.20
Florida	60.63	61.40	54.90	63.70	2.32
Georgia	65.95	66.30	59.40	69.30	2.34
Hawaii	65.58	66.40	56.20	69.90	2.54
Idaho	66.82	66.60	62.70	71.40	2.33
Illinois	66.42	66.20	60.40	70.00	1.70
Indiana	66.09	66.10	61.20	70.90	1.96
Iowa	69.72	70.00	64.10	73.50	2.53
Kansas	68.98	69.10	64.90	71.50	1.61
Kentucky	61.51	62.00	56.00	63.70	1.59
Louisiana	60.54	60.80	54.60	68.70	1.45
Maine	64.84	65.15	58.60	68.80	2.35
Maryland	68.78	69.00	63.00	71.50	1.65
Massachusetts	66.93	67.10	60.40	69.40	1.25
Michigan	64.09	64.20	57.40	68.80	2.34

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Table A.1 – continued from previous page

States	Mean	Median	Min	Max	S.D.
Minnesota	71.87	71.50	65.40	75.70	2.37
Mississippi	59.63	59.80	53.30	63.30	2.39
Missouri	66.18	66.00	59.80	71.00	2.65
Montana	65.95	66.60	61.40	69.00	1.91
Nebraska	70.59	71.30	64.80	74.10	2.53
Nevada	68.72	69.70	58.00	73.50	3.37
New Hampshire	70.35	70.90	65.10	73.60	1.84
New Jersey	65.36	65.90	61.40	67.60	1.48
New Mexico	61.56	62.40	55.00	63.90	2.07
New York	61.42	61.60	56.80	63.60	1.41
North Carolina	65.68	66.60	56.20	69.00	2.52
North Dakota	69.65	70.50	62.30	74.70	2.96
Ohio	64.82	64.65	59.80	67.70	1.78
Oklahoma	62.96	63.60	58.90	65.50	1.60
Oregon	65.71	66.00	59.20	68.90	2.31
Pennsylvania	62.56	63.10	58.30	65.30	1.88
Rhode Island	66.13	66.30	59.40	68.40	1.44
South Carolina	63.30	63.90	56.60	66.90	2.73
South Dakota	69.92	70.10	64.30	73.20	2.32
Tennessee	62.90	62.90	58.00	67.20	2.02
Texas	66.90	67.30	60.20	69.40	1.96
Utah	69.22	69.40	62.50	73.40	2.77
Vermont	69.34	70.45	60.90	72.60	2.36
Virginia	67.58	67.80	63.20	70.90	1.54
Washington	66.20	66.30	60.60	69.90	2.22

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Table A.1 – continued from previous page

States	Mean	Median	Min	Max	S.D.
West Virginia	54.09	54.65	51.00	56.20	1.55
Wisconsin	69.76	69.30	65.40	74.50	2.44
Wyoming	69.69	70.35	64.10	72.40	2.01

Note: Statistics reflect the state-level labor force participation rates over the sample period January 1976 – December 2020. S.D refers to the standard deviation.

Table A.2: **Composition of Appalachia by State**

State	Counties in Appalachia (%)	Percent of Appalachia
Alabama	55.22	8.81
Georgia	23.27	8.81
Kentucky	45.00	12.86
Maryland	12.50	0.71
Mississippi	29.27	5.71
New York	22.58	3.33
North Carolina	29.00	6.90
Ohio	36.36	7.62
Pennsylvania	77.61	12.38
South Carolina	13.04	1.43
Tennessee	54.74	12.38
Virginia	18.38	5.95
West Virginia	100.00	13.10

Table A.3: **Composition of Regions By State**

States	Non-Appalachia	Appalachia	Plains	Mideast	Great Lakes
Alabama		✓			
Alaska	✓				
Arizona	✓				
Arkansas	✓				
California	✓				
Colorado	✓				
Connecticut	✓				
Delaware	✓			✓	
District of Columbia	✓			✓	
Florida	✓				
Georgia		✓			
Hawaii	✓				
Idaho	✓				
Illinois	✓				✓
Indiana	✓				✓
Iowa	✓		✓		
Kansas	✓		✓		
Kentucky		✓			
Louisiana	✓				
Maine	✓				
Maryland		✓		✓	
Massachusetts	✓				
Michigan	✓				✓
Minnesota	✓		✓		

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Table A.3 – continued from previous page

States	Non-Appalachia	Appalachia	Plains	Mideast	Great Lakes
Mississippi		✓			
Missouri	✓		✓		
Montana	✓				
Nebraska	✓		✓		
Nevada	✓				
New Hampshire	✓				
New Jersey	✓			✓	
New Mexico	✓				
New York		✓		✓	
North Carolina		✓			
North Dakota	✓		✓		
Ohio		✓			✓
Oklahoma	✓				
Oregon	✓				
Pennsylvania		✓		✓	
Rhode Island	✓				
South Carolina		✓			
South Dakota	✓		✓		
Tennessee		✓			
Texas	✓				
Utah	✓				
Vermont	✓				
Virginia		✓			
Washington	✓				
West Virginia		✓			

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Table A.3 – continued from previous page

States	Non-Appalachia	Appalachia	Plains	Mideast	Great Lakes
Wisconsin	✓				✓
Wyoming	✓				

Note: We define states to be included in the Appalachian region if they have at least one county located in the region as defined by the Appalachian Region Commission (ARC). States included in Plains, Mideast and Great Lakes regions are defined by the U.S. Bureau of Economic Analysis.

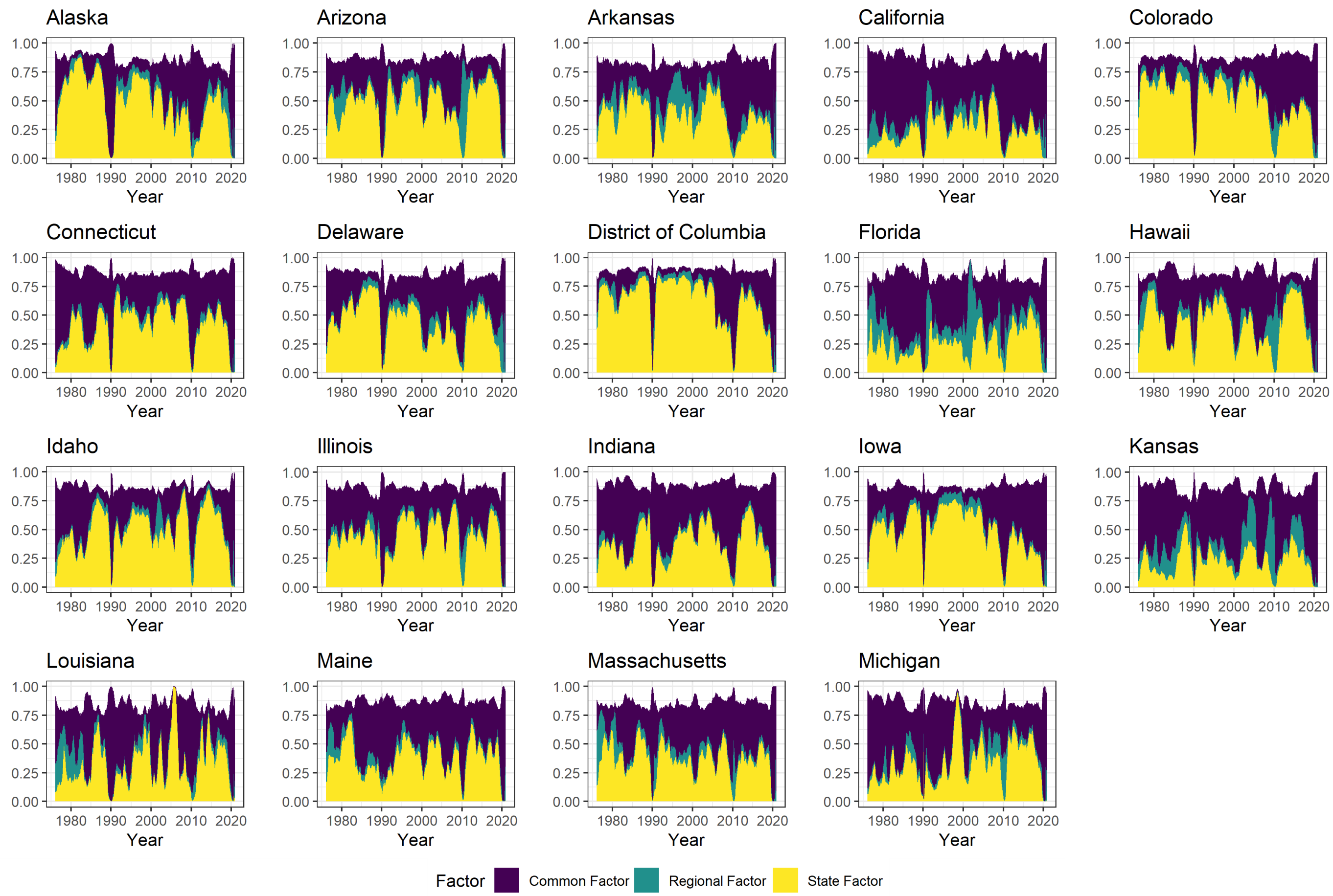

Figure A.1: **Variance Contribution of Factor by State Not in the Appalachian Region**

Note: These estimations include 2020 and the rest of the state results that are not included in the main body of the paper.

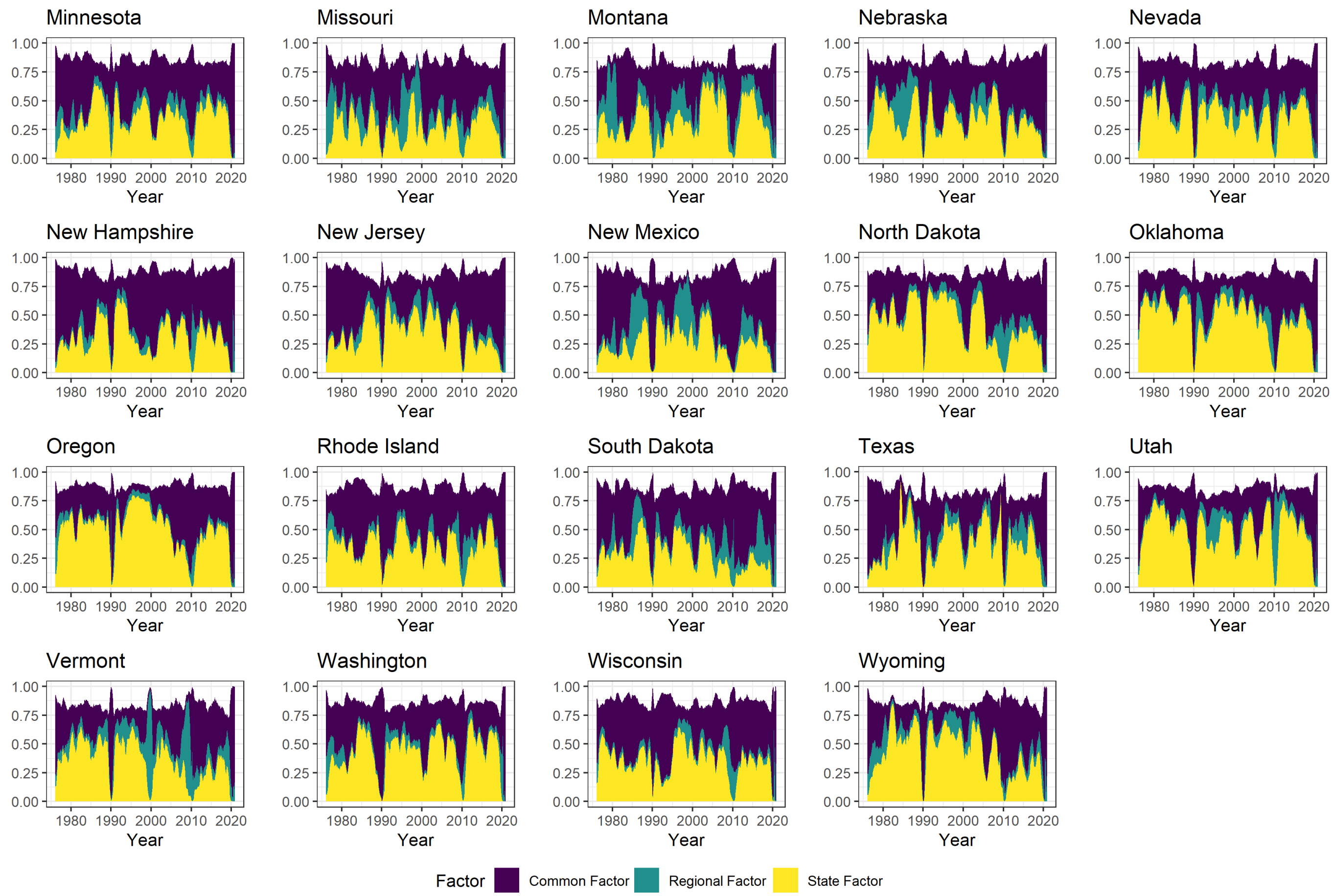

Figure A.2: **Variance Contribution of Factor by State Not in the Appalachian Region**

Note: These estimations include 2020 and the rest of the state results that are not included in the main body of the paper.

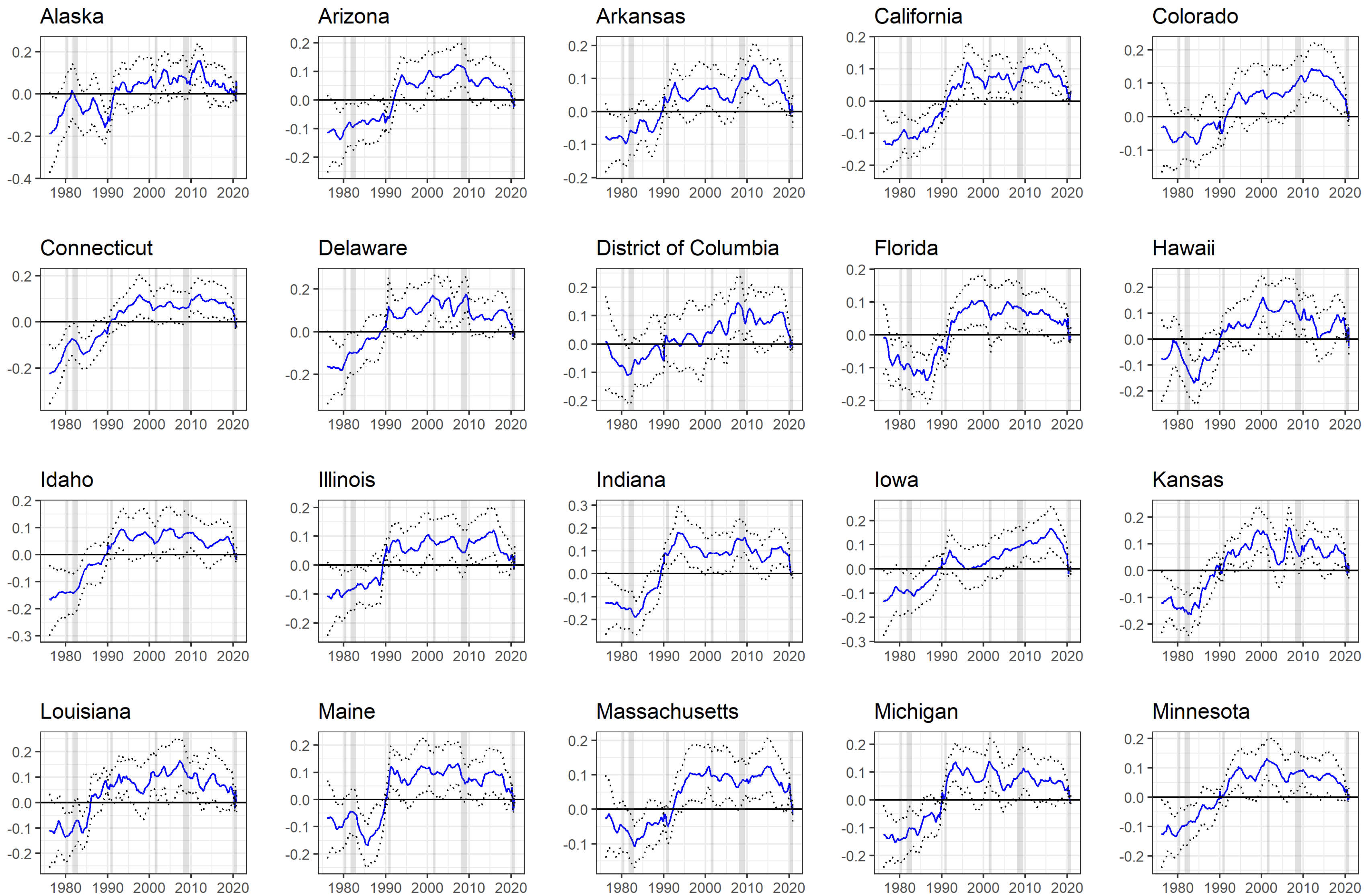

Figure A.3: **National Factor Loadings by State**

Note: Shaded regions are the NBER-dated recessions. The blue solid lines represent the median of the posterior distribution. Dashed lines represent the 5th and 95th percentiles. These include state results that are not included in the main body of the paper.

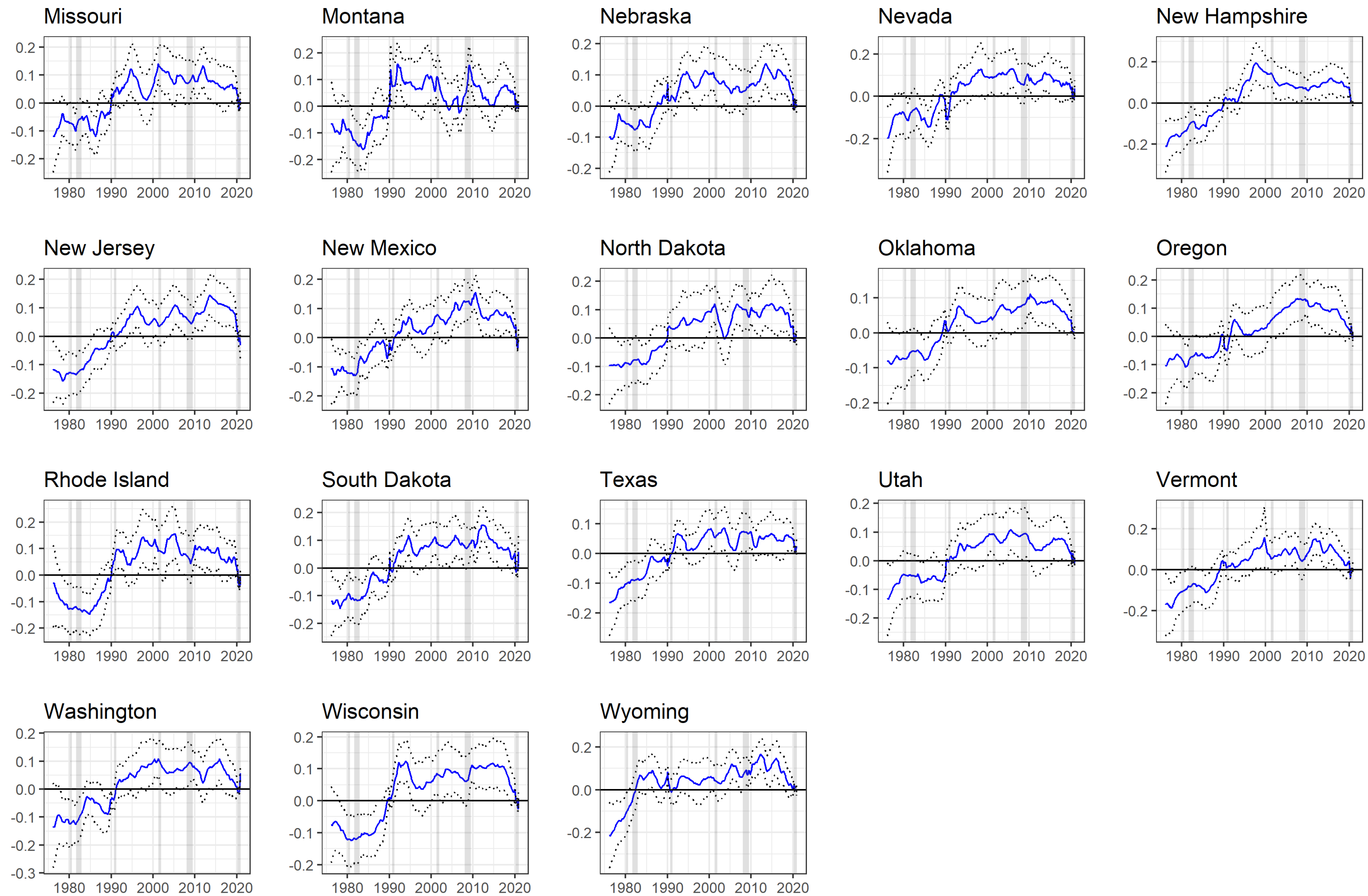

Figure A.4: **National Factor Loadings by State**

Note: Shaded regions are the NBER-dated recessions. The blue solid lines represent the median of the posterior distribution. Dashed lines represent the 5th and 95th percentiles. These include state results that are not included in the main body of the paper.