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The dynamics of labor force participation: Is all quiet on the Appalachian front?

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Abstract
This study examines the divergence and synchronicity of labor force participation rate (LFPR) dynamics across the USA. Using a dynamic factor model with time-varying stochastic volatility, we decompose each state's LFPR into a national, regional, and state-specific latent factor. We find significant time variation in our factors and heterogeneous labor market responses and relative sensitivities. Our results show that, save for West Virginia, there is no strong Appalachian regional component, and instead, the national and state-specific components explain much of the variation in state LFPRs. Our results suggest the need for more targeted and localized labor market policies during periods of divergence in LFPRs (i.e., recessions and shocks) and federal policies during national economic booms or periods of recovery.

Keywords Labor force participation · Dynamic factor model (DFM) · Stochastic volatility · Appalachia · Bayesian analysis · Time series analysis

JEL Classification C11 · C32 · C38 · E24 · J01 · R10

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1 Introduction

The effects of labor market shocks often vary across and within geographical regions. For instance, while most areas around the USA experienced declines in economic activity during the OPEC oil embargo of the 1970s, the Appalachian region experienced increased employment, labor force participation (LFP), and earnings (Juhn 1992; Black et al. 2002; Van Zandweghe et al. 2017). Later, in the 1980s, these economic experiences were reversed due to a subsequent bust in the coal market, one of the Appalachian region's main industries (Black et al. 2002). While heterogeneous labor market responses to macroeconomic shocks have been explained by industry composition (Zens et al. 2020), increases in automation (Autor and Dorn 2013), capital replacement (Dolado et al. 2021), time effects (Mumtaz and Zanetti 2015), and disproportionate and compound negative effects on low-skilled workers (Heathcote et al. 2020), little-to-no work has been done on the intertemporal dynamics and heterogeneous labor market responses of US states and regions.

Specific to Appalachia in the USA, there is a growing strand of literature centered on determining how labor force participation (and general labor market dynamics) has changed and whether there is a structural difference in the region (see Dorsey 1991; Isserman and Rephann 1993; Bradley et al. 2001; Stephens and Deskins 2018). While this strand is limited, it is buoyed by recent developments in the macroeconomic labor market heterogeneity literature. For example, Zens et al. (2020) demonstrate that workers and industries are disproportionately affected by monetary policy shocks. Zens et al. (2020) also show that occupations with many manual tasks are strongly connected to the effect that increases in interest rates have on unemployment. The positive response of the Appalachian labor markets compared to the negative responses of the rest of the USA to the shock on the natural resource supply in the 1970s, as one example, provides credence for the existence of a unique or at least heterogeneous Appalachian labor market.

In this paper, we help to fill the gap for US state and regional labor market heterogeneity literature by determining whether national, regional, or state components drive labor force participation rates. With a particular focus on the Appalachian region, we determine if labor force participation rate (LFPR) dynamics within the region, in general, might explain its heterogeneous labor market responses. We reserve investigations into specific driving forces, such as industry composition, for future research. To answer these questions, we decompose state LFPR into national (also referred to as a common component), regional (Appalachia, Northeast, South, Midwest, and West), and state-specific (idiosyncratic) latent factors estimated using a Dynamic Factor Model (DFM) with time-varying (TV) and stochastic volatility (SV) components. We assume that changes in state LFPR are described by these latent variables which capture national, regional, and state comovements and measure shocks or trends at the respective geographic levels. By calculating the time-varying correlation of LFPR in each US state with these factors, we determine the role and relative contribution to the volatility of LFPRs across labor market and macroeconomic conditions.

We focus on the Appalachian region (see Fig. 1), for three reasons. First, literature documents evidence of a unique relationship between the LFPR and this geographic region itself (Stephens and Deskins 2018; Dorsey 1991). Researchers often attribute

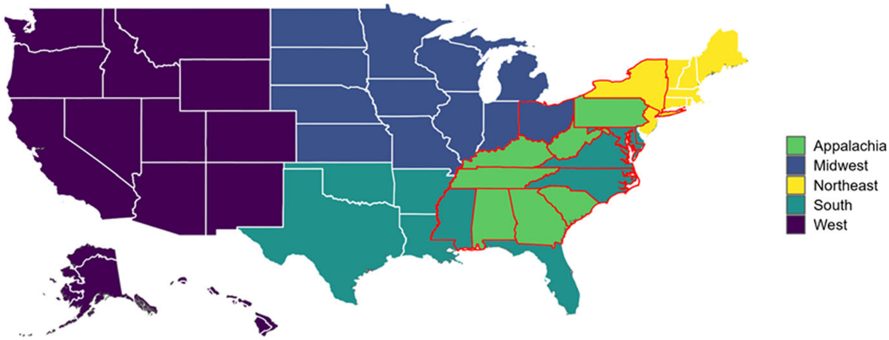

Fig. 1 US Regional Composition. *Note* The regions depicted are defined primarily using the US Census region definitions. The official Appalachian region, as defined by the Appalachian Regional Commission, consists of 420 counties across 13 states (presented with the red outline)—Alabama, Georgia, Kentucky, Maryland, Mississippi, New York, North Carolina, Ohio, Pennsylvania, South Carolina, Tennessee, Virginia, and West Virginia. For the purposes of this paper, we select only the seven 'core states' to define the Appalachian region (i.e., Alabama, Georgia, Kentucky, Pennsylvania, South Carolina, Tennessee, and West Virginia). This is driven by the fact that our analysis is at the state level and states such as Maryland, Mississippi, New York, North Carolina, Ohio, and Virginia include large urban populations and few Appalachian counties. Instead, we include them in their respective Census Bureau-defined regions. This determination was based on a 15% of total population residing in an Appalachian county threshold (Column 4 of Table 2). The reader is directed to Table 3 for a detailed lists of the states included in each region. *Source*: Appalachian Regional Commission, US Census Bureau. (Colour figure online)

this connection to the abundant natural resources, such as coal, oil, natural gas, and timber, which have comprised the primary industries in the region for many years. Dorsey (1991) suggests that the labor market history as well as other factors have created an "Appalachian effect" or unique Appalachian culture that persistently and independently decreases the LFPR in the region compared to the rest of the USA. Stephens and Deskins (2018) investigate the drivers of LFP between the Appalachian and non-Appalachian regions and find the rural indicator to be significant in explaining lower LFPR but also attributed the unexplained portion of their results to a potential Appalachian effect. While we do include the Northeast, South, Midwest, and West regions of the USA in this analysis, we find no other region with a geographic relationship to LFP that is steeped in so much historical rhetoric as the Appalachian region (Behringer and Friedell 2006; Billings 1974; Grossman and Levin 1961; Rogers et al. 1997). Therefore, if a strong regional component that drives LFPRs and rate comovements were to exist in the USA, we would expect to find it in the Appalachian region.

Secondly, by virtue of its low LFP, the Appalachian region arguably has the largest potential to contribute to economic growth compared to other regions of the USA. This region is often characterized by its economic disparity, persistent poverty, and historically low levels of skilled labor (Grossman and Levin 1961; Rogers et al. 1997; Bollinger et al. 2011; Partridge et al. 2013; Stephens and Deskins 2018; Appalachian Regional Commission 2020). As seen in Fig. 2, the LFPR in Appalachia has been consistently lower than in the rest of the USA over the past 45 years. Studies show that increases in LFP, specifically, have large and positive effects on employment growth and gross domestic product (GDP) (see Bryant et al. 2004; Juhn and Potter

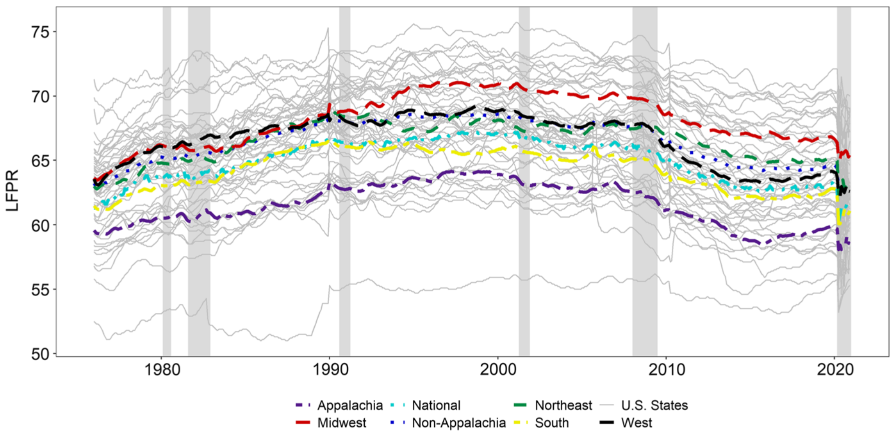

Fig. 2 US Labor Force Participation Rate Dynamics. *Note* NBER-dated recessions are in gray. The Appalachian values displayed reflect the average LFPR across the 7 "core" Appalachian states (Alabama, Georgia, Kentucky, Pennsylvania, South Carolina, Tennessee, and West Virginia, as seen in Fig. 1) for each year from 1976 to June 2022. The Northeast, South, Midwest, and West calculations are averages of LFPRs for the states included in each region, respectively, as defined by the US Census Bureau . *Source*: Bureau of Labor Statistics (BLS); Authors' calculations

2006; Shoven 2007; Cai and Lu 2013; Bustelo et al. 2019, for example). Taylor (2016) suggests that policy-induced increases in LFPR are an essential part of both short-term and long-run increases for the growth rate of the economy. All things equal, one would expect, therefore, that increasing LFPR at the state and regional levels would not only have positive effects on local growth but on national growth as well.

Lastly, while Appalachia performs poorly in LFP relative to the rest of the USA, the 13 official states within the region accounts for approximately 31% of national GDP between 1976 and 2020, as seen in Fig. 3. Other regions in the USA. such as the Midwest and the Northeast have declined to about 18% (Bureau of Economic Analysis 2021). Figure 3 also shows that Appalachia's contribution to national GDP has remained relatively stable since the 1970s. These observations illuminate the Appalachian region's importance in terms of labor activity and productive potential. As such, even small improvements in the region's LFP could have substantial impacts not only for the region but on national growth as well.

Through our analysis, we find substantial variation in state LFPR comovement over time, geographic level, and during different macroeconomic conditions. We find that the choice of time and state is crucial to the relative importance of the estimated geographic components on observed change in LFPR variations. For example, around 97% of the variation in the LFPR in West Virginia is explained by the Appalachian regional factor in 1982, but less than 1% of the variation is explained by this same factor in 2010. Additionally, West Virginia's LFPR is strongly connected with the Appalachian region component for periods coinciding with regional labor market shocks such as the coal boom (1970s) and bust (1980s). We also find that in the last three decades, there has been an increase in the influence of a national component on state LFPRs.

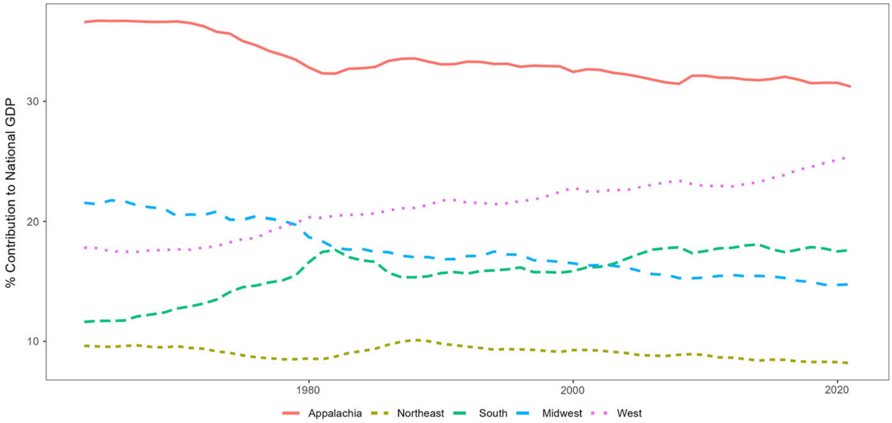

Fig. 3 Percent Contribution to National GDP. *Note* The Appalachian values displayed reflect the sum of the GDP for the 13 states (Alabama, Georgia, Kentucky, Maryland, Mississippi, New York, North Carolina, Ohio, Pennsylvania, South Carolina, Tennessee, Virginia, and West Virginia) in the ARC defined Appalachian region as a percentage of the total US GDP. A breakdown of the relative contribution of each state to the composition of the Appalachian region can be found in Table 2 of "Appendix." The Northeast, South, Midwest, and West calculations are sums of the GDP for the states included in each region, respectively, as defined by the US Census Bureau and seen in Fig. 1 as a percentage of the total US GDP . *Source*: Bureau of Economic Analysis (BEA); Authors' calculations

Yet, we find divergence in state LFPRs due to a national component occurring around periods of national recessions, regional labor market shocks or restructuring, and state-specific labor shocks like natural disasters. Thus, we suggest that labor market policies that are broader or more national in scope may be appropriate during business-cycle expansions as they would take advantage of the increased synchronization of LFPR. These broad policies would potentially induce employment and GDP growth for both struggling and prospering areas alike. In contrast, during recessionary periods or idiosyncratic (state-specific) shocks, more localized and targeted labor policies would be more efficient. In other words, targeting less aggregated geographic levels when LFPR changes are heterogeneous across states could induce employment and GDP growth for struggling areas without the risk of unintended effects from "one-size fits all" policies.

To the best of our knowledge, this is the first study to apply the DFM framework to evaluate regional US labor force participation dynamics. Other studies have used this methodology to investigate variables such as output growth (Bian et al. 2020), bond yield (Bhatt et al. 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 et al. 2018), commodities (West and Wong 2014), oil (Aastveit et al. 2015), and cattle prices (Foster et al. 1995; Walburger and Foster 1998).

In addition, related work on labor force dynamics has been done in the macroeconomic literature with a majority focused on investigating the cyclicality of the LFPR (see Van Zandweghe et al. 2017; Cajner et al. 2021; Veracierto 2008; Strand and Dernburg 1964; Hornstein 2013, for example). While we do not directly study the cyclicality of LFPR, our dynamic analysis of LFPRs provides insight into the relationship between LFPR and the business cycle. Other literature on LFPR dynamics includes studies on labor income variation (Vidangos 2009), dynamics between LFP, GDP, and labor force productivity (Epstein 2018), labor force exit and entry behavior in the USA over time (Blau 1998), and identifying trends and disequilibria affecting labor market adjustments in Romania (Voicu 2001). We contribute to this strand of literature by applying LFPR dynamic analysis to US state and regional levels. We also contribute to the methodology of examining LFPR by applying DFMs to study labor comovements.

Another strand of the literature particularly focused on the impact of single economic events (like the 2008/9 recession) on LFPR or unemployment and on national level data (see Van Zandweghe 2012; Hotchkiss and Rios-Avila 2013; Aaronson et al. 2014; Council of Economic Advisors 2014; Erceg and Levin 2014, for example). Additionally, the extant literature investigating the Appalachian region uses data before the most recent economic downturns and analyzes only one or two years at a time. These studies, however, fail capture longer horizons and the spatiotemporal variance of LFPR simultaneously. Therefore, we seek to fill the gap in the literature by examining the long-run trends in LFPR across multiple economic events. We also add to the literature on Appalachia by assessing the connection between state LFPR with regional components and emphasize the important implications for Appalachia's labor and economic growth potential, in particular.

The remainder of the paper is organized as follows. Section 2 presents a description of the data and summary statistics. A discussion of the empirical methodology is found in Sect. 3. Discussion of our results is outlined in Sects. 4 and 5, we conclude and offer potential policy recommendations.

2 Data

To investigate the synchronicity and response of the Appalachian region's LFPRs to changing economic environments, we use monthly labor force participation rates for the 50 US states and Washington D.C. over the period January 1976 - December 2020. The LFPR represents the percentage of the civilian and noninstitutional working-age population that is either working or actively looking for work. Table 1 highlights that the LFPR varies within the Appalachian region and across all states. We estimate our model using the first difference of the state-level LFPR and the differenced data averaged nationally and across regions can be seen in Fig. 4.[1] Thes data are collected from the Bureau of Labor Statistics (BLS).[2]

Regional labor market heterogeneity can be observed in Fig. 4 as each region shows differences in responses during periods of recessions, financial crises, and the COVID-19 pandemic. For example, the Appalachian and Midwest regions show large increases

[1] In Sect. 4, 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 (Fig. 4) 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.

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

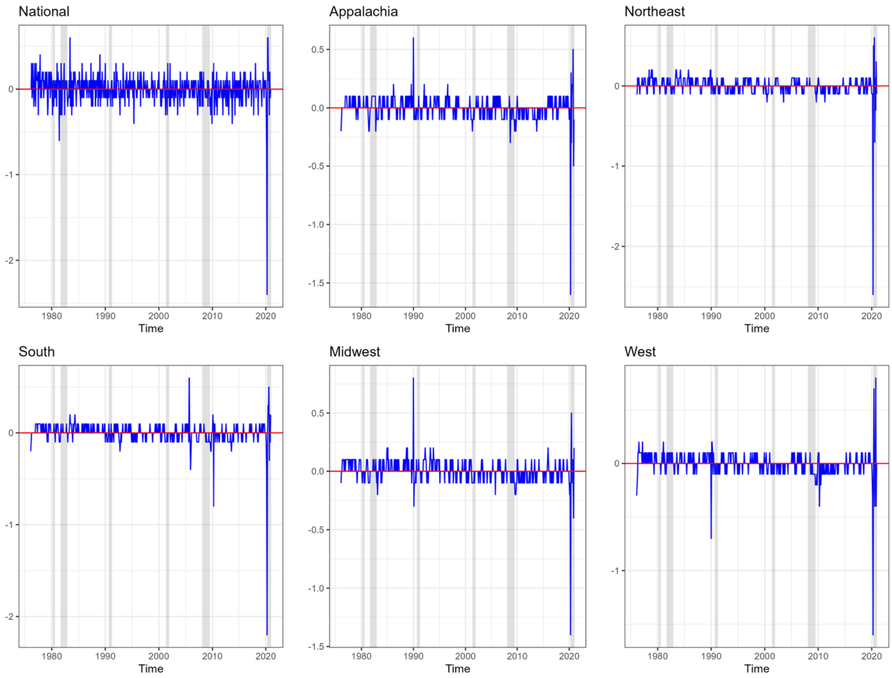

Fig. 4 Change in US Regional Labor Force Participation Rates. *Note* Shaded regions are the NBER-dated recessions

in LFPR in the late 1980s, whereas the West region displays a large decrease at the same time. However, the South region shows a couple of shocks corresponding to 2006 and 2010 whereas the Northeast region displays more constant variation over time except for the COVID-19 pandemic in 2020. Overall, changes in US regional LFPRs exhibit heterogeneous responses to periods of economic shock, labor market distress, and high unemployment across states and time.

While the unemployment rate is often used for empirical analysis and economic policies, we use the LFPR as it provides a more accurate 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 (Juhn and Potter 2006; Hotchkiss and Rios-Avila 2013; 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).[3] 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, but not necessarily in other cases. For example, since 2000, West Virginia reported an average rate of unemployment of 6.2% compared to the national average of 6%.

[3] 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 et al. 2001).

Yet, West Virginia has persistently lower LFPR (Table 1), ranks higher in negative health indicators (Raghupathi and Raghupathi 2018; Behringer and Friedell 2006), and is often characterized by its economic disparity relative to the rest of the country (Dorsey 1991). While we focus on the LFPR in this study, investigations into other labor market variables and connections to specific industries in the region may prove insightful. However, these alternate investigations are outside the scope of this paper and we reserve them for future research.

Previous literature suggests that 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 the Great Recession were felt worldwide. The USA 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, and major economic events, and measure the evolution and relative importance of the Appalachian region. While more granular data are 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 USA (3143), the computational burden of our model estimation prevents convergence. Therefore, 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 actionable policy at the state level, since potentially, only a few metropolitan areas may be able to implement local labor market policy.

3 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 that 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 an unobserved single index or dynamic factor. We build off this premise and model changes in state LFPR as functions of 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 Monte Carlo Markov Chain (MCMC) Bayesian estimation method using uninformed conjugate inverse-gamma priors to estimate this general model for a panel of state LFPR data in the USA for the past few decades.

3.1 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[4] for state (and Washington, D.C.) $i = 1, 2, \ldots n$, $(n = 51)$ and 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 five regional factors, $\mathcal{R}_{j,t}$, $j = 1, \ldots, 5$ corresponding to Appalachia, the North, South, Midwest, and West regions of the USA.

We should note that the Appalachian region is officially defined at the county level. Thirteen (13) states (Alabama, Georgia, Kentucky, Maryland, Mississippi, New York, North Carolina, Ohio, Pennsylvania, South Carolina, Tennessee, Virginia, and West Virginia) contain at least one (1) of such Appalachian county. However, given that our analysis is at the state level, we exclude Maryland, Mississippi, New York, North Carolina, Ohio, and Virginia from our definition of the Appalachian region. This decision to exclude these states was largely predicated on the fact that the actual population living in an Appalachia-designated county was less than our 15% threshold. To this end, we contend that a state below this threshold is more heterogeneous and could potentially confound the findings and the estimations of the regional factor.[5] For the sake of brevity, and the fact that the Appalachian region is of primary interest, we focus our discussion and results on Appalachia.[6] Lastly, in our specification, $\xi_{i,t}$ are 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 correlation between the national (common) factor, which measures national shocks or trends in the changes in LFPR for all $n = 51$ states, and the change in LFPR for each state, i, at each time, t. The row vector $\widetilde{\beta}_{i,t}$ has a nonzero time-varying regional loading parameter $\beta_{i,t}$ for the position corresponding to the region for state i and zeros for all other elements. Accordingly, each regional factor, $\mathcal{R}_{j,t}$, measures shocks or trends in the changes in the LFPR specific to each region and is separately identified by setting other regional loadings to zero.[7] We capture the dynamics of each factor by including time-varying factor loading parameters.

[4] All Augmented Dickey–Fuller tests supported the conclusion of a unit root process and high persistence. Therefore, we will estimate in first differences (*changes* in LFPRs)

[5] We thank the referees for pointing out this potential heterogeneity issue in an earlier version of this manuscript. We note here that, barring South Carolina, the states included in the 15% population-share threshold also represent the 6 states with the highest percentage of their counties belonging to Appalachia. See Table 2. In our specification we include New York in the Northeast region, Ohio in the Midwest region and Maryland, North Carolina, Mississippi, and Virginia in the South region.

[6] Full results are available upon request.

[7] Regions are mutually exclusive; states can only belong to one region.

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. $e^{h_t^{\mathcal{C}}}$ represents the stochastic volatility components, and $\nu_t^{\mathcal{C}}$ the innovation to the law of motion for the national (common) factor.

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

where $\phi_{j,t}^{\mathcal{R}},\ j \in \{1, 2, \ldots, 5\}$ is the autoregressive coefficient for each regional factor, $e^{h_{j,t}^{\mathcal{R}}}$, 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 $\phi_q,\ i \in \{1, 2, \ldots, 51\}$ is the autoregressive coefficient for the idiosyncratic shock. The stochastic volatility components are denoted as $e^{h_{i,t}^{\mathcal{S}}}$, and $\nu_{i,t}^{\mathcal{S}}$ is the innovation to the law of motion for the idiosyncratic factor.

Following the standard approach in the literature, we set the optimal number of lags in our transition equations to 2 (that is, $Q = P = L = 2$) (see Ma et al. 2018; Neely and Rapach 2011, for example). Additionally, we assume that the innovations ($\nu_t^{\mathcal{C}},\ \nu_{j,t}^{\mathcal{R}}$, and $\nu_{i,t}^{\mathcal{S}}$) are orthogonal to each other. The functional forms of the stochastic volatilities are detailed in turn below.

3.2 Dynamic factor model with time-varying stochastic volatility

To capture the dynamics in the volatility over time, we follow Del Negro and Otrok (2008) and employ stochastic volatility in the laws of motion of the national, regional, and idiosyncratic factors (Eqs. 2–4), This extension of the standard DFM framework allows for random, rather than constant, innovations (error terms) of each factor.[8] Importantly, this assumption and specification allow us to capture changes in the sensitivity of our factors to labor conditions across our sample and economic conditions. To this extent, we capture potential volatility changes due to new or amended labor policy and major localized and national economic shocks such as the COVID-19 pandemic and natural disasters.

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

Formally, the innovations, $e^{\bullet}$, vary over time and each stochastic volatility term, $h_{\bullet}$, evolves according to a random walk process without drift such that[9]:

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

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

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

where $\sigma_{\mathcal{C}}^h, \sigma_{j,\mathcal{R}}^h, \sigma_i^h$, for $i \in \{1, 2, \ldots, 51\}$, and $j \in \{1, 2, \ldots, 5\}$, 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 orthogonal volatility shocks. We use uninformed or diffuse conjugate inverse-gamma distributions for the key priors $\sigma_{\mathcal{C}}^h, \sigma_{j,\mathcal{R}}^h, \sigma_i^h$. This ensures we avoid any preconceived notions about the location and shape of the distributions. In addition, this in practice focuses on the belief that volatilities evolve slowly over time and capture permanent trend changes in the labor market (Del Negro and Otrok 2008). This prior setup is typically robust to various prior assumptions and distributions (Del Negro and Otrok 2008). For these reasons, we follow this setting which is standard across applications (see Del Negro and Otrok 2008; Neely and Rapach 2011; Bhatt et al. 2017; Ma et al. 2018; Bian et al. 2020, for example).

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 $\sigma_{\mathcal{C}}^2 = \sigma_{j,\mathcal{R}}^2 = 1, \ \ j \in \{1, 2, \ldots, 5\}$. This is also consistent with the standard approach in the literature (see Del Negro and Otrok 2008; Sargent et al. 1977; Stock and Watson 1989, for example). Given that the idiosyncratic factor represents the fluctuations in the state time series that are not attributed to either national or regional factors, normalization of σ_i^2 is not necessary. 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 (Eqs. 5 – 7) to a starting value of zero. That is, $h_0^{\mathcal{C}} = h_{j,0}^{\mathcal{R}} = h_{i,0}^{\mathcal{S}} = 0$. This assumes no stochastic volatility before the sample period but allows for the derivation of an ergodic distribution for the initial conditions (Del Negro and Otrok 2008).

3.3 Gibbs sampling

Following Del Negro and Otrok (2008); Bhatt et al. (2017); Bian et al. (2020), we estimate our model via a Markov chain Monte Carlo (MCMC) Bayesian estimation utilizing the Gibbs-sampling algorithm a lá Kim et al. (1999). We take 50,000 draws of each parameter estimated in the model. The first 10,000 draws serves as "burn-ins,"

[9] 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 an innovation to previous studies on Appalachia's LFPR (Dorsey 1991; Isserman and Rephann 1993; Stephens and Deskins 2018) as they do not account for long-term trends or changes in national- and state-level labor force conditions. We contend that our approach offers greater flexibility and accounts for potential long term trends and structural changes in LFP conditions. This DFM-TV-SV model approach, therefore, provides added value and contributes to previous literature.

which are discarded in order to reach confidence in the initial conditions imposed. We use the remaining 40,000 draws as keepers, which are saved after the allotted burn-in values have been reached. While other papers with similar methodologies use fewer draws [for example Del Negro and Otrok (2008): 22,000 and Ma et al. (2018):10,000], we use 50,000 to ensure appropriate signs and convergence of our model given the number of parameters being estimated. For additional information about our execution of the procedure and the Gibbs sampler, the interested reader is directed to "Appendix A.1" and the technical appendix of Bhatt et al. (2017).

4 Results

We find that, over time, the economic structure of the states and their connection to the national and regional economies exhibit varying sensitivities. This provides a strong justification for using a model with time-varying loading parameters and stochastic volatility. Figure 5 shows the national and regional factors or components estimated by our model. These values are the median values of the 40,000 kept draws from the posterior distribution plotted with the 5th and 95th percentiles. Our results reveal several shocks, by geography, over the sample period. These shocks are represented as peaks in a given factor. A positive spike for a factor indicates that a shock in that region explains a divergence or a relatively large change in the LFPRs. The National factor hovers around its mean (zero) for much of the sample period. The major shocks are observed at or near recessionary periods (1990, cerca 2010) and during the recent COVID-19 pandemic. The regional factors appear to be more time varying and pass through their means on several occasions. On account of the tight confidence intervals, it would appear that all the factors are estimated relatively accurately.

Figures 6 and 8 present the time-varying loading parameters (posterior medians) of the latent national/common factor and the Appalachian regional factor for Appalachian states. The factor loadings reflect changes in the sensitivity or correlation between the change in a given state's LFPR with the respective factor. That is, these loadings indicate whether a national/regional shock is correlated with an increase or decrease in LFPR for a given state, i, and time t. In short, relatively strong nonzero factor loadings reflect a higher measure of synchronization of regional/national LFPR. The tight confidence intervals around our median estimates indicate a low level of parameter uncertainty. The results and key takeaway from the dynamics of each factor are explained in the subsections that follow.

For the sake of brevity, we suppress the results for all regions except Appalachia. For a quick reference and comparison, the averaged values for the other regions are presented in Figs. 10, 11 and 12 of "Appendix."[10]

4.1 National factors loadings

In Fig. 6, we observe considerable time variations in the national factor loading parameters across states. The lower bound of the 90% confidence bands in the latter part

[10] The full results are available from the authors upon request.

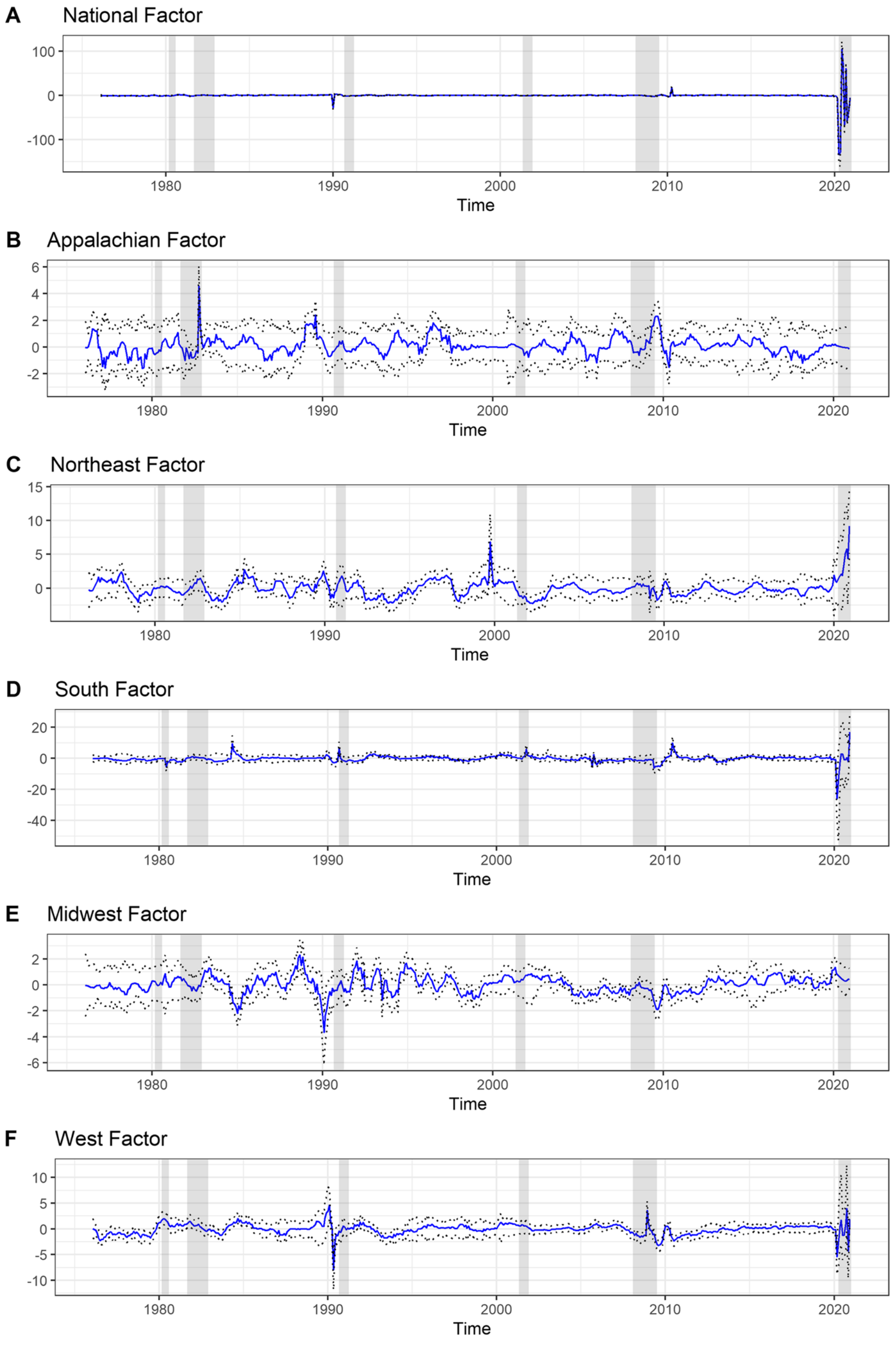

Fig. 5 Estimated Factors. *Note* This graph presents the latent factors over time. Shaded regions here correspond to the NBER-dated recessions. The blue solid lines represent the median of the posterior distribution. Dashed lines represent the 5th and 95th percentiles. (Colour figure online)

of the sample period is above the upper bound of the confidence bands for several periods over the sample. This indicates that with increases in the national component, changes in state LFPRs tend to increase together. For the middle two decades of our sample, increases in the synchronization of state LFPR changes coincide with greater susceptibility to national labor market conditions. This has implications for both positive and negative labor shocks. During periods of high synchronization that coincide with economic prosperity, business-cycle expansions, or implementation of participation-encouraging policy, large positive increases in LFPR are most likely to ensue.

Uniformly across states, we also see several periods of negative factor loadings. This indicates that with increases in a common component, changes in state LFPRs decreased together or experienced relatively more stable LFPR. The zero correlation seen around the years 1990, and 2010 correspond to the national shocks seen in Fig. 5. These periods are then characterized by a lack of synchronization across states and no relationship between the national factor and increases (decreases) in LFPR. These disparate results not only provide further justification for using a more generalized approach for modeling comovement among state LFPR, but it also validates our use of time-varying parameters.

4.2 Cross-state correlation

Figure 7 presents the average cross-state time-varying correlation for the change in LFPR for all states (Panel A), Appalachia (Panel B), the Northeast (Panel C), the South (Panel D), the Midwest (Panel E), and the West (Panel F). The estimates depicted are the computed median values of the average pair-wise correlations coefficients at each point in time as implied by the factor model.

As seen in Fig. 7, the sample can be crudely split into four sub-samples (1976–1980; 1980–1990; 1990–2010 and 2010–2020). These demarcations generally follow the business cycle and exhibit peaks in correlation near the middle of each cycle. This trend, along with the similarity of the results across panels, supports that LFPR movements are relatively synchronized across states during growth and expansion periods. These findings are in congruence with our national factor loading results displayed in Fig. 6. A couple of notable difference across the panels in Fig. 7 is the divergence in the Midwest (Panel E) and Southern (Panel D) regions, as cross-state correlation for the change in LFPR increases sharply in 1990 and 2010, respectively. Together with the national factor loading results, these findings demonstrate that labor force participation rate dynamics are relatively more synchronized across the USA regardless of regional designation.

4.3 Regional factor loadings

Turning our attention to the loading parameters of the Appalachian regional factor, Fig. 8 reveals that the sensitivity of statewide LFPR to the Appalachian region factor is much more heterogeneous (compared to their national factor counterpart). Although we observe a large degree of parameter uncertainty for most Appalachian states over

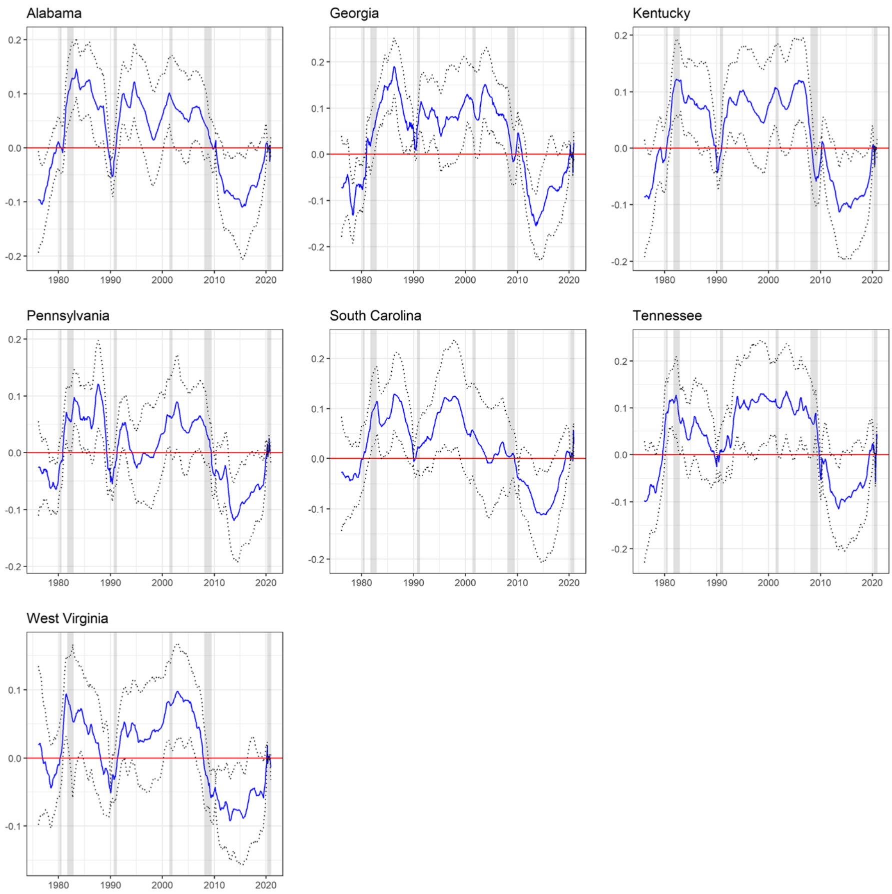

Fig. 6 National Factor Loadings for Appalachian States. *Note* This figure presents time plots of the common factor loadings ($\omega_{i,t}$ in Eq. 1) of each state. Shaded regions correspond to NBER-dated recessions. The blue solid lines represent the median of the posterior distribution. Dashed lines represent the 5th and 95th percentiles. (Colour figure online)

much of the sample period, West Virginia is a notable exception. The confidence bounds are much tighter around that West Virginia's median estimates during the early and late 1980s. In the early 1980s, West Virginia exhibits strong and negative regional factor loadings. This would indicate a strong sensitivity and negative correlation with the Appalachian region factor. That is, with increases in the influence of an Appalachian region component, changes in West Virginia LFPR tend to decrease. West Virginia and the Appalachian region experienced plummeting and persistently low LFPR during this time. This is attributed to a coal bust which was followed by high levels of unemployment contemporary with the early 1980s national recession (Black et al. 2005). Our results indicate that the West Virginia LFPR became low to stable in subsequent years.

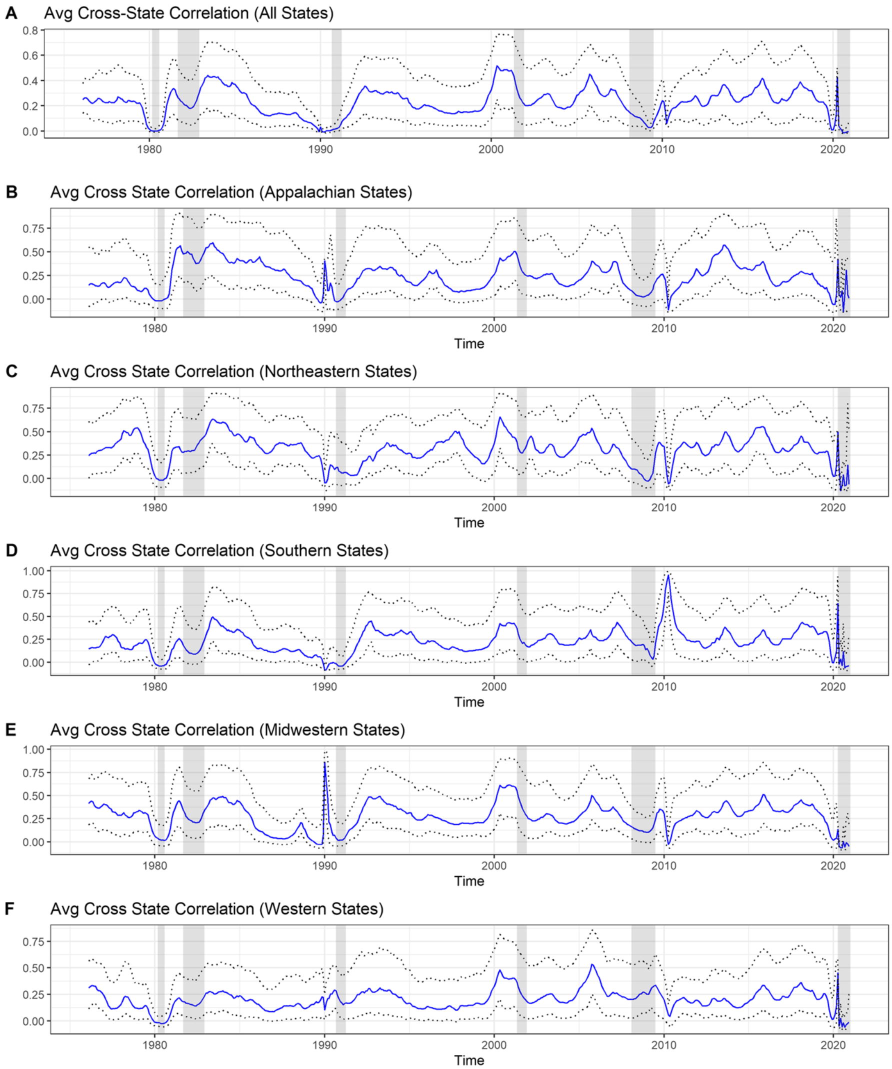

Fig. 7 Pairwise Cross-State Correlation Average by Region. *Note* This figure presents the average cross-state correlation, at each point in time. The average cross-state correlation is computed by averaging the correlation coefficients for each state-pair within the region of interest at each time point, t. The shaded regions correspond to NBER-dated recessions. The blue solid lines represent the median of the posterior distribution. Dashed lines represent the 5th and 95th percentiles. (Colour figure online)

A decade later, LFPR in West Virginia finally returned to pre-coal bust and pre-recession levels during a period of growth and expansion contemporaneously with a movement away from natural resource dependency (Howe and Parks 1989). Much of the regional economy shifted away from the reliance on coal and restructured the West Virginia labor market into other industries (Stevens 1986). This is indicated by the positive factor loadings in the late 1980s which attribute a trend of increasing changes

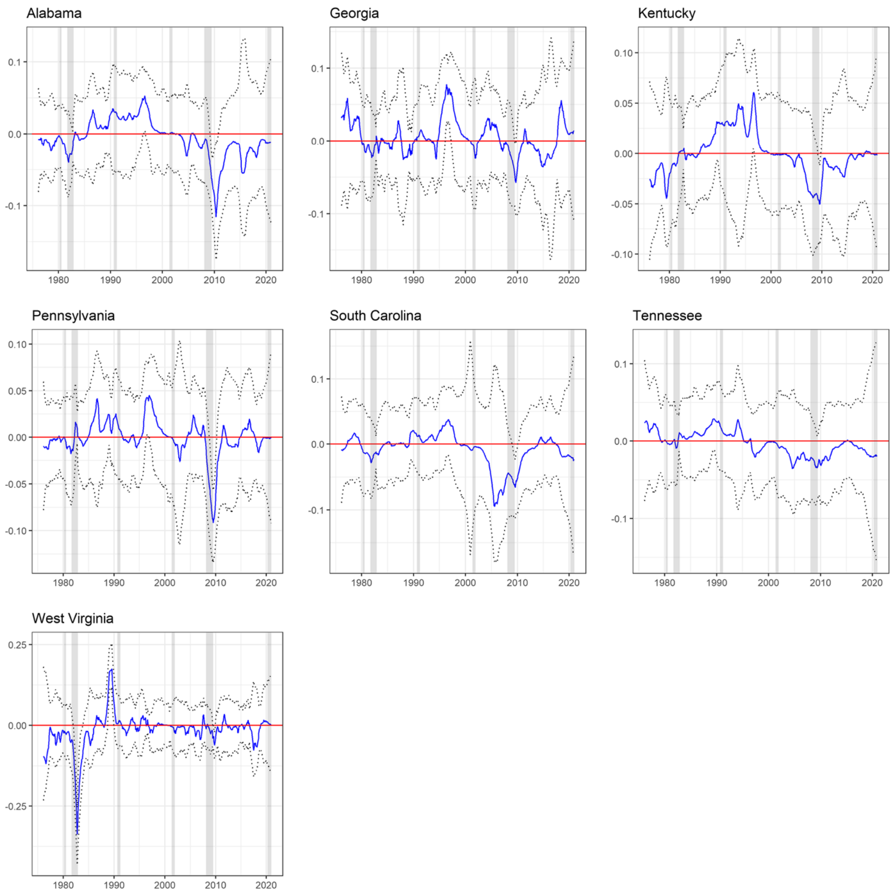

Fig. 8 Regional Factor Loadings by State in the Appalachian Region. *Note* Shaded regions are the NBER-dated recessions. The blue solid lines represent the median of the posterior distribution. Dashed lines represent the 5th and 95th percentiles. (Colour figure online)

in LFPR to the Appalachian region factor. Together with the decline in the sensitivity to the national factor (see Fig. 6) for West Virginia during this time, our results point to a potentially more regionally dependent West Virginian economy, suggesting higher susceptibility to regional shocks. We note that these results also justify our use of methodology as our model not only differentiate the national from regional sensitivity but reveals that while the connection to the national economy is relatively strong during this time, the connection to the regional economy for West Virginia is stronger.

4.4 Variance decompositions

From Eq. 1, our model implies the following variance structure:

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

Therefore, the fraction of volatility attributable to, say the national factor, $\mathcal{C}$, can be computed as:

$$\frac{\omega_{i,t}^2 \operatorname{Var}(\mathcal{C}_t)}{\operatorname{Var}(y_{i,t})} \tag{9}$$

The variance contributions of the regional and idiosyncratic factors would be computed similarly. Below, we discuss the computed contribution of each of the three components (of Eq. 8) to the state LFPR.

Figure 9 plots the percentage contributions of the national, regional, and state factors to the total change in LFPR variations for all states within the Appalachian region.[11] These plots allow us to ascertain the relative importance of each factor in explaining labor market dynamics. We observe that, in general, the national and idiosyncratic factors are consistently the dominant contributors. This implies that much of the variation in the change in state LFPR is explained by either national or individual labor market trends or shocks.

Despite the dominance of the national and idiosyncratic factors, we also observe heterogeneity across space and time. Concerning time, the contribution of the national factor is most pronounced during periods of recessions, financial crises, or the COVID-19 pandemic. At times, close to 100% of the variation in the change in LFPR is explained by the national factor which corresponds to most of the zero correlation of the state changes in LFPR with the national factor observed in Fig. 6. Naturally, the stark changes in LFPR across states induced by these national shocks manifest as a strong common component picked up by our model. However, outside these periods, the idiosyncratic factor is more important. This implies that states are more influenced by state-specific labor and economic shocks (potentially positive and negative) outside of national recessions or trends. For example, Fig. 9 shows a stark increase in variations in the change in LFPR explained by the idiosyncratic factor for Georgia in 1992 and 2008. The first time period coincides with a notable period of growth and expansion in the state. The second corresponds to a potential heterogeneous labor market response to the 2008–09 recession. We also find a stark increase for variations in the change in LFPR explained by the idiosyncratic factor for Southern states such as Louisiana and Mississippi corresponding to the devastating impacts of Hurricane Katrina (which we do not display for brevity).

Throughout our analysis, we find West Virginia to be rather curious. Unlike its Appalachian counterparts, the state appears to be much more connected to the regional economy outside of national crisis windows. Figure 9 reveals that the Appalachian factor explains a large portion of West Virginia LFPR dynamics compared to the other states. On several occasions, the computed regional variance contribution surpasses 75%. In fact, in the mid-1980s, the Appalachian factor explains almost 100% of the change in LFPR for West Virginia. During those same periods, most other Appalachian states experience much smaller contributions from this "Appalachian factor." For these remaining Appalachian states, incidents of increased relative impor-

[11] Our estimation algorithm included all 50 states (plus Washington D.C.). The full results, including figures for non-Appalachian states, are available upon request.

Fig. 9 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. (Colour figure online)

tance of the Appalachian factor appear to coincide with periods of economic recovery and booms.

We believe it pertinent here to place our study and findings in the context of existing studies on Appalachian state LFPR. These studies investigate the open-ended question about whether an "Appalachian effect" or measurable Appalachian region component contributes to the lower LFPR in the region (Dorsey 1991; Isserman and Rephann 1993; Stephens and Deskins 2018). However, a consensus has yet to be reached and the question remains unanswered. While our model and results do not attempt to measure how the Appalachian region itself affects LFPR, we suggest that our findings, which are based on time series data over a large sample period than the existing studies, may provide context for the contrasting results and ensuing debate in this literature. As a part of this debate, Isserman and Rephann (1993) criticizes Dorsey (1991) for using only one year of data. The authors contend that it may produce misleading conclusions, especially if empirical results depend on the choice of year, which the authors conclude to be the case. As we have determined in this study, changes in individual state LFPR are variably correlated with increases in national synchronization of LFPR for most of our sample. Additionally, both convergence and divergence of state LFPR at the national and regional levels explain large proportions of the variation in LFPR across states and time. We find it conceivable that prolonged labor market shocks such as national recessions or regional industry and labor market restructuring (compounded on an already distressed Appalachian region) may help explain results found in Dorsey (1991), Isserman and Rephann (1993), and Stephens and Deskins (2018). We come to this conclusion based on a few comparative examples between our results and these previous studies.

Dorsey (1991) specifically focuses on West Virginia as it is the only state to be completely encompassed in the Appalachian region. Dorsey (1991) and Isserman and Rephann (1993) find the strongest relative Appalachian region effects on West Virginia LFPR in 1987. Additionally, Dorsey (1991) attributes the unexplained variance in the modeling over this year to an "Appalachian effect" as well. This coincides with the strong negative correlation between change in West Virginia LFPR and the distinct Appalachian region factor we observe in the late 1980s, shown in Fig. 9. Isserman and Rephann (1993) subsequently find little to no Appalachian effect on West Virginia LFPR for 1980 and 1991. For these years, we also find zero correlation between the change in West Virginia LFPR and the Appalachian region factor. We contend therefore that these results found in Dorsey (1991) and Isserman and Rephann (1993) may have been driven by regional shocks, such as the coal bust during the late 1980s, or the state of the regional economy and its connection to West Virginia at the time.

Placing our findings in the context of a more recent study, Stephens and Deskins (2018) investigate LFPR for all US counties focusing on Appalachian counties and a rural vs. urban county comparison for the years 2000 and 2010. Through a Blinder-Oaxaca decomposition, the authors find a 1.1 percentage point unexplained difference for Appalachian counties. Like Dorsey (1991), they posit this as evidence supporting an "Appalachian effect." Additionally, Stephens and Deskins (2018) find strongly significant and negative coefficients on the state fixed effect for West Virginia, suggesting other phenomena unexplained by their model. Our median results show a slight negative relationship between change in West Virginia LFPR and the regional economy surrounding 2010 as seen in Fig. 8, but the confidence bands are relatively wide during this time. However, as we discussed earlier, the early 2000s and 2010 are characterized by dominance in the national factor's contribution to explained LFPR variations. Figure 9 shows that for Pennsylvania, South Carolina, and West Virginia, the variation explained by the national factor for each state exceeds 98% for the middle part of 2010. Specific to West Virginia's LFPR, while our model highlights a slight regional connection, it clearly emphasizes the connection to national trends at the time. Given our results, we suggest that the unexplained variation and significant West Virginia state fixed effect found in Stephens and Deskins (2018) may be related to a disproportionate or compounded effect of national economic shocks or trends on the already economically distressed Appalachian region and state of West Virginia.

5 Conclusion and policy implications

In this paper, we demonstrate that comovement of the change in state LFPR varies over time and geographic level – much of which can be attributed to economic and labor market fluctuations. We examine the connection between state changes in individual state labor force participation rates and national and Appalachian regional measures of LFPR synchronization. We also investigate the relative contribution of these measures to the labor force participation dynamics of US states over time. We pay particular attention to the Appalachian region to explore a different angle of the documented connection between the region and LFP, as well as to inform policy targeted at increasing employment growth and LFP in the region and the rest of the USA. Using a dynamic factor model with time-varying parameters and stochastic volatility, we determine that in the last three decades as the national synchronization of state LFPR increase, the change in individual state LFPR tend to increase as well. We also find two periods where the change in the West Virginia LFPR is strongly connected with the synchronization of LFPR in the Appalachian region. Finally, we show that the choice of time and state together with given economic conditions are crucial to the relative importance of the level of synchronization on observed change in LFPR variations.

Our results are important for policymakers and potential improvements in regional and national output growth. Our results suggest that federal labor policy may be more effective during periods of economic growth. Policies implemented during these times would take advantage of the potential positive increases in LFPR and be less likely to jeopardize struggling areas with "one-size-fits-all" policies. 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 "blanket" policies in the future to assist depressed labor markets, it also reduces the nation's ability to absorb negative labor market shocks. This has important long-term implications for the Appalachian region since poor and rural areas are already more vulnerable to economic shocks (Börner et al. 2015).

During periods of divergence (e.g., recession) in state LFPR, more localized and targeted labor policies may be more efficient. Given the heterogeneous behavior of changes in LFPR during recessions and other shocks, it is conceivable that "blanket" policies may have positive effects for some areas but negative for others (Tödtling and Trippl 2005). Given the importance of time, place, and economic conditions highlighted by our analysis, federal policy on the Appalachian region's behalf should be state and region-specific during periods of LFPR divergence.

5.1 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 a more disaggregated geographic level of the data may significantly contribute to certain findings.[12] A future avenue for research would be to circumvent this issue and focus instead on a county level

[12] Due to the high computational burden of our model and the curse of dimensionality, we are not able to use this methodology and explore this issue at the county level, for example. We would expect to see

disaggregation to analyze the Appalachian region and the differences across the rural–urban spectrum. 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 be structurally different– as evidenced by the persistently low labor force participation and relatively large variance contributions of the Appalachian region factor in addition to findings in Dorsey (1991) and Stephens and Deskins (2018). While our results for Appalachia indicate that "all is quiet on the Appalachian front," West Virginia stands out. Since West Virginia is the only state with all counties designated in the Appalachian Region, further research into why the state is different may provide insight into helping struggling sub-regions and identifying why certain areas, in general, 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. For example, studying how industry composition, health, and other variables are related to the comovements of LFRPs within the region is a natural next step. Other examples of avenues for future work 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. Ultimately, more research is needed to alleviate 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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Declarations

Conflict of interest The authors have no conflict of interest to declare.

Ethical approval This article does not contain any studies with human participants or animals performed by any of the authors.

A.1 Appendix

Gibbs sampling algorithm

Below, we provide a brief description of our model estimation.

more diversity within and between states and counties and a potentially more pronounced (and estimable) Appalachian factor.

Model estimation method and priors

We employ the Monte Carlo Markov Chain (MCMC) Bayesian estimation method using uninformed or diffuse conjugate inverse-gamma priors for the standard deviations of the innovations to the law of motions of the loadings, stochastic volatilities, and the non-time-varying part of the idiosyncratic volatility. We use normal distribution priors for the initial condition of the loadings, for the constant terms, and the autoregressive coefficients for the factors and idiosyncratic shocks (Figs. 10, 11, 12).

In our estimation, we take 50,000 draws of each parameter in the model to ensure appropriate signs and convergence of our model given the number of parameters. The first 10,000 draws are used as burn-ins, which are discarded in order to reach confidence in the initial conditions. We then use the remaining 40,000 draws as keepers, which are saved after the allotted burn-in values have been reached (Tables 1, 2, 3).

Algorithm

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

$$\Xi = \left(\omega^{T\prime}, \beta^{T\prime}, \varphi_{\mathcal{C}}', \varphi_{\mathcal{R}}', \varphi_{\mathcal{S}}', g^2, \{h_{1,t}^{\mathcal{C}}\}_{t=1}^T, \{h_{1,t}^{\mathcal{R}}\}_{t=1}^T, \{h_{2,t}^{\mathcal{R}}\}_{t=1}^T, \{\{h_{1,t}^{\mathcal{S}}\}_{t=1}^T\}_{i=1}^{n\prime}\right),$$

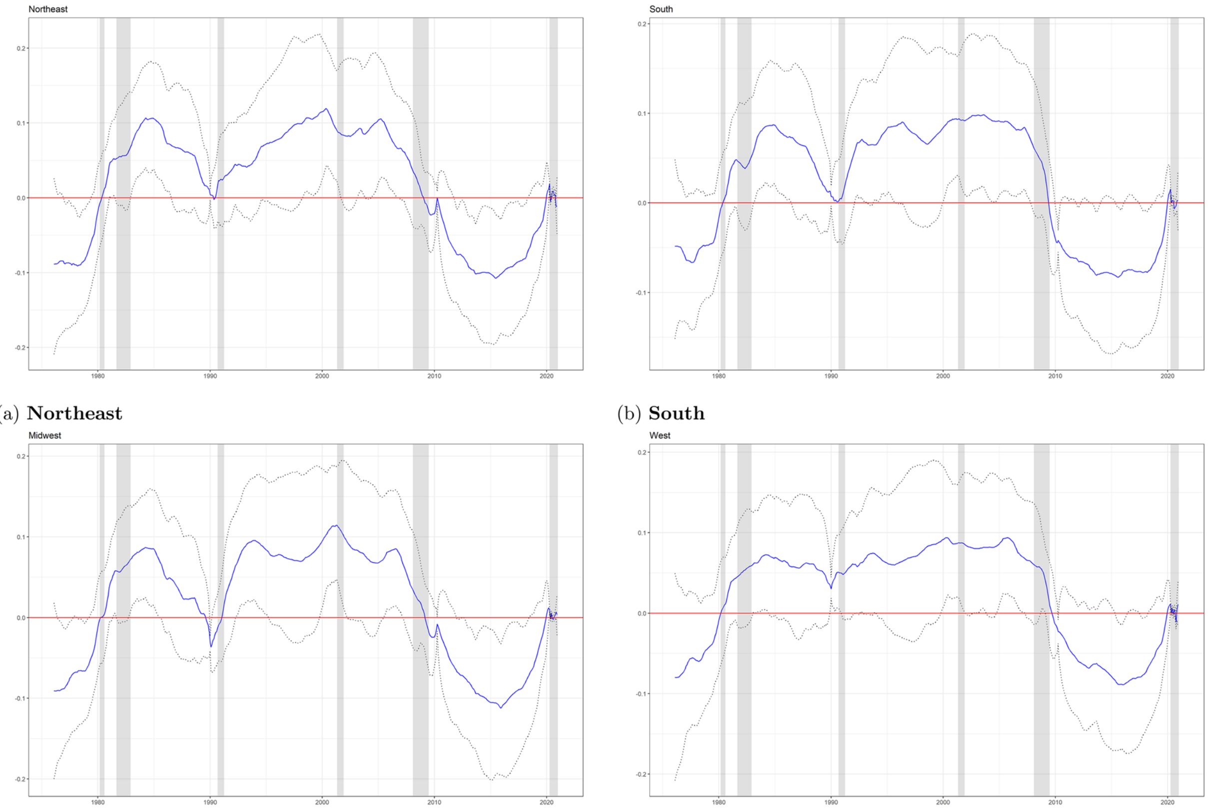
where $\omega^T = \{(\omega_1, \omega_2, \ldots, \omega_n)'\}_{i=1}^T$ and $\beta^T = \{(\widetilde{\beta}_1, \widetilde{\beta}_2, \ldots, \widetilde{\beta}_n)'\}_{t=1}^T$ denote our time-varying coefficients. $\varphi_{\mathcal{C}} = (\phi_1^{\mathcal{C}}, \phi_2^{\mathcal{C}})$, $\varphi_{\mathcal{R}} = (\phi_{1,1}^{\mathcal{R}}, \phi_{1,2}^{\mathcal{R}}, \phi_{2,1}^{\mathcal{R}}, \phi_{2,2}^{\mathcal{R}} \ldots \phi_{5,1}^{\mathcal{R}}, \phi_{5,2}^{\mathcal{R}})$, $\varphi_{\mathcal{S}} = (\phi_{1,1}, \phi_{1,2}, \phi_{2,1}, \phi_{2,2}, \ldots, \phi_{n,1}, \phi_{n,2})$, and $g^2 = \{\sigma_i^2\}_{i=1}^n)$ are the time invariant variances. Lastly, the $h_\bullet$ represent the latent stochastic volatilities and n = 51.

1. Draw the national and regional (5) (i.e., Appalachia, Northeast, South, Midwest, and West) 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.

   $$f\left(\{\mathcal{C}_t\}_{t=1}^T, \{\mathcal{R}_{1,t}\}_{t=1}^T, \{\mathcal{R}_{2,t}\}_{t=1}^T, \ldots, \{\mathcal{R}_{5,t}\}_{t=1}^T \middle| \Xi\right)$$

   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.

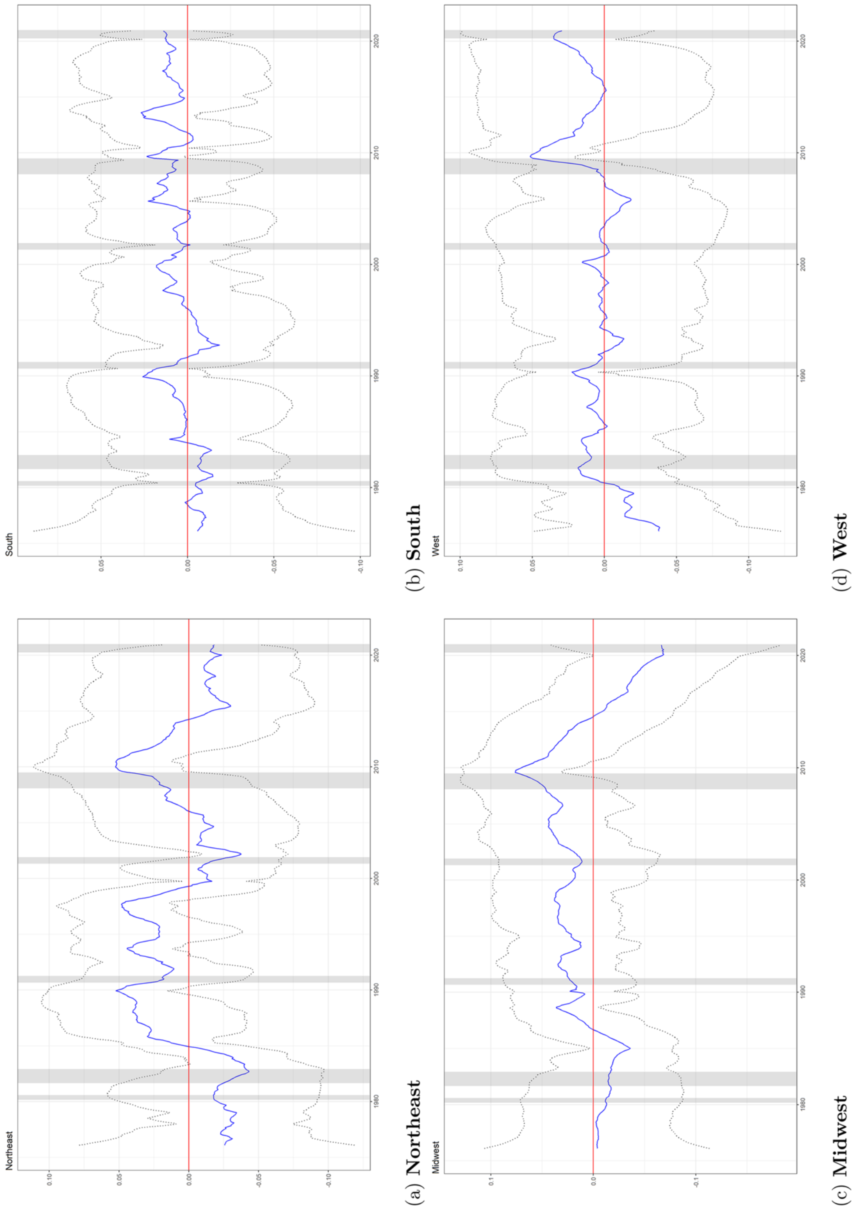
   $$f\left(\varphi_S, g^2 \middle| \{\mathcal{C}_t\}_{t=1}^T, \{\mathcal{R}_{1,t}\}_{t=1}^T, \{\mathcal{R}_{2,t}\}_{t=1}^T, \ldots, \{\mathcal{R}_{5,t}\}_{t=1}^T, \omega, \widetilde{\beta}, \{h_{i,t}\}_{t=1}^T\right)$$



(a) **Northeast** (b) **South**

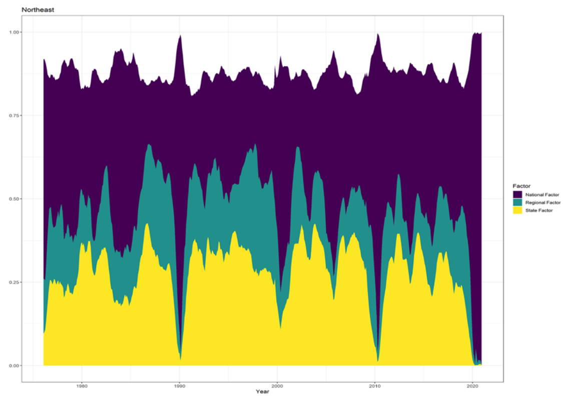
(c) **Midwest** (d) **West**

Fig. 10 Average Common Factor Loadings by 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. (Colour figure online)

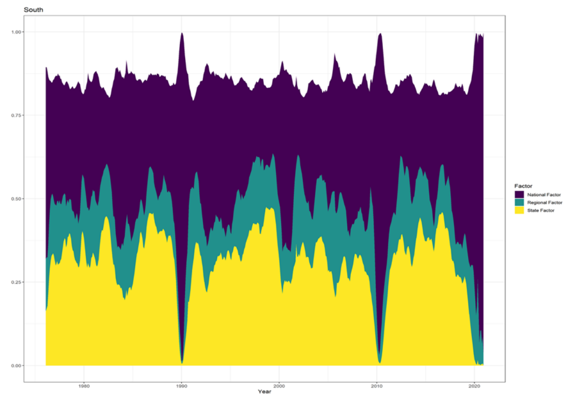


(a) **Northeast** (b) **South** (c) **Midwest** (d) **West**

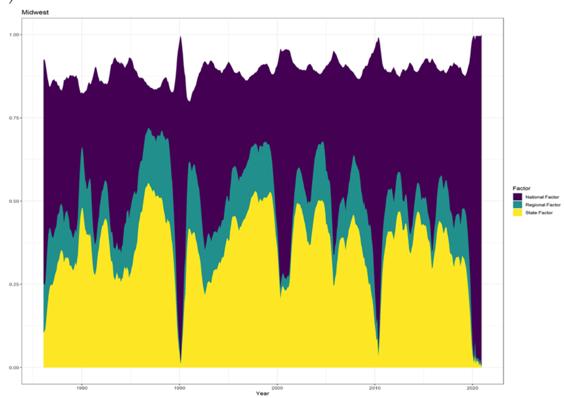
Fig. 11 Average Regional Factor Loadings by Geographical Region. *Note* Shaded regions are the NBER-dated recessions. The blue solid lines represent the median of the posterior distribution. Dashed lines represent the 5th and 95th percentiles. (Colour figure online)



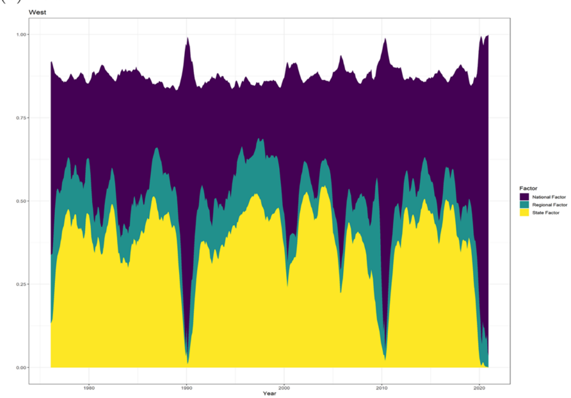
(a) **Northeast**



(b) **South**



(c) **Midwest**



(d) **West**

Fig. 12 Average Variance Contribution by Factor and Geographical Region. *Note* Colored areas represent the percent contribution of each factor to observed variation in the change in LFPR. Since the percent contributions are computed as the medians of the posterior distribution at each time point, they might potentially not sum to 1. (Colour figure online)

Table 1 Descriptive statistics—state labor force participation rates

States	Mean	Median	Min	Max	S.D.	States	Mean	Median	Min	Max	S.D.
Alabama	60.50	60.90	55.90	64.50	2.29	Montana	65.95	66.60	61.40	69.00	1.91
Alaska	70.87	71.90	61.10	75.30	2.72	Nebraska	70.59	71.30	64.80	74.10	2.53
Arizona	63.16	63.50	59.10	67.10	2.00	Nevada	68.72	69.70	58.00	73.50	3.37
Arkansas	60.98	61.15	56.20	64.20	2.02	New Hampshire	70.35	70.90	65.10	73.60	1.84
California	65.12	65.70	59.20	68.00	1.77	New Jersey	65.36	65.90	61.40	67.60	1.48
Colorado	70.54	70.60	64.90	74.30	2.06	New Mexico	61.56	62.40	55.00	63.90	2.07
Connecticut	67.64	67.60	63.30	71.30	1.71	New York	61.42	61.60	56.80	63.60	1.41
Delaware	65.95	66.60	60.10	70.90	3.00	North Carolina	65.68	66.60	56.20	69.00	2.52
District of Columbia	67.50	67.40	63.00	72.10	2.20	North Dakota	69.65	70.50	62.30	74.70	2.96
Florida	60.63	61.40	54.90	63.70	2.32	Ohio	64.82	64.65	59.80	67.70	1.78
Georgia	65.95	66.30	59.40	69.30	2.34	Oklahoma	62.96	63.60	58.90	65.50	1.60
Hawaii	65.58	66.40	56.20	69.90	2.54	Oregon	65.71	66.00	59.20	68.90	2.31
Idaho	66.82	66.60	62.70	71.40	2.33	Pennsylvania	62.56	63.10	58.30	65.30	1.88
Illinois	66.42	66.20	60.40	70.00	1.70	Rhode Island	66.13	66.30	59.40	68.40	1.44
Indiana	66.09	66.10	61.20	70.90	1.96	South Carolina	63.30	63.90	56.60	66.90	2.73
Iowa	69.72	70.00	64.10	73.50	2.53	South Dakota	69.92	70.10	64.30	73.20	2.32
Kansas	68.98	69.10	64.90	71.50	1.61	Tennessee	62.90	62.90	58.00	67.20	2.02
Kentucky	61.51	62.00	56.00	63.70	1.59	Texas	66.90	67.30	60.20	69.40	1.96
Louisiana	60.54	60.80	54.60	68.70	1.45	Utah	69.22	69.40	62.50	73.40	2.77
Maine	64.84	65.15	58.60	68.80	2.35	Vermont	69.34	70.45	60.90	72.60	2.36
Maryland	68.78	69.00	63.00	71.50	1.65	Virginia	67.58	67.80	63.20	70.90	1.54
Massachusetts	66.93	67.10	60.40	69.40	1.25	Washington	66.20	66.30	60.60	69.90	2.22
Michigan	64.09	64.20	57.40	68.80	2.34	West Virginia	54.09	54.65	51.00	56.20	1.55
Minnesota	71.87	71.50	65.40	75.70	2.37	Wisconsin	69.76	69.30	65.40	74.50	2.44
Mississippi	59.63	59.80	53.30	63.30	2.39	Wyoming	69.69	70.35	64.10	72.40	2.01
Missouri	66.18	66.00	59.80	71.00	2.65						

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 2 Composition of Appalachia by State

State	% of State in Appalachia (Counties)	% of Appalachia (Counties)	% of State in Appalachia (Population)	% of Appalachia (Population)
Alabama	55.22	8.81	42.53	11.77
Georgia	23.27	8.81	19.80	10.50
Kentucky	45.00	12.86	18.51	4.64
Maryland	12.50	0.71	2.89	0.96
Mississippi	29.27	5.71	13.97	2.40
New York	22.58	3.33	3.66	4.24
North Carolina	29.00	6.90	11.93	6.26
Ohio	36.36	7.62	11.50	7.93
Pennsylvania	77.61	12.38	30.03	22.66
South Carolina	13.04	1.43	17.04	4.45
Tennessee	54.74	12.38	29.17	10.51
Virginia	18.38	5.95	5.99	2.71
West Virginia	100.00	13.10	100.00	10.97

The (13) states listed in this table are apart of the officially defined Appalachian Region by the (ARC), given that they all contain at least one Appalachian county. Column 2 is calculated by taking the number of counties in each state that are designated in the Appalachian Region and dividing by the total number of counties in each respective state. Column 3 is calculated by taking the number of counties in each state that are designated in the Appalachian Region and dividing by the total number of counties in the Appalachian Region

Table 3 Compositions of regions

Appalachia	Northeast	South	Midwest	West
Alabama	Connecticut	Delaware	Indiana	Arizona
Georgia	Maine	District of Columbia	Illinois	Colorado
Kentucky	Massachusetts	Florida	Michigan	Idaho
Pennsylvania	New Hampshire	Maryland	Ohio	New Mexico
South Carolina	Rhode Island	North Carolina	Wisconsin	Montana
Tennessee	Vermont	Virginia	Iowa	Utah
West Virginia	New Jersey	Mississippi	Kansas	Nevada
	New York	Arkansas	Minnesota	Wyoming
		Louisiana	Missouri	Alaska
		Oklahoma	Nebraska	California
		Texas	North Dakota	Hawaii
			South Dakota	Oregon
				Washington

We define states to be included in the Appalachian region if over 15% of the state population resides in Appalachian counties (seen in Table 2). States included in Northeast, South, Midwest, and West regions are otherwise defined by the US Census Bureau

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.

$$f\left(\omega, \widetilde{\beta} \,\middle|\, \{\mathcal{C}_t\}_{t=1}^{T}, \{\mathcal{R}_{1,t}\}_{t=1}^{T}, \{\mathcal{R}_{2,t}\}_{t=1}^{T}, \ldots, \{\mathcal{R}_{5,t}\}_{t=1}^{T}, \varphi_c, \sigma^2, \{h_{i,t}\}_{t=1}^{T}\right)$$

Since we assume the errors, conditional on the factors in Eq. 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.

$$f\left(\varphi_{\mathcal{C}} \,\middle|\, \{\mathcal{C}_t\}_{t=1}^{T}, \{h_{1,t}^{\mathcal{C}}\}_{t=1}^{T}\right)$$
$$f\left(\varphi_{\mathcal{R}} \,\middle|\, \{\mathcal{R}_{1,t}\}_{t=1}^{T}, \{\mathcal{R}_{2,t}\}_{t=1}^{T}, \ldots, \{\mathcal{R}_{5,t}\}_{t=1}^{T}, \{h_{1,t}^{\mathcal{R}}\}_{t=1}^{T}, \{h_{2,t}^{\mathcal{R}}\}_{t=1}^{T}, \ldots, \{h_{5,t}^{\mathcal{R}}\}_{t=1}^{T}\right)$$

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 et al. (1998)

$$f\left(\{h_{1,t}^{\mathcal{C}}\}_{t=1}^{T}, \sigma_{\mathcal{C}}^{h} \,\middle|\, \{\mathcal{C}_t\}_{t=1}^{T}, \varphi_{\mathcal{C}}\right)$$
$$f\Bigg(\{h_{1,t}^{\mathcal{R}}\}_{t=1}^{T}, \{h_{2,t}^{\mathcal{R}}\}_{t=1}^{T}, \ldots \{h_{5,t}^{\mathcal{R}}\}_{t=1}^{T}, \sigma_1^{h}, \sigma_2^{h}, \ldots, \sigma_5^{h} \,\Bigg|\, \{\mathcal{R}_{1,t}\}_{t=1}^{T}, \{\mathcal{R}_{2,t}\}_{t=1}^{T}, \ldots, \{\mathcal{R}_{5,t}\}_{t=1}^{T}, \varphi_{\mathcal{R}}\Bigg)$$
$$f\left(\{h_{1,t}^{\mathcal{S}}\}_{t=1}^{T}, \sigma_i^{h} \,\middle|\, \{\mathcal{C}_t\}_{t=1}^{T}, \{\mathcal{R}_{1,t}\}_{t=1}^{T}, \{\mathcal{R}_{2,t}\}_{t=1}^{T}, \ldots, \{\mathcal{R}_{5,t}\}_{t=1}^{T}, \omega, \widetilde{\beta}, \varphi_{\mathcal{S}}\right)$$

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.

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