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What drives labor force participation rate variability? The case of West Virginia[☆]

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ABSTRACT

This study examines the dynamics of labor force participation rates across counties in West Virginia to better understand local labor market integration and the factors influencing fluctuations in participation. Drawing on county-level data from January 1990 to July 2020, the research employs a dynamic factor model to decompose labor force participation rates into latent factors at the state, metropolitan/non-metropolitan, and county levels. The findings reveal a general lack of labor market integration across West Virginia, highlighting potential opportunities for growth through enhanced integration. Further analysis using panel data models identifies key determinants of labor force participation, including personal income, education, infrastructure, and the prominence of industries such as agriculture and natural gas. The results underscore the necessity for targeted county-level policies to bolster employment and promote economic expansion within the state.

1. Introduction

The Great Moderation, which began in the early 1980s, refers to the noticeable decrease in economic activity volatility in most developed economies. This reduction in volatility is visible across different industrial sectors, as well as in output and employment at various economic levels (Adao et al., 2019). When local labor markets are integrated and share a common component, the volatility and impact of shocks may be compounded for better or worse (Decressin and Fatas, 1995; Adao et al., 2019). Severe shocks like the 2008–09 recession and the COVID-19 pandemic can negatively impact integrated labor markets and economies more profoundly. However, there is growing empirical evidence that suggests small positive shocks can have substantial impacts. For example, Juhn and Potter (2006), Cai and Lu (2013), and Cooray et al. (2017) show that marginal improvements in labor force participation (LFP) can lead to improved welfare through increases in employment growth and GDP. This evidence, coupled with the decline in U.S. labor force participation rates (LFPRs) over the past two decades, has sparked a growing interest in various aspects of labor force participation (LFP) as a channel for future employment and economic growth.

The main objectives of this paper are (1) to model the dynamic behavior of LFPRs at the county level to determine the extent to which local U.S. labor markets (West Virginia, in particular) are integrated and (2) to understand what drives LFPR volatility in these labor markets.[1] Addressing the first objective allows for assessing the susceptibility/resilience of county-specific labor markets to severe adverse

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[1] Our choice of West Virginia for this case study was primarily driven by the scarcity of existing literature focused on explaining the state's anemic employment and economic growth patterns compared to other states in the U.S. The confluence of socioeconomic factors posing as barriers to growth and prosperity has created an overall dire economic situation. Further, many of the counties in that state have been designated as either economically Distressed or At-Risk (see https://www.arc.gov/wp-content/uploads/2023/06/CountyEconomicStatusFY2024WestVirginia.pdf). We discuss our motivation in greater detail in Section 2.

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shocks and the potential of benefiting from positive ones. In short, we are able to ascertain whether these labor markets are more synchronized or isolated (idiosyncratic). Within Objective (2), we assess the socioeconomic drivers of the observed volatility dynamics in Objective (1) and outline the pathways toward more directed labor market policy and intervention programs.

To empirically assess these questions, this study employs a unique two-stage procedure on data for the state of West Virginia. In the first stage of this study, we use a novel Dynamic Factor Model with time-varying parameters and stochastic volatility (DFM-TV-SV) to decompose West Virginia county-wide LFPRs into three latent factors or "economic communities of influences". This innovative approach allows us to capture relevant dynamics at the state (referred to interchangeably as the common factor), metropolitan/non-metropolitan, and county-specific (idiosyncratic) levels.[2] Through this process, we determine the relative importance of each factor in explaining county LFPR volatility over time. Our primary focus at this step is to evaluate the relative importance of state-wide, metropolitan/non-metropolitan forces' influence on West Virginia county LFPR volatility. Second, we develop a novel approach to assess the explanatory power of county-specific socioeconomic characteristics (demographics, income, social program participation, industry composition, life expectancy, among others) on the variance contributions of each factor from the first stage. In this second stage, we determine which county characteristics best explain the relative volatility in LFPRs attributed to each factor.

Our findings in the first stage indicate that labor market integration in West Virginia is generally weak, leading to heterogeneous labor market dynamics at the county level. However, during national recessions and in the later years of our study, the influence of the common factor on volatility in county LFPRs increases. In such a case, West Virginian counties become more vulnerable to broad labor market shocks. On average, about 65% of the variation in county LFPRs outside periods of recession can be attributed to the idiosyncratic factor. In our second stage analysis, we identify linkages or mechanisms through which the influences of the economic community levels are manifested. Changes in the number of gas wells and the share of manufacturing jobs best explain the volatility in LFPRs attributed to the idiosyncratic factors. We also find that changes in personal income and the percentage of production jobs in the agricultural industry best explain the volatility in LFPRs attributed to the non-metropolitan factor. Our findings indicate that it is necessary to tailor policy responses to labor market disruptions at a local level instead of adopting uniform statewide measures. For specific counties and non-metropolitan areas, we recommend that policymakers concentrate on formalizing informal or nonstandard employment and enhancing wage-based income, job prospects, and workforce development initiatives.

This study illuminates the pathways through which such integration influences various facets of economic activity by addressing the question of the degree of integration within local labor markets. One crucial aspect is the efficiency gains achieved through a more streamlined allocation of labor supply, leading to increased economic productivity and growth. As local labor markets become more integrated, barriers to worker mobility decrease, reducing search costs and enabling a better match of skills with job opportunities. This improved efficiency enhances overall economic output and creates an environment for sustained development. Furthermore, integrated labor markets tend to exhibit lower levels of volatility, which not only strengthens market confidence but also supports the resilience of economies against external shocks. However, while integrated labor markets can lead to efficiency, economic growth, and decreased volatility, they may also lead to potential contagion effects or vulnerability to adverse shocks that can threaten broader labor market stability. These insights are valuable for policymakers aiming to mitigate risks and foster robust labor market environments conducive to sustainable growth and social well-being (Vega and Elhorst, 2014).

By answering our second question: What drives LFPR volatility in local labor markets? This study offers insights into how shocks at different economic community levels affect LFPR volatility. As described in Section 4, we examine how various social, demographic, and economic characteristics may influence changes in LFPR volatility resulting from broader macroeconomic trends. The research provides policymakers and stakeholders with valuable insights to develop targeted interventions for stabilizing and enhancing labor force participation in various economically distressed areas.

The remainder of the paper follows the following organization. Section 2 discusses the relevant literature and background surrounding our research. In Section 3, we present summary statistics and describe the data we use in our DFM (stage one) and panel regression (stage two) analyses. Section 4 discusses the conceptual framework and empirical methodology for both stages. We discuss our results in Section 5, and Section 6 concludes and offers potential policy recommendations. In short, our focus on LFPR at the sub-state level shifts the scope of labor policy prescriptions from national to intrastate interventions and programs.

2. Literature review and background

To the best of our knowledge, this study is the first to jointly investigate county-specific U.S. LFPR volatility and the extent of local labor market integration. Most other the extant literature focused on labor dynamics tend to be centered on (un)employment (see Decressin and Fatas, 1995; Petrongolo and Pissarides, 2008; Elsby et al., 2009, 2013, 2019, for example). The unemployment rate is commonly used to assess economic health, but its reliability as an indicator of overall labor market and economic health has come under scrutiny. This is because the unemployment rate may not fully capture the extent of labor market weakness (Juhn and Potter, 2006; Halleck Vega and Elhorst, 2017). When employment prospects are unfavorable and individuals opt out of the workforce, a phenomenon known as the Discouraged Worker Effect (DWE), there is a decrease in the LFPR rather than an increase in the unemployment rate (Long, 1953; Mincer, 1962; Halleck Vega and Elhorst, 2017; Martín-Román et al., 2020). Additionally, if these individuals were already unemployed before dropping out of the workforce entirely, the unemployment rate decreases, falsely indicating an improvement in overall economic conditions. Thus, we opt to study the LFPR instead. While the LFPR is known to be sensitive to the business cycle and potentially cointegrated with unemployment, we suggest it provides a more accurate representation of labor market conditions as it better accounts for individuals who have dropped out of the labor force and are no longer engaged in the (formal) productive sector (see Elmeskov and Pichelmann, 1994; Lührmann and Weiss, 2010; Hotchkiss and Rios-Avila, 2013; Lee and Parasnis, 2014; Stephens and Deskins, 2018; Martín-Román et al., 2020; Martín-Román, 2022, as examples.).

The recent literature on LFPRs has focused on exploring labor market dynamics using various spatial methods. Martín-Román et al. (2020) studied the bandwagon effect, which examines how social factors influence the sensitivity of labor force participation rates to fluctuations in the business cycle. Vega and Elhorst (2014) used a regional labor market model to analyze how regional labor markets respond to shocks specific to particular regions. Maté-Sánchez-Val et al. (2018) assessed the impact of geographical location on business failure, providing valuable insights into the spatial dimension of labor market dynamics. While our research generally contributes to this broad body of spatial labor market dynamics literature (see Patacchini and Zenou, 2007; Elhorst, 2008; Yu et al., 2008; Lee and Yu, 2010; Baltagi et al., 2012; Elhorst, 2012; Vega and Elhorst, 2014; Halleck Vega and Elhorst,

[2] By construction, we assume that these few unobserved "economic community level" factors (state, metropolitan/non-metropolitan, and county) adequately capture the observed dynamics in each county's LFPR.

2017; Martín-Román, 2022, in addition to the previous examples), our approach focuses on analyzing types of U.S. counties rather than just their locations. Instead of focusing on physical clustering or nearest neighbors, we concentrate on economic community levels such as state, metropolitan/non-metropolitan status, and county levels. Therefore, instead of using a spatial approach, we analyze the unobserved effects of these community levels on the change of LFPRs. Our approach provides a fresh perspective in this area of research. We will provide further explanation of the conceptual framework and methodology of this method in Section 4.

The issue of LFPR and economic growth is particularly significant for the Appalachian region, given the persistent problems of LFP and unemployment rates trailing other U.S. regions (Dorsey, 1991; Isserman and Rephann, 1993; Stephens and Deskins, 2018; Beverly et al., 2023; Ferreira Neto, 2023). Within Appalachia, West Virginia is one of the most economically distressed states, primarily due to low income, poor education, inadequate healthcare resources, high poverty levels, and geographic isolation (Billings, 1974; Isserman and Rephann, 1993; Behringer and Friedell, 2006; Stephens and Deskins, 2018; Muntaner and Barnett, 2000). Efforts to increase education and income levels in the area began in 1960 with a visit from then-presidential candidate John F. Kennedy to McDowell County, West Virginia. Since then, the state has remained a focus of economic development, given the creation of the Appalachian Region Development Act in 1965. Improving labor force participation in West Virginia could have ripple effects, potentially boosting labor force participation, employment, and GDP growth in the Appalachian region and the nation.

While the dire economic situation and potential for growth in West Virginia make it essential to assess the effects of socioeconomic variables and business cycle dynamics on statewide LFPR, we propose four additional reasons for selecting that state for our case study. First, the disparities in LFPRs between counties and between metropolitan and non-metropolitan areas are significantly larger than those observed across the entire United States. The average LFPR in West Virginia ranges from 42.35% to 77.15%, while the average LFPR across U.S. states ranges between 54% and 71%. This wider disparity underscores the need for policies to prioritize local labor market dynamics in order to address county and regional welfare disparities.

Second, the significant differences in LFPRs underscore an overarching economic inefficiency that hinders growth. West Virginia's average LFPR over several years is comparable to that of countries in Southeast Europe and the Balkan region, such as Greece, Bulgaria, and Croatia, which have some of the lowest LFPRs in the European Union. Similarly, other European countries like Turkey and Spain also have similar LFPRs to West Virginia. Researchers have linked the lack of growth in these countries to employment disparities (Esteban, 1999; Altux and Filiztekin, 2006; Filiztekin, 2009). These comparisons emphasize the urgent need for targeted interventions to bolster LFPRs in West Virginia, as persistent disparities can impede economic development and exacerbate socioeconomic challenges.

Third, the employment gap in West Virginia remains to be fully understood. While some attribute the gap to differences in labor market institutions, such as legislation, minimum wages, and labor unions, these factors are generally consistent across U.S. states and cannot fully account for the observed disparities (Dorsey, 1991; Isserman and Rephann, 1993; Esteban, 1999; Altux and Filiztekin, 2006; Filiztekin, 2009; Stephens and Deskins, 2018). Other theories that explain the gap include differences in amenities, real wages, cultural effects, and rural–urban status (Dorsey, 1991; Isserman and Rephann, 1993; Stephens and Deskins, 2018). Therefore, we chose West Virginia as our case study to investigate whether integrated labor markets and influences from state and regional-level shocks explain LFPR volatility within the state.

Last, LFP in West Virginia has received less attention from economists compared to other states (Stephens and Deskins, 2018). While policymakers and media have noticed the inequality in skills, income, and other indicators in the state, it is crucial to identify the factors contributing to regional variations in the long-term equilibrium for effective policy making. Previous studies that have included West Virginia in their regional LFPR analyses have found unique results for the state, offering opportunities for further research and investigation (Dorsey, 1991; Isserman and Rephann, 1993; Stephens and Deskins, 2018; Beverly et al., 2023). Beverly et al. (2023) performed a state-level analysis of LFP dynamics. They observed that West Virginia often stands out from the larger Appalachian region and appears to be more closely connected to the national labor market conditions during economic turmoil than to other labor markets within the geographical region. However, they were agnostic on the potential reasons for the structural differences between West Virginia and other states within the region. Therefore, this study aims to address the lack of empirical research for the region.

The choice of West Virginia was thoroughly motivated above, and we offer two just justifications for conducting our analysis at the county level and considering the metropolitan/non-metropolitan status as our primary "regions" of interest. First, significant specialization at the county and regional levels means that aggregating them into the state labor market would result in a somewhat arbitrary representation. Thus, exploring regional patterns is likely to reveal more compelling insights. Secondly, as labor market integration increases, the impact of region-specific shocks becomes more pronounced and discernible. One explanation for general labor market heterogeneity concerns the urban/rural divide (see Kilkenny and Huffman, 2003; Fogli and Veldkamp, 2011; Mryyan, 2014; Stephens and Deskins, 2018; Sakanishi, 2020, for example). Stronger linkages between such areas can lead to more significant impacts on the larger economy (Adao et al., 2019). On the other hand, labor markets with weaker inter-linkages will require disparate responses but will possess a more remarkable ability to absorb macroeconomic shocks.

3. Data

Labor force participation rates

This study uses monthly county-level LFPRs, which are calculated as the fraction of the population between the ages of 16 and 64 participating in the labor force.[3] We obtain labor force and population data for January 1990–July 2020 from the Bureau of Labor Statistics (BLS) and the U.S. Census Bureau, respectively.[4] The long span of the data (30 years) allows us to capture long-term trends with major economic events (and business cycles) that might have affected the state of West Virginia.

To classify counties as metropolitan or non-metropolitan, we follow the Office of Management and Budget (OMB) delineation of metropolitan areas and the United States Department of Agriculture (USDA) Rural–Urban Continuum Codes (RUCC). OMB-defined metropolitan counties are subdivided into three categories based on the population size of their metropolitan area. OMB-defined non-metropolitan counties are subdivided into six categories based on proximity to metropolitan areas and their degree of urbanization. These subcategories are described in Table 1. We use the OMB metropolitan/non-metropolitan assignments for the counties in West Virginia. As a result, thirty-four (34) counties are classified as non-metropolitan and twenty-one (21) as metropolitan.

[3] The Bureau of Labor Statistics (BLS) defines those participating in the labor force as individuals working or actively searching for work.

[4] Monthly county labor force values are divided by annual county populations between the ages of 16 and 64 to calculate pseudo-monthly LFPRs for each county. Our sample was constrained to end in 2020 to match the latest available census data at the time of writing. The full details are provided in the following subsection.

Table 1
USDA Rural–Urban Continuum Code (RUCC) descriptions.

Code	Description
1	Counties in metro areas of 1 million population or more
2	Counties in metro areas of 250,000 to 1 million population
3	Counties in metro areas of fewer than 250,000 population
4	Urban population of 20,000 or more, adjacent to a metro area
5	Urban population of 20,000 or more, not adjacent to a metro area
6	Urban population of 2500 to 19,999, adjacent to a metro area
7	Urban population of 2500 to 19,999, not adjacent to a metro area
8	Completely rural or less than 2500 urban population, adjacent to a metro area
9	Completely rural or less than 2500 urban population, not adjacent to a metro area

Note: As assigned by the Office of Management and Budget (OMB), counties in Codes 1–3 are classified as Metropolitan and 4–9 as Non-metropolitan.

Table 2
Summary statistics of regional labor force participation rates.

	# of Counties	Mean	SD	Minimum	Maximum
Metropolitan	21	66.22	7.32	45.30	84.73
Non-Metropolitan	34	62.82	8.78	38.82	97.80
Total	55	64.11	8.78	38.82	97.80

Note: This data represents the LFPR in levels. We use the differenced and demeaned labor force participation rates for our analysis, outlined in Section 4. Counties are classified as metropolitan or non-metropolitan using the 2013 classifications. Full descriptions of the RUCC codes are presented in Table 1. SD refers to the standard deviation.

First, we differenced the data to render each county LFPR data series stationary in our first stage model (DFM). All Augmented Dickey–Fuller tests support the conclusion of a unit root process and high persistence (Dickey and Fuller, 1979). Summary statistics, aggregated by metropolitan/non-metropolitan status in Table 2, highlight that the LFPR varies within and across the metropolitan/non-metropolitan divide. The lowest and highest average LFPR are exhibited in Non-metropolitan counties. Summary statistics for individual counties are presented in Table A.1. The LFPR for non-metropolitan counties appears less stable than the metropolitan counterparts, given the larger reported standard deviations in both Tables 2 and A.1. Since we use differenced data in our model, we plot the LFPRs change aggregated by OMB metropolitan/non-metropolitan status in Fig. 1. From the Figure, we observe that the change in LFPRs across these two groups also varies over time. Fig. 1 also shows more considerable variance in non-metropolitan LFPRs.[5]

County characteristics

In the second stage of our analysis, we examine the relationships between county-specific socioeconomic variables and the proportion of variance explained by our estimated factors. Since most county variables are unavailable monthly, we collect annual county data to create a panel of the 1990, 2000, 2010, and 2020 censuses. Several studies highlight that heterogeneity can be driven by differences in industry composition, demographics, education, among other social and economic variables (see Phimister et al., 2002; Elhorst, 2003; Kilkenny and Huffman, 2003; Weingarden et al., 2017; Stephens and Deskins, 2018; Zens et al., 2020; Beverly et al., 2023, for example). We consider 22 explanatory variables potentially influencing a county's sensitivity to LFPR comovements. We briefly describe these variables next but provide additional descriptions and summary statistics in Tables A.2 and A.3 of Appendix.

[5] Individual county LFPR change plots are presented in the Supplementary Appendix and are available upon request.

First, we include measures of industry composition (i.e., the share of government, agriculture, manufacturing, coal mining, and non-farm employment in a county) constructed from local area data from the Bureau of Economic Analysis (BEA). Different industry sectors may induce change in LFPRs, as Isserman and Rephann (1993) and Chinitz (1961) point out that shift work, such as manufacturing and mining jobs, may constrain the LFPR of partners in the household. Given the dependencies of counties, regions, or states on specific industries, the composition of industry in a county may be necessary in explaining the sensitivity to each factor. Beverly et al. (2023) note that shocks, specifically to major local or regional industries like the coal/gas industry in West Virginia and the Appalachian region, also impact changes in LFPR.

In addition to each county's industry composition, we use the number of natural gas wells and the volume of natural gas produced in each county in thousands of cubic feet (Mcf) as controls. Since persistent unemployment and negative economic opportunity may also affect LFPRs, we include the unemployment rate for each county. Workers living in a county with low economic opportunities may become discouraged, which would induce changes in LFPRs at the county, regional, and state levels (Isserman and Rephann, 1993; Stephens and Deskins, 2018). Therefore, county labor market conditions may also explain the portion of the variance explained by the different estimated factors.

Studies have shown that LFPR differences persist across racial, gender, and age demographics (Compton and Pollak, 2014; Cajner et al., 2017; Stephens and Deskins, 2018). Changes in these demographics may also affect how much the state, metropolitan/non-metropolitan, and county factors explain the variation in LFPRs via migration patterns/restrictions and concentrations of said groups throughout the state. We use data from the decennial U.S. Census to control for these differences. We calculate the population shares for each county for the two subgroups, including black or African American and other races (i.e. non-white and non-black). We use the share of the white population as the base category. We also include the shares of females under 25, between 25 and 54 years of age, and between the ages of 54–65. The share of the population over 65 serves as the reference category since, all else equal, a larger older- and retired-population will reduce LFPRs.

Additionally, changes in a county's education levels may also explain a factor's sensitivity to influencing changes in LFPRs, as we know that individuals with higher education are more likely to migrate and, therefore, more likely to participate in the labor force. To control for these differences across levels of education, we use Economic Research Service (ERS) education data from the United States Department of Agriculture (USDA) for 1990, 2000, and 2010, in conjunction with education data from the U.S. Census 2020 decennial census and the American Community Survey 2020. We calculate the fractions of the county population over 25 with a high school diploma (or equivalent) and some college experience from these sources.

We control for geographical county characteristics that may be related to the variance in the change in LFPRs explained by a given factor. We include the land area in square miles for each county from the U.S. Census Bureau and the average rainfall in inches for each county for our panel years from the National Centers for Environmental Information (NCEI). We also include county highway data from the U.S. Department of Transportation's Federal Highways Administration to create an indicator variable for counties with at least one interstate highway to measure access to infrastructure and jobs. The extant literature argues that such geographic variables may affect the LFPR in a given county since remoteness provides barriers to labor force participation (Marston, 1985; Isserman and Rephann, 1993; Rickman and Wang, 2017; Stephens and Deskins, 2018). Infrastructure and wealth in metropolitan and non-metropolitan counties may attract workers and businesses, therefore affecting the LFPR and the levels of variation in the change in LFPRs, as explained by our factors.

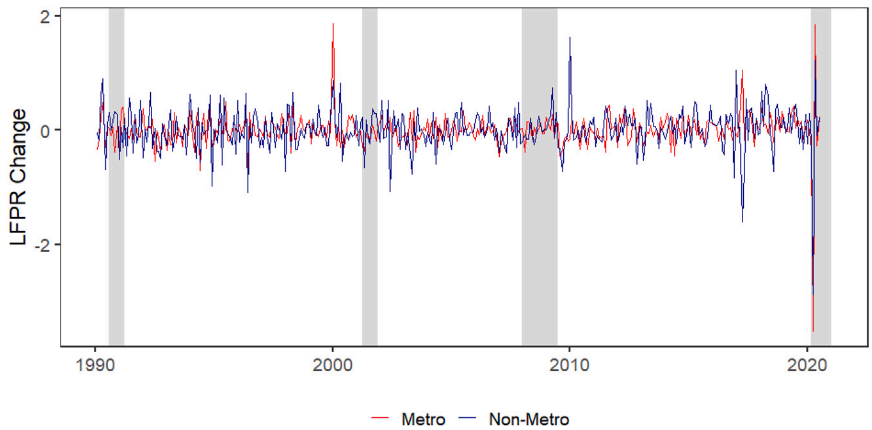

Fig. 1. Change in labor force participation rates by Metro/Non-metro Status. Note: Shaded regions are the NBER-dated recessions. This data represents the differenced labor force participation rates average across Metropolitan and Non-metropolitan counties. We use the differenced and demeaned county LFPRs for our analysis outlined in Section 4.

Lastly, to capture a county's overall lifestyle and other economic outcomes, we first use the Institute for Health Metrics and Evaluation (IHME) data on life expectancy as a proxy for county health. Poor health can lead to difficulties finding and keeping jobs, leading to withdrawal from the workforce. Poor health induced by unhealthy habits increases morbidity and can also cause changes in LFPRs. Behringer and Friedell (2006) note strong health trends in Appalachia and, by extension, West Virginia. These regional/cultural health trends potentially link labor markets across counties and are crucial in determining how well our spatial factors explain the variation in county LFPRs. Secondly, we gather poverty rate data from the U.S. Census Bureau, Temporary Aid to Needy Families (TANF) data compiled by West Virginia Kids Count at the U.S. Department of Health and Human Resources, and personal income data from the BEA. We include these indicators since income from transfer payments may cause disincentives to work (Isserman and Rephann, 1993; Kodras, 1986; Jones and Kodras, 1990). Also, the number of people accepting transfer income depends on the local and state economies, therefore linking assistance regionally (Isserman and Rephann, 1993; Spieler, 1993).

4. Conceptual framework and methodology

4.1. Stage 1: Dynamic factor model

In the first stage of this analysis, we use the dynamic factor model with time-varying factor loadings and stochastic volatility (DFM-TV-SV), developed by Del Negro and Otrok (2008). DFM models have been used to study several variables including commodities (West and Wong, 2014; Kagraoka, 2016), output growth (Bian et al., 2020; Jiang et al., 2017), labor market conditions (Chung et al., 2014), and others. Our specification of a DFM-TV-SV model decomposes the observed LFPRs into three latent components: state (also referred to interchangeably as the common component), metropolitan/non-metropolitan, and county-specific (idiosyncratic).

Formally, our measurement equation is given by

$$y_{i,t} = \lambda_{i,t}\mathcal{S}_t + \widetilde{\gamma}_{i,t}\mathcal{M}_t + \varepsilon_{i,t} \tag{1}$$

where $y_{i,t}$ is the change in labor force participation rate for West Virginia county $i = 1, 2, \dots, 55$ at month t. $\mathcal{S}_t$ captures the common factor while $\mathcal{M}_t$ is a $T\times 2$ matrix of the non-metropolitan/metropolitan factors explained earlier in Section 3. The state ($\lambda_{i,t}$) and metropolitan/non-metropolitan ($\widetilde{\gamma}_{i,t}$) loadings measure the responses of each county's LFPR to changes in the associated factors. An increase in the state loadings for county i, for example, would indicate that county i's LFPR responds more strongly to the state LFPR factor. Finally, $\varepsilon_{i,t}$ represents the idiosyncratic factors which captures county influences or shocks on LFPRs after the state and metropolitan/non-metropolitan influences are removed.

Despite maintaining the classical assumption of orthogonality of the factors, the specification in Eq. (1) extends the standard constant parameter Dynamic Factor Model (DFM) by allowing the factor loading parameters to vary over time. Allowing for time variations enables us to capture the changes in the relative contribution of each factor to the change in LFPR variation over time. From Eq. (1) and the assumptions of independence, the following variance decomposition structure arises:

$$\mathrm{Var}(y_{i,t}) = \lambda^2_{i,t}\ \mathrm{Var}(\mathcal{S}_t) + \widetilde{\gamma}_{i,t}\ \mathrm{Var}(\mathcal{M}_t)\widetilde{\gamma}'_{i,t} +\ \mathrm{Var}(\varepsilon_{i,t}) \tag{2}$$

To capture the volatility dynamics over time, we must include stochastic volatility in the laws of motion of the national, regional, and idiosyncratic factors (Eqs. (3)–(7)). This extension assumes random, rather than constant, innovations (error terms) of each factor. This is consistent with the rational expectation that we would observe differing volatility across time and economic/business cycle conditions. Importantly, this assumption and our model specification allow us to capture changes in the sensitivity of our factors to labor conditions over our sample. To this extent, we can capture potential volatility changes due to new or amended labor policy and major shocks to the local economies like natural disasters. Since our data only extends to July 2020, we are not able to adequately assess the volatility changes due to the COVID-19 pandemic.

The transition equations for each factor evolve as stationary processes:

$$\mathcal{S}_t = \sum_{p=1}^{P} \phi^S_p \mathcal{S}_{t-p} + e^{h^S_t} \cdot v^S_t; \quad v^S_t \sim i.i.d.\mathcal{N}(0, \sigma^2_S) \tag{3}$$

where ϕ^S_p is the autoregressive coefficient for the state factor and $P = 2$. $e^{h^S_t}$ represents the stochastic volatility components, and v^S_t the innovation to the law of motion for the state factor or factor that is common to all counties. Following the standard literature, the stochastic volatility for the state factor is assumed to follow a random walk process:

$$h^S_t = h^S_{t-1} + \sigma^h_S \cdot \eta^S_t; \quad \eta^S_t \sim i.i.d.\mathcal{N}(0, 1) \tag{4}$$

where σ^h_S is the standard deviation of the innovation to the law of motion for the state factor and η^S_t is the volatility shock.

Likewise, the metropolitan/non-metropolitan factors are assumed to follow AR(l) processes:

$$\mathcal{M}_{j,t} = \sum_{l=1}^{L} \phi^{\mathcal{M}}_{j,t} r_{t-l} + e^{h^{\mathcal{M}}_{j,t}} \cdot v^{\mathcal{M}}_{j,t}; \quad v^{\mathcal{M}}_{j,t} \sim i.i.d.\mathcal{N}(0, \sigma^2_{j,s})\ j = 1, 2 \tag{5}$$

again $\phi^{\mathcal{M}}_{j,t}$ is the autoregressive coefficient for each regional factor, $L = 2$, $e^{h^{\mathcal{M}}_{j,t}}$ represents the stochastic volatility components, and $v^{\mathcal{M}}_{j,t}$ is the innovation to the law of motion for the regional factor. The stochastic volatility for the regional factors are also assumed to follow random walk processes:

$$h^{\mathcal{M}}_{j,t} = h^{\mathcal{M}}_{j,t-1} + \sigma^{h}_{j,\mathcal{M}} \cdot \eta^{\mathcal{M}}_{j,t}; \quad \eta^{\mathcal{M}}_{j,t} \sim i.i.d.\mathcal{N}(0,1) \tag{6}$$

where $\sigma^{h}_{j,\mathcal{M}}$ is the standard deviation of the innovation to each law of motion of the regional factor and $\eta^{\mathcal{M}}_{j,t}$ is the volatility shock.

The idiosyncratic factor for each county similarly follows a stationary AR(q) process:

$$\varepsilon_{i,t} = \sum_{q=1}^{Q} \phi_q \varepsilon_{t-q} + e^{h_{i,t}} \cdot v_{i,t}; \quad v_{i,t} \sim i.i.d.\ \mathcal{N}(0, \sigma_i^2) \tag{7}$$

where ϕ_q is the autoregressive coefficient for the idiosyncratic shock, $Q = P = L = 2$. $e^{h_{j,t}}$, denotes the stochastic volatility components, and $v_{i,t}$ the innovation to the law of motion for the idiosyncratic factor. The stochastic volatility for each county factor follow random walk processes:

$$h_{i,t} = h_{i,t-1} + \sigma^{h}_{i} \cdot \eta_{i,t}; \quad \eta_{i,t} \sim i.i.d.\ \mathcal{N}(0,1) \tag{8}$$

where σ^{h}_{i} is the standard deviation of the innovation to each law of motion and $\eta^{S}_{i,t}$ is the volatility shock. As mentioned earlier, for proper identification, we follow the standard literature and assume that $v^{S}_{t}, v^{\mathcal{M}}_{j,t}$, and $v_{i,t}$ are orthogonal to each other. We also assume that, $\eta^{S}_{t}, \eta^{\mathcal{M}}_{j,t}$, and $\eta^{S}_{i,t}$ are orthogonal to each other.

It is worth noting that the scale of the factor loadings and the standard deviations for each factor cannot be separately identified. Against this background, we follow the macroeconomics literature standard normalization procedures (See Del Negro and Otrok, 2008; Bhatt et al., 2017, for example). We first restrict the shocks of the state and metropolitan/non-metropolitan factors $\sigma^2_{S} = \sigma^2_{1,\mathcal{M}} = \sigma^2_{2,\mathcal{M}} = 1$. Additionally, we constrain the starting values of each $h_{\bullet}$ in the stochastic volatility equations (4), (6), (8) to a value of zero since the scale of stochastic volatility term $h_{\bullet}$ is determined by the initial condition. (i.e $h^{S}_{0} = h^{\mathcal{M}}_{j,0} = h_{i,0} = 0$) While this implies no stochastic volatility before the sample period, it allows us to derive equally representative distributions for the initial conditions (Del Negro and Otrok, 2008).

Following Beverly et al. (2023), we estimate the above DFM-TV-SV using the Monte Carlo Markov Chain (MCMC) Bayesian estimation method and naive conjugate priors with Inverse Gamma distributions as per the literature (see Del Negro and Otrok, 2008; Neely and Rapach, 2011; Ma et al., 2018; Bian et al., 2020, for example). We also follow Kim et al. (1999, 1998) for the standard Gibbs-Sampling algorithm and procedure to draw stochastic volatility, respectively.[6] In this initial estimation, we take 50,000 draws of each parameter for each county i, and each month t (keeping 40,000 and discarding the first 10,000) to ensure convergence of our model.

4.2. Stage 1: Conceptual framework

In this section, we first examine our assumptions for the Dynamic Factor Model, which we specify below, using a Directed Acyclic Graph (DAG). The DAG in Fig. 2 graphically represents the mechanism by which the change in West Virginia county LFPRs are explained or decomposed into latent economic community levels called factors. In this DAG, the observed outcome variable, the change in county LFPR ($y_{i,t}$) is represented as a solid circle. The dashed circles represent the unobserved latent factors which we have separated into three main effects or "community level" influences on changes in LFPRs. These include the state ($\mathcal{S}_t$), regional (metropolitan/non-metropolitan) ($\mathcal{M}_t$), and county idiosyncratic ($\varepsilon_{i,t}$) factors. The solid black arrows indicate the pathways of inference between the variables. The conventional macroeconomic theory of dynamic equilibrium aligns with the idea of restricting factors affecting the outcome variable to a small number (Stock and Watson, 2016). A similar approach has been used in several macroeconomic studies (see Bhatt et al., 2017; Ma et al., 2018; Beverly et al., 2023; Neely and Rapach, 2011, for example).

As seen in the Figure, we assume any national or global trends and influences, are manifested through the state factor which is already common to all counties in West Virginia. While we use the term "regional" to describe the factors capturing the effect of Metropolitan and Non-metropolitan status on changes in county LFPR, we do want to distinguish our methodology from the approaches employed in the conventional spatial analysis. Rather than study LFPR dynamics by incorporating a county's physical location in relation to other counties and estimating spillover effects we divide counties by type or status (Metropolitan/Non-metropolitan). Therefore, as seen in Fig. A.1 in the Appendix, counties that are on opposite sides of the state geographically will have the same designation. In this way, we offer a fresh perspective on "regional" labor market dynamics.

4.3. Stage 2: Determinants of observed variances

After estimating Eq. (2) in the first stage, we then compute each factor's contribution to the total variability of LFPR for county i. Using Eq. (2), the fraction of volatility attributable to the state factor, $\mathcal{S}$, for example, would be computed as:

$$\theta^{S}_{it} = \frac{\lambda^2_{i,t}\ \mathrm{Var}(\mathcal{S}_t)}{\mathrm{Var}(y_{i,t})} \tag{9}$$

The shares attributable to the metropolitan/non-metropolitan and county factors are calculated similarly and are denoted herein as $\theta^{\mathcal{M}}_{it}$ and θ_{it}, respectively.

In the second stage of our analysis, we investigate how well county characteristics explain a county's sensitivity to state, metropolitan/non-metropolitan, and idiosyncratic influences. To this end, we regress the volatility shares of the state, metropolitan/non-metropolitan, and county factors (θ^{S}_{it}, $\theta^{\mathcal{M}}_{it}$, θ_{it} respectively) on the 22 explanatory variables (detailed earlier) for the census years 1990, 2000, 2010, and 2020.

While the literature does mix Bayesian and frequentist approaches (see Kose et al., 2003; Neely and Rapach, 2011, for example), we conjecture that there is a philosophical inconsistency in evaluating the panel regressions in a frequentist framework after having estimated the variance contributions (θ^{S}_{it}, $\theta^{\mathcal{M}}_{it}$, θ_{it}) using Bayesian methodology. We novelly reconcile this by incorporating Bayesian concepts into our panel regressions and placing distributions around our parameter estimates (coefficients). From the Gibbs-Sampler in stage one, we start with the 40,000 draws of θ^{S}_{it}, $\theta^{\mathcal{M}}_{it}$, and θ_{it}. Consequently, this equates to 1.68 million draws of θ^{S}, $\theta^{\mathcal{M}}$, and θ for each county, i, across the four panel years. We follow the procedure outlined below to reduce the number of draws and incorporate Bayesian concepts in this second-stage analysis.

1. Randomly select 1000 draws (out of 40,000 kept from Stage 1) from each month of the panel years (1990, 2000, 2010, 2020). This reduces the original 1.68 million draws to 42,000 (11,000 + 12,000 + 12,000 + 7000) for 1990, 2000, 2010, and 2020, respectively.[7]
2. From the reduced draws, randomly select 5000 for each panel year. This is our final reduction, resulting in 20,000 (5000 for each year) final draws for each ($\widetilde{\theta}^{S}_{i}$, $\widetilde{\theta}^{\mathcal{M}}_{i}$, $\widetilde{\theta}_{i}$).
3. Draw a single observation for each factor $\widetilde{\theta}^{S}_{i}$, $\widetilde{\theta}^{\mathcal{M}}_{i}$, $\widetilde{\theta}_{i}$ (1 of 5000) from each panel year and regress them on the 22 explanatory variables.

[6] The interested reader is directed to the technical appendix of Bhatt et al. (2017) for additional information about the Gibbs-Sampling algorithm.

[7] Due to differencing of the data, we lost observations for January in 1990 (the first year of our sample). Also, since our data only extends to July 2020, we only have 7 months of data for 2020.

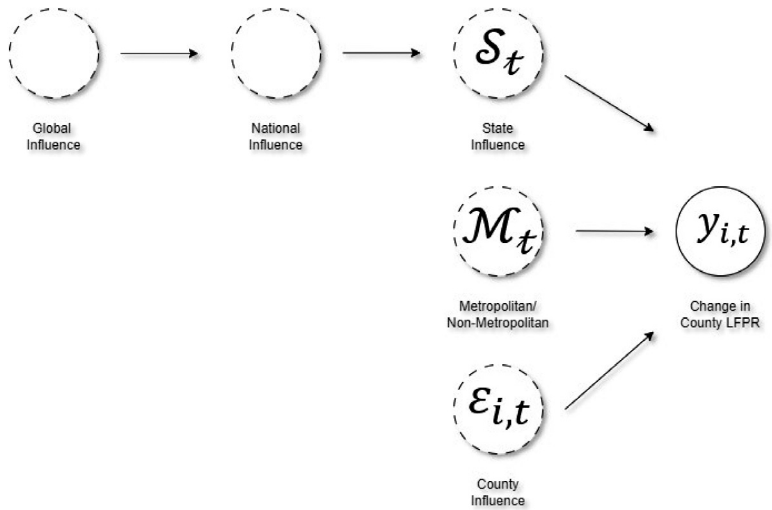

Fig. 2. Directed acyclic graph for dynamic factor model. Note: The solid circle represents the observed outcome variable, $y_{i,t}$. The dashed circles represent the unobserved latent factors or community level influences on the outcome variable. The solid arrows suggest the paths of inference between the factors and the outcome, $y_{i,t}$.

4. Repeat Step 3 for all 5000 draws of the θ's and regress on the same 22 explanatory variables. This produces distributions for the β_k's of our regressors.

We use this random data reduction and repeated regressions method as a way to underpin the frequentist approach with the Bayesian estimation procedure from Stage 1.[8] Also, we can generate more credible estimates of the coefficients of interest.

For completeness, a single panel regression model, for the state factor, $\mathcal{S}$, for example, is given as follows:

$$\widetilde{\theta}^{S}_{it^*}\Big|_{1}^{5000} = \beta_{it^*} + \sum_{k=1}^{22} \beta_k \mathcal{X}_{k,it^*} + e^{S}_{it^*}, \quad t^* \in \{1990, 2000, 2010, 2020\} \tag{10}$$

where $\widetilde{\theta}^{S}_{it^*}\Big|_{1}^{5000}$ is one of 5000 draws of the proportion of the variance in the change in a county's LFPR explained by the state factor for county i ($i = 1, \dots, 55$), and for time t^*. $\mathcal{X}_{k,i,t^*}(k = 1, \dots, 22)$ contains the matrix of characteristics in county i at time t^*. Similar regressions are used to explain $\widetilde{\theta}^{\mathcal{M}}_{it^*}$ and $\widetilde{\theta}_{it^*}$ and are also repeated 5000 times. We estimate each iteration of Eq. (10) using fixed effects.[9] The full model results are presented in Table A.4 of Appendix. Since the magnitudes of the coefficients are not particularly meaningful, we focus instead on the strength of the connectedness of county characteristics and the dependent variables and the signs of these relationships. Additionally, rather than arbitrarily decide how many of the 5000 coefficients of each variable need to be statistically different from zero to be meaningful for inference, we employ Bayesian Highest Posterior Density intervals (HPDIs) which are also often called credible intervals. Using HPDIs we determine the 95% credible interval or the shortest interval that contains the true coefficient with .95 probability for each distribution of 5000 coefficients for each variable. If zero lies outside this interval for a given variable, we determine it to have a significant effect. In the interest of brevity, Table 3 reports only the variables with the strongest non-zero relationships and presents the percentage of the coefficient distribution that is above zero. In Figs. 10, 11, and 12 we plot the distributions of these variables along with the means of the distributions and the 95% Highest Posterior Density Intervals (HPDI) as credible intervals for our results.

4.4. Stage 2: Conceptual framework

Next, we examine our assumptions and the relationships between factors, explanatory variables, and outcome variables for the stage two panel regressions using the DAG in Fig. 3. This DAG graphically represents the mechanism by which the change in county LFPR volatility attributed to the state factor ($\mathcal{S}_t$) is explained by county characteristics. The relationship between the change in county LFPR volatility attributed to each of the regional and idiosyncratic factors would be graphically represented by similar DAGs. We only present the state factor DAG in Fig. 3 for brevity. In this DAG, the outcome variable, estimated in stage one of the analysis, is the county LFPR volatility or the percent of the variance in changing county LFPRs that is explained by the state factor (θ^{S}_{it}). Again, this outcome variable is represented as a solid circle. The dashed circle, in this case, represents the unobserved latent state factor that is common to all counties in West Virginia. The solid black arrows indicate the direction of potential relationships between the variables and the solid squares represent various county characteristics or explanatory variables that we have grouped broadly into social, demographic, or economic categories. When making the final selections for the variables to include in our models, we use variance inflation factors (VIF) to test for interactions and multicollinearity.

5. Results

The estimated state and metropolitan/non-metropolitan factors, depicted in Fig. 4, are orthogonal by construction. The state factor identifies a common component in the changes in LFPRs among all counties in West Virginia. After subtracting out the common component, the metropolitan/non-metropolitan factors then capture variation in the change in LFPRs within the metropolitan and non-metropolitan counties, respectively. The state factor, Panel (A) of Fig. 4, displays several spikes in a common component in the change in LFPRs. These occur in the years 2000, 2009, 2010, and 2020, marking significant shifts in the LFPRs. We also note that the state factor is estimated relatively accurately, as the confidence intervals remain tight to the median values, underscoring the robustness of our model. The metropolitan factor, Panel (B), displays an increase in variability and less mean reversion near the end of the sample period. In contrast, the non-metropolitan factor, Panel (C), displays a decrease in variance between 2005 and 2015. Overall, Fig. 4 indicates that outside of a few national or state-wide shocks, West Virginia county LFPRs are influenced more

[8] Visualization of the full distribution of coefficients can be seen in Figs. A.2–A.5 of Appendix.

[9] In Stage 1, by construction, θ^{S}_{it}, $\theta^{\mathcal{M}}_{it}$ and θ_{it} sum to one in a single iteration. However, due to the randomization process outlined above and the unequal number of months in the panel years in Stage 2 of the analysis, this property is not necessarily preserved for $\widetilde{\theta}^{S}_{it}$, $\widetilde{\theta}^{\mathcal{M}}_{it}$ and $\widetilde{\theta}_{it}$.

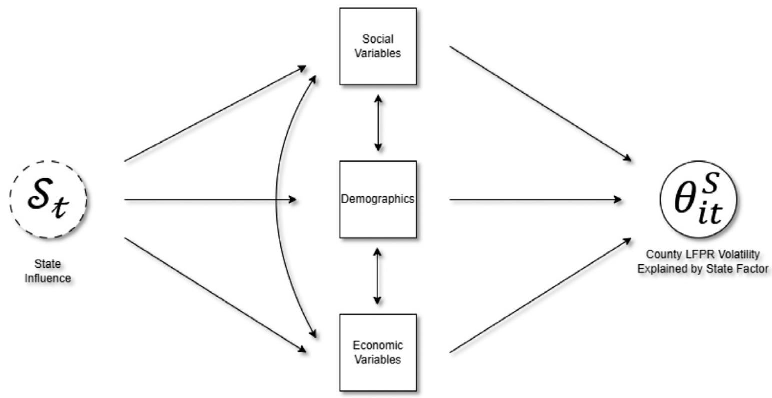

Fig. 3. Dynamic acyclic graph for state factor panel regressions. Note: The solid circle represents the variable, θ^S_{it} that was estimated in the first stage of the analysis. The dashed circle represents the unobserved latent factor or community level influence from the state factor on the outcome variable. The solid arrows suggest potential relationships or connections between the factors and the outcome, θ^S_{it}, through and among the explanatory variables.

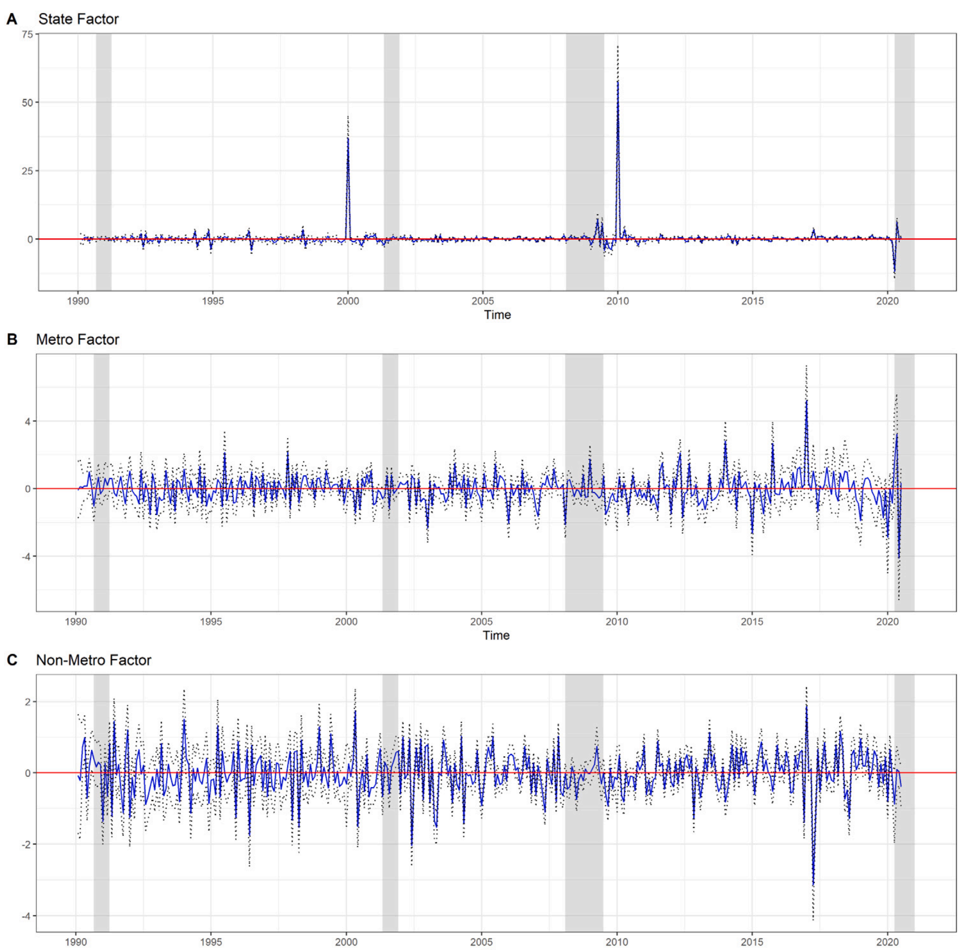

Fig. 4. State and metropolitan/non-metropolitan factor estimates. Note: Shaded regions are the NBER-dated recessions. The blue solid lines represent the medians of the posterior distribution averaged across each group: All West Virginia counties (Panel A), all metropolitan counties (Panel B), and all non-metropolitan counties (Panel C). Dashed lines represent the 5th and 95th percentiles.

at the metropolitan/non-metropolitan and county levels. This lack of persistence in any of these influences on the change in county LFPR speaks to a lack of integration across local labor markets at the state level, a crucial insight for policymakers.

5.1. State factor loadings

The state factor loadings ($\lambda_{i,t}$ in Eq. (1)) represent the correlation between individual LFPRs of counties in West Virginia and the state (common) factor. In essence, this captures an unobserved state-level effect on the movement of all West Virginia county LFPRs. These state factor loadings measure the relationship between changes in a state-wide influence and changes in county LFPRs. Positive (negative) loadings indicate that as the state-level influence increases, the change in county LFPRs also tends to increase (decrease). In other words, if LFPRs increase (decrease) as the state-level influences increase (decrease), then local labor markets become more (less) volatile. When

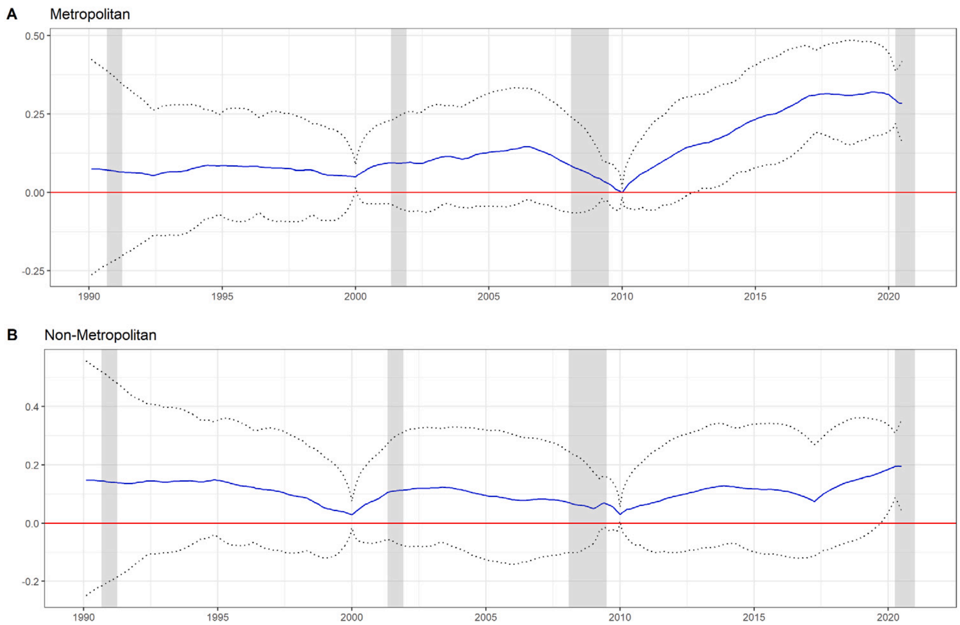

Fig. 5. Average state factor loadings by RUCC status. Note: Shaded regions represent the NBER-dated recessions. The blue solid lines represent the average of the medians of the posterior distribution. Dashed lines represent the 5th and 95th percentiles. Panels (A) and (B) show the state factor loadings averaged across the (21) metropolitan counties and (34) non-metropolitan counties, respectively.

Table 3
Percentage of the panel regression coefficient distributions above zero.

Variable	State	Metro	Non-Metro	County
% Government Jobs				
% Agriculture Jobs			2.06%	
% Manufacturing Jobs				96.98%
Unemployment Rate (%)				
Life Expectancy (years)				
% female <25 years old				
Personal Income (000's)	98.92%		3.44%	
% with HS Diploma				
% with Some College		98.32%		
% Receiving TANF				
Gas Production (Mcf)			5.62%	
Gas Wells (#)				97.02%
Interstate		93.26%		
Average R^2	0.38	0.37	0.25	0.40

Note: This table reports the percentage of the distribution of coefficients from the 5000 regressions that are above zero. Only the variables with non-zero results are reported. That is, zero lies outside the calculated HPDI credible interval. The full results are available upon request. The mean values of the coefficient estimates are presented in Table A.4 of the Appendix. Interstate is a dummy variable that captures whether at least one interstate passes through the county.

averaged by metropolitan/non-metropolitan status, the common state-level component, reported in Fig. 5, shows a near-zero correlation with the state factor for most periods for both metropolitan (Panel A) and non-metropolitan (Panel B) counties. This is unsurprising given the estimated factor results, shown in Fig. 4, and further indicates a weak relationship between changes in the state factor and changes in either metropolitan or non-metropolitan LFPRs. This suggests that labor markets and labor force participation are not driven by a common component across the entire state and provides evidence for isolated labor markets at lower than the state level.

The data in Fig. 5 indicates that after 2010, there were positive loadings on the state factor for metropolitan (Panel A) counties. These positive loadings suggest that in recent years, state factor increases have been linked to changes in metropolitan LFPRs, making these changes more volatile. Similarly, non-metropolitan counties also showed positive loadings on the state factor in 2019 and 2020. This data reveals that in the years leading up to the COVID-19 pandemic, both metropolitan and non-metropolitan counties experienced increased volatility in LFPRs due to a common influence, with non-metropolitan counties lagging by several years. These national labor market shocks were severe enough to impact even the more isolated and rural parts of West Virginia. The increased integration of the labor markets around a common state-level influence, coupled with increased volatility, resulted in both metropolitan and non-metropolitan areas being vulnerable to wider labor market shocks in the state, such as the COVID-19 pandemic. Unfortunately, rather than leading to a more efficient labor market, the integration of local labor markets in the last few years has increased labor market instability, which is likely not only experienced in West Virginia.

While we find a generally weak state-level influence on labor market activity over the sample period, the increasing trend in the average cross-county correlation (see Fig. 6) suggests that changes in West Virginia county LFPRs are becoming more connected across the state. Fig. 6 depicts the median values of the computed pair-wise correlations implied by the factor model using estimates of the factor loadings and stochastic volatilities at each time point and averaged across each of the three groups (e.g., State, Metro/Non-Metro, County). The labor market integration in recent years is again exhibited here. Fig. 6 reveals that during the periods following the 2008–09 recession and the COVID-19 pandemic, the cross-county correlation in LFPRs falls due to heterogeneous county responses in each recessionary period. However, outside these windows, the cross-county correlation exhibits an increasing trend for all three groups, especially since 2015. These increases again coincide with increasing volatility in LFPRs for counties in West Virginia. This presents the opportunity for state-level policy to mitigate the vulnerability and encourage labor market stability as the county connection across the state grows over time.

5.2. Metropolitan and non-metropolitan factor loadings

Recall that $\widetilde{\gamma}_{i,t}$ in Eq. (1) reflects the sensitivity (correlation) between individual West Virginia county LFPRs and their respective metropolitan vs. non-metropolitan classifications. The metropolitan (non-metropolitan) factor loadings measure the relationship between changes in a metropolitan (non-metropolitan) influence to changes in

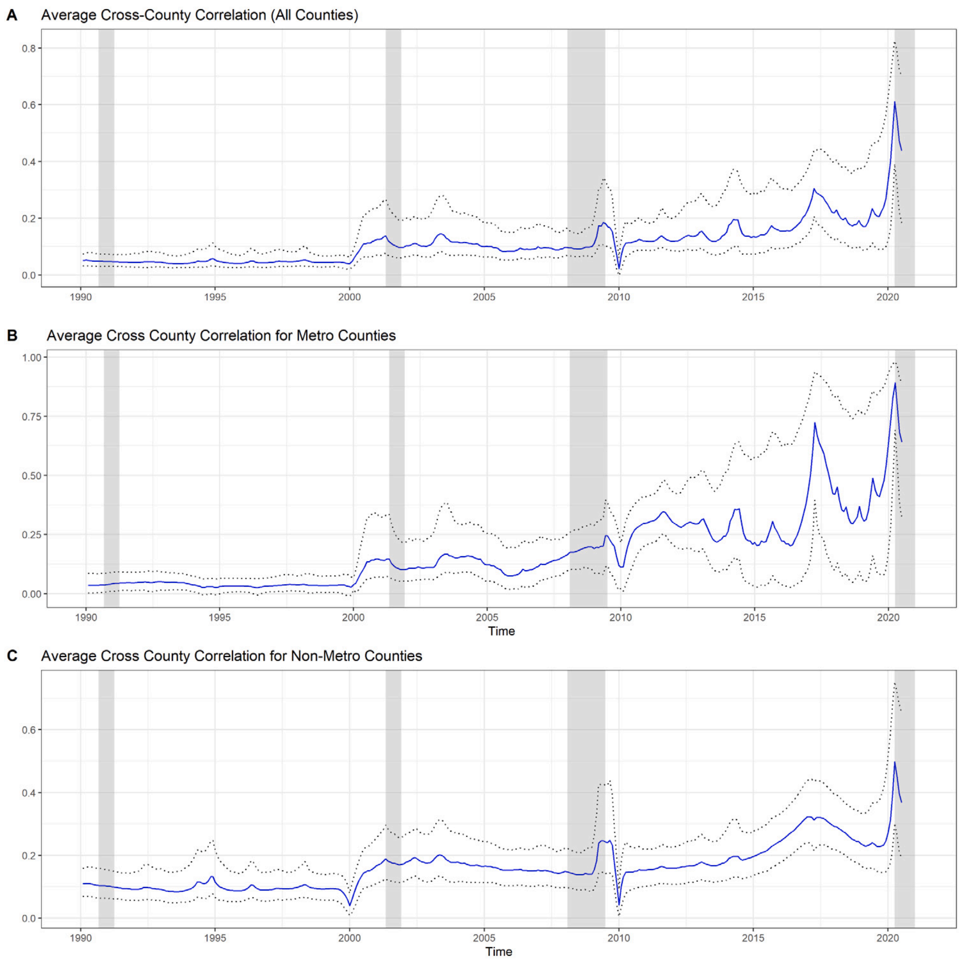

Fig. 6. Average cross-county correlation. Note: Shaded regions represent the NBER-dated recessions. The blue solid lines represent the medians of the posterior distribution averaged across each group: All West Virginia counties (Panel A), all metropolitan counties (Panel B), and all non-metropolitan counties (Panel C). Dashed lines represent the 5th and 95th percentiles.

county LFPRs. Similar to the state factor loadings, positive (negative) metropolitan/non-metropolitan factor loadings indicate that as the metropolitan/non-metropolitan factor increases, the change in county LFPRs also tends to increase (decrease). Once again, we average these individual county sensitivities to the metropolitan/non-metropolitan factors across counties in each designation. Fig. 7 Panel (A) shows that metropolitan factor loadings for metropolitan counties are non-zero during and immediately following the 2008–9 recession. These positive factor loadings indicate that increases in the change in metropolitan LFPRs were associated with increases in the influence of a metropolitan component apart from any state-wide influence. In other words, during this period, as the metropolitan factor increased, change in metropolitan county LFPRs increased as well, which implies increased instability in metropolitan LFPRs during the 2008–09 recession. This response to the 2008–09 recession compared to the previous two recessions during the sample period is most likely a derivative of the severity of the recession and the unusually steep decline in LFPRs in 2010 (Daly et al., 2009; Elsby et al., 2011). It is unsurprising that such a severe recession would cause a discernible increase in metropolitan labor market volatility. Outside this shock, the metropolitan labor market appears relatively insulated and stable.

In Fig. 7 Panel (B), we plot the non-metropolitan factor loadings, which we find to positive over the entire sample period. These persistently positive factor loadings indicate that increases in the non-metropolitan factor signal an increase in the change in LFPRs for non-metropolitan counties over the last three decades. This persistent correlation between non-metropolitan county LFPRs and the non-metropolitan factor demonstrates a strong relationship between a non-metropolitan influence and labor market volatility. Given the characteristics and nature of rural labor markets, it is unsurprising that synchronized non-metropolitan LFPRs are less stable and more susceptible to larger swings in LFPRs. These findings align well with Hamrick (1997), who finds non-metropolitan areas to be more sensitive to business cycle, exchange rate, and unemployment rate movements compared to metropolitan areas across the U.S. Our finding of a relatively strong relationship between increases in a non-metropolitan influence and increases in non-metropolitan labor market volatility highlights a need for more disparate labor market policy for rural and non-metropolitan areas. Tailored policy for non-metropolitan areas may be necessary to encourage sustainable growth and social well-being amid heightened labor market volatility (Vega and Elhorst, 2014).

5.3. Variance contribution dynamics

Next, we turn to our variance decomposition results (from Eqs. (2) and (9)) and assess the strength of intra-state comovements in the change of West Virginia county LFPR. These results allow us to determine the relative importance of each factor in explaining West Virginia county LFPR dynamics. These maps show which economic community influence explains each county's LFPR volatility more. These are calculated as the percentage contributions of the state, metropolitan/non-metropolitan, and county factors to the total change in LFPR variations averaged over our sample period (i.e. $\bar{\theta}_i^S$, $\bar{\theta}_i^{\mathcal{M}}$, $\bar{\theta}_i$, respectively). Fig. 8

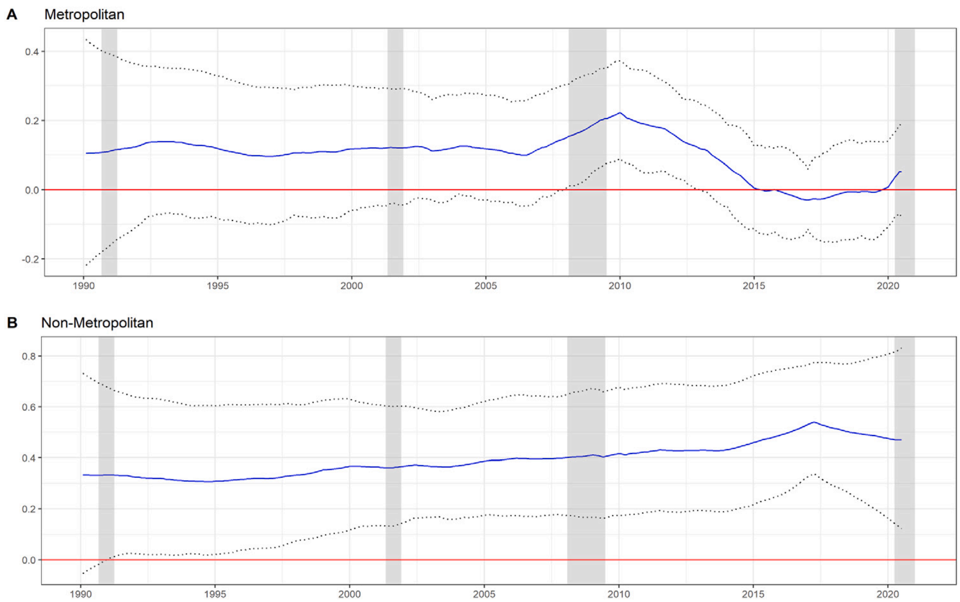

Fig. 7. Average Metro/Non-Metro factor loadings by county status. Note: Shaded regions represent the NBER-dated recessions. The blue solid lines are the average of the medians of the posterior distribution. Dashed lines represent the 5th and 95th percentiles. Panel (A) shows the metropolitan factor loadings averaged across the 21 metropolitan counties and Panel (B) shows the non-metropolitan factor loadings averaged across the 34 non-metropolitan counties.

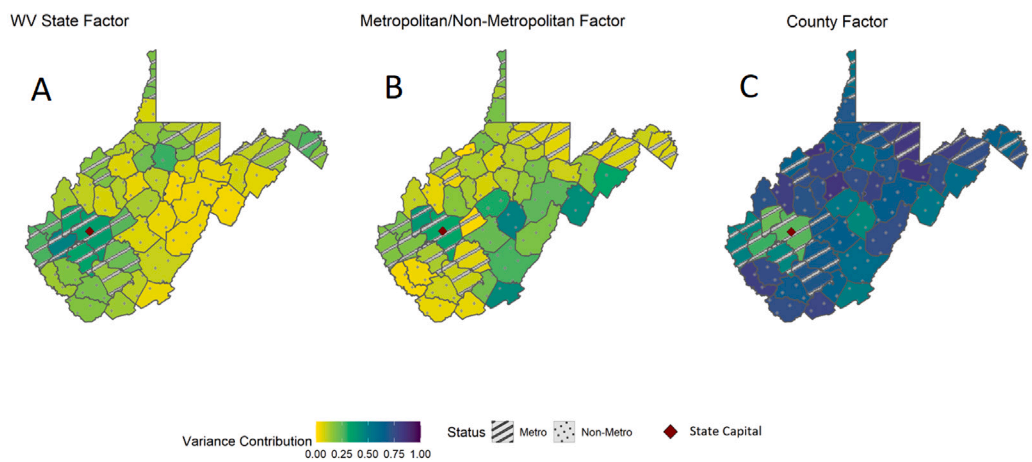

Fig. 8. Median percent variance contribution by factor. Note: This figure reports the median percent contribution of each factor to observed variation in the labor force participation rates averaged over the sample period.

Panel (A) shows the average percent of variance explained by the state factor for each county.[10] State influences on the change in LFPRs are relatively important for metropolitan counties, especially those surrounding the state capital (Kanawha County, 38%; Boone County, 37%; Putnam County, 36%; and Lincoln County, 48%). While this is expected, the overall weak contribution of the common state factor (20%) demonstrates the stark heterogeneity at the county level and overall weak integration.

The average percent of variance explained by each county's metropolitan and non-metropolitan factors, Fig. 8 Panel (B), further supports our non-metropolitan factor loading findings. Non-metropolitan counties, especially in the eastern part of the state, show relatively large percentage contributions of the non-metropolitan factor to LFPR variations (Pendleton County, 43%; Hardy County, 33%; Webster County, 47%; and Monroe County, 42%; for example). These counties are more rural and isolated, demonstrating that a non-metropolitan influence is important in explaining rural labor market volatility.

There is a stark contrast between Fig. 8 Panel (A) and Panel (C), which shows the average percent of variance explained by the county idiosyncratic factor for each county. For counties outside the state capital area, the idiosyncratic state factor explains the change in WV county LFPR variability (65%). This result is interesting, given that most general labor market policies and other legislation are conducted at the state or federal levels. The dominant role of the idiosyncratic factor is especially stark for northern and panhandle counties. With proximity to Pennsylvania, Maryland, and Virginia and greater distance from the state capital, we suspect this result reflects extra-state influence, resulting in idiosyncratic behavior compared to other West Virginia counties. Since we do not perform a traditional spatial analysis, we cannot account for spillover effects. However, this demonstrates the lack of an overall West Virginia state influence and labor market integration across counties.

Turning to the average variance contribution of each factor to the total variance over time in Fig. 9, Panel (A) shows that the state factor contributes larger percentages to LFPR variations in metropolitan counties (27% compared to 16% in non-metropolitan counties). Also, the influence of the state factor has grown in the last few years. In contrast, Fig. 9 Panel (B) shows that the influence of the county factor on

[10] For visual reference, Fig. A.1 (of the Appendices) presents a map of West Virginia with county names and metropolitan/non-metropolitan statuses.

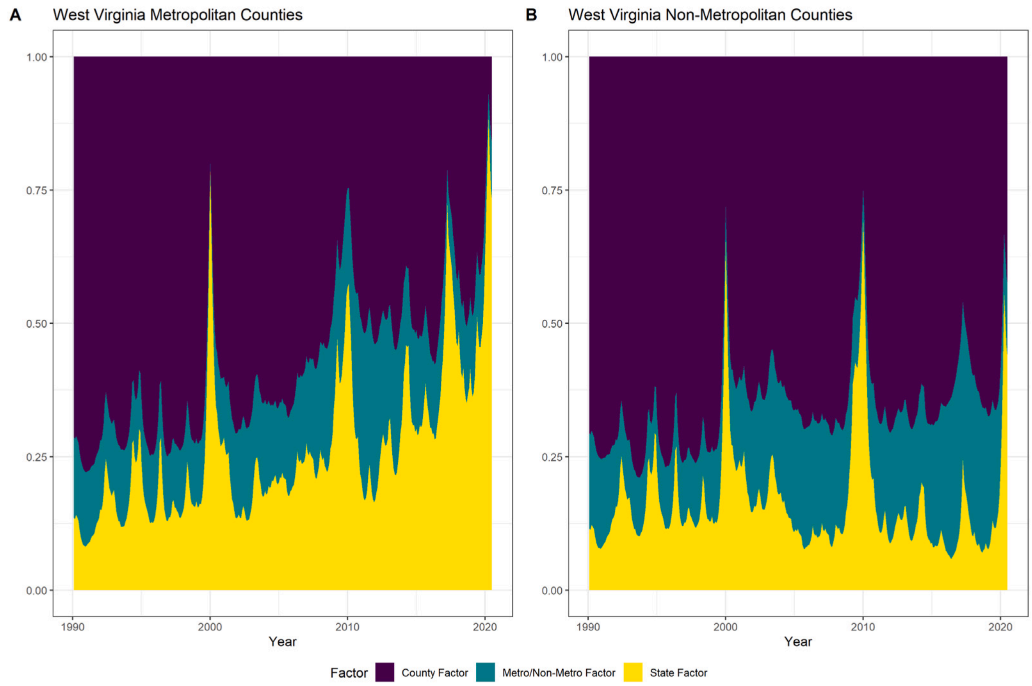

Fig. 9. Average variance contribution by factor in west virginia. Note: Colored areas represent the percent contribution of each factor to observed variation in the change in LFPR. Percent contributions are respective means of the posterior distribution. Panel (A) shows the percent contribution of each factor overtime average across all metropolitan counties. Panel (B) shows the percent contribution of each factor overtime average across all non-metropolitan counties.

non-metropolitan counties (excluding a few state-wide shocks) remains relatively stable over time and explains about 65% of the variation overall. Moreover, the contributions of the non-metropolitan factor rose after 2000 and have remained relatively stable in the last two decades. The non-metropolitan factor explains about 18% of the total variation in non-metropolitan LFPRs. These results bolster our previous findings and demonstrate that while individual counties' LFPRs are primarily independent of others, in recent years, metropolitan LFPRs have been influenced more by state-wide trends. Non-metropolitan counties, however, appear to be more greatly influenced by non-metropolitan labor market trends. This suggests that labor market policy and efforts to increase LFPRs in the state may be more effective if tailored by the county's status (metropolitan/non-metropolitan) or at the individual county level.

Importantly, these results also reveal the length of shocks to the change in county LFPR variations. We find that state-wide shocks, such as national recessionary periods, at most last only a few years before other influences dominate. While the impacts of these shocks may induce longer-lasting effects, they provide a short window for actionable policy. Taylor (2016) suggests that more permanent and predictable institutional reforms may increase long-run growth rates and boost growth in the short run.

5.4. Do county characteristics matter?

Next, we present the regression results from the second stage of our analysis regarding how well county characteristics explain a county's sensitivity to state, metropolitan/non-metropolitan, and idiosyncratic influences. After performing the panel regressions 5000 times for each factor, we save the 5000 coefficients for each regressor. To determine if a given variable is significant, we focus on the sign of the coefficients and the probability that it is different from 0 rather than the magnitude and standard errors. We report the results of the variables where zero lies outside (or close to outside) the Highest Posterior Density Interval (HPDI) or credible intervals for the distribution of 5000 coefficients. We report the percentage of the distributions of these significant variables above zero in Table 3. Small positive percentages are reported for the distributions that are mostly negative. Together, these correspond to the respective distributions in Figs. 10, 11, and 12. The means are plotted in each figure along with the upper and lower bounds of the 95% HPDI. Full results that include the magnitudes of the mean of each coefficient distribution can be found in Table A.4 of Appendix.

The results in Table 3, suggest a strong link between several county characteristics and the proportion of the variance in the change in LFPRs explained by each of our estimated factors. First, there is a positive link between the importance of the state factor and personal income. Fig. 10 shows zero lies outside the 95% HPDI. This indicates that increases in personal income statistically and positively impact the volatility in county LFPR, as explained by the state factor, over time. Personal income is an important linkage for a state-wide influence on the change in West Virginia county LFPRs. Isserman and Rephann (1993) point out that LFPRs tend to increase with higher wages. However, with higher non-wage income, LFPRs tend to decrease. Given the lower LFPR levels in the state, the latter case explains the association with state-wide integration of labor markets and conditions. In 2010, government transfer payments made up nearly 25% of West Virginia's personal income, more than any other state. Recipients of government payments, such as the aging population, tend to be more vulnerable to economic turbulence (Lalé, 2018). This link, manifested primarily at the state level, demonstrates important implications for the future of the labor market and the overall economy in West Virginia. As non-wage personal income increases with larger shares of government payments, labor force participation rates, employment growth, and economic activity will continue to decrease in West Virginia. This result explains the vulnerability and instability associated with the increased labor market integration we found in the first stage. Therefore, a strategy for policymakers to reduce the vulnerability and increased instability associated with labor market integration would be to increase wage income in the state by incentivizing the younger and healthier generations to stay and work in West Virginia.

Additionally, while zero lies inside the HPDI for state factors associated with natural gas production, the distribution is primarily positive. This indicates that as gas production increases, the percent of the volatility in LFPRs, as explained by the state factor, also increases. This

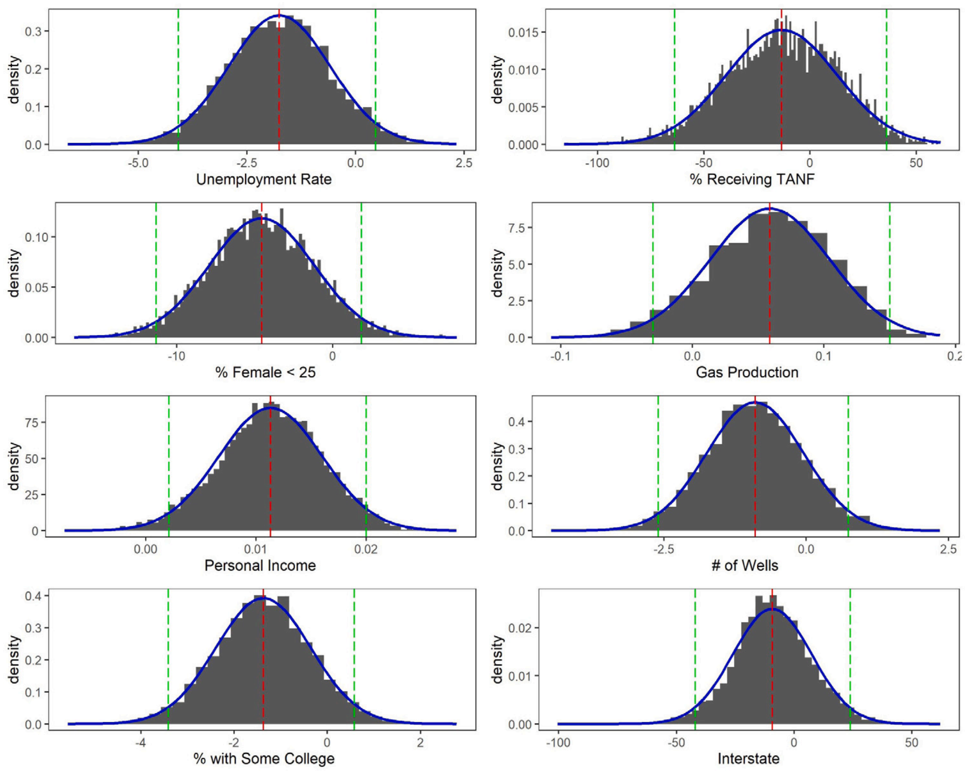

Fig. 10. Distributions of panel regression coefficients (State factor variance contribution). Note: The variables reported display the strongest connection with the randomly-drawn variance contributions of the common factor, $\widetilde{\theta}_{it}^{S}$, as over 800 of p-values saved from the 5000 regressions are significant at the 5% level. The shaded bars present the distribution of coefficients from the 5000 regressions while the red lines denotes the mean of each distribution and blue lines represent the density curves associated with a normal distributions with the same mean and standard deviation as the collection of coefficients. The green dashed lines are the lower and upper bounds of the 95% Highest Posterior Density Interval (HPDI).

finding aligns well with recent trends in West Virginia. First, the natural gas industry has become West Virginia's primary industry, replacing coal in recent years. West Virginia ranks 4th in U.S. energy production and accounts for 5% of the U.S. total. As the state's primary industry, it makes sense that its labor markets become more integrated with increased natural gas production. However, this highlights a vulnerability for West Virginia. More integrated labor markets around a single or small number of industries make West Virginia more susceptible to labor market shocks through sources such as natural resources and other environmental regulations (Partridge et al., 2013; Betz et al., 2015).

Secondly, we find strong positive links between the importance of the metropolitan factor with higher education and the number of interstates. Fig. 11 shows zero lies outside the 95% HPDI, supporting a strong non-zero and non-negative relationship. This indicates that as education attainment increases, the volatility in LFPRs explained by the metropolitan factor, also increases. Higher education is usually associated with urban areas and higher LFPRs (Bowen and Finegan, 1966; Isserman and Rephann, 1993; Stephens and Deskins, 2018). Therefore, it is unsurprising that higher education serves as a strong linkage between a metropolitan influence on the change in West Virginia county LFPRs. Since education is known to increase LFPR, integrated labor markets at the Metropolitan level will result in more stability and less vulnerability due to increased education attainment. This result supports increasing education and retaining college graduates to increase LFPRs in the state. It provides another strategy for policymakers to mitigate the negative aspects of labor market integration and capitalize on the positive. We also find that having at least one interstate increases the importance of the metropolitan factor. Interstate systems typically connect infrastructure or urban areas, which tend to have higher LFPRs. In this way, they contribute to the streamlined allocation of labor supply by reducing the barriers to the movement of workers and facilitating optimal worker-job matching. Since counties with interstate highways are physically linked, it is not surprising that for these counties, the metropolitan factor captures more of the variation in the change in LFPRs. Given the rurality and isolation of many parts of West Virginia, an emphasis on building access infrastructure such as roads and broadband internet in the state may be an easy way to take advantage of this linkage that is already in effect. While building roads and related infrastructure takes time and money, increased labor market integration through increases in access provides a mechanism for increasing LFPRs and economic growth.

Next, we observe that zero lies outside the HPDI for the metropolitan factor's association with the share of persons engaged in production in the government industry. However, the relationship is still strongly negative. This implies that as the share of employment in government jobs increases in metropolitan counties, the metropolitan factor becomes less important in explaining the change in LFPR variations. In congruence with Stephens and Deskins (2018), we suggest that the stability of government jobs, even through periods of economic turmoil, underpins the small contribution of the metropolitan factor to the variability of the LFPRs. In this case, the volatility is reduced with increases in stable industries. This provides another insight for policymakers as they devise strategies to reduce risk and instability.

Additionally, we find that the non-metropolitan factor is negatively related to personal income and the share of agriculture and natural gas industries. Fig. 11 shows that zero lies outside (or close to outside) the 95% HPDI for these variables. As the share of industries in agriculture and natural gas production and total personal income in non-metropolitan counties increase, labor markets become less integrated and less vulnerable. These three variables serve as important linkages for heterogeneous labor market responses within non-metropolitan areas. With increases in these variables, non-metropolitan county LFPRs become more stable. This result seems plausible since increases in

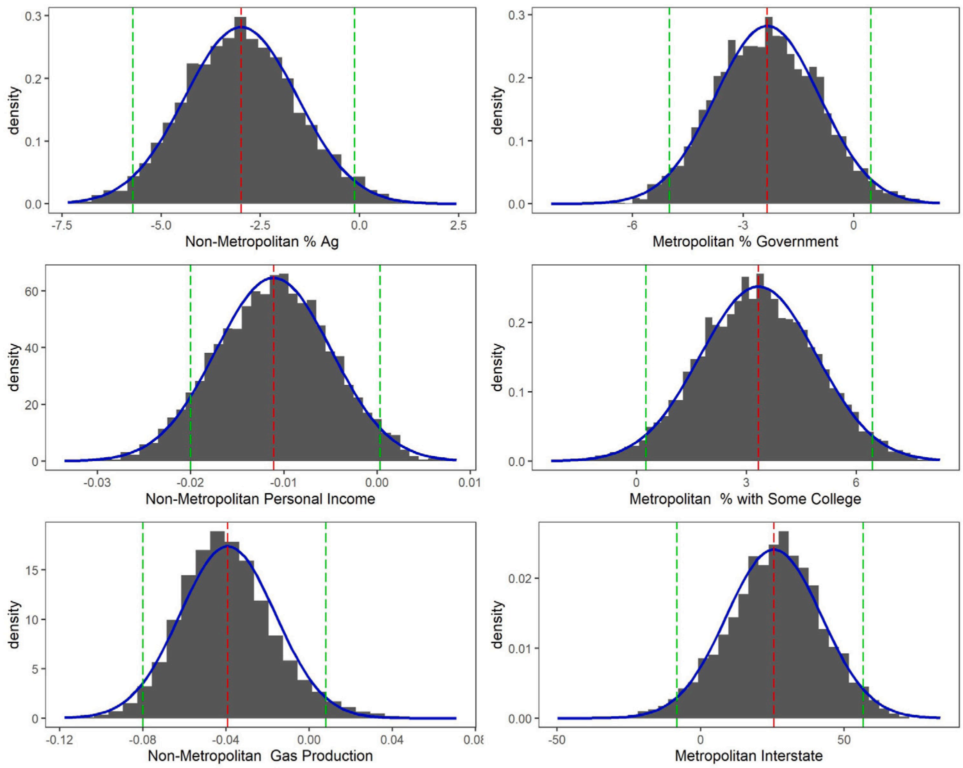

Fig. 11. Distributions of panel regression coefficients (Metro/Non-metro factors variance contribution). Note: The variables reported display the strongest connection with the randomly-drawn variance contribution of the metropolitan/nonmetropolitan factor, $\widetilde{\theta}_{it}^{\mathcal{M}}$, as over 800 of p-values saved from the 5000 regressions are significant at the 5% level. The shaded bars present the distribution of coefficients from the 5000 regressions while the red lines denotes the mean of each distribution and blue lines represent the density curves associated with a normal distributions with the same mean and standard deviation as the collection of coefficients. The green dashed lines are the lower and upper bounds of the 95% Highest Posterior Density Interval (HPDI).

wealth and industry infrastructure may result in increases in economic stability, increases in labor market decision variability, and divergence in count labor market behavior (Isserman and Rephann, 1993; Phimister et al., 2002; Fernández, 2013). Also, it makes sense, given that it is easier to engage in underground activities or informal work in rural areas and the agricultural sector (Isserman and Rephann, 1993). As workers can secure food, heating materials, and income outside the formal economy, the influence of a common non-metropolitan influence naturally decreases. We suggest that these different options emerge as divergence in LFPRs across non-metropolitan counties and explain the increased stability indicated by the negative relationship between the proportion of LFPR variations explained by the non-metropolitan factor and these three county characteristics.

Lastly, we find strong positive links between the importance of the county factor and industry share in manufacturing and the number of gas wells in a county, as seen in Table 3 and Fig. 12. Manufacturing jobs are often highly unionized, which may result in less job access and employment opportunities (Isserman and Rephann, 1993). Isserman and Rephann (1993) also posit that decisions in response to job loss or economic turmoil associated with less job security vary by household, county, and economic status, which we suggest drives significant idiosyncratic results. In addition, we are not surprised that increases in the number of gas wells in a county are associated with the idiosyncratic factor explaining more LFPR volatility. The economic impact of a gas well within a county will only reach so far. On the other hand, natural gas production, processing, storage, and transportation support more jobs, counties, and other industries, which most likely accounts for its association with the state-wide factor. Increasing the number of wells in a given county would not link LFPRs across West Virginia and may only benefit the individual counties. Accordingly, supporting gas production, storage, and transportation over natural gas well construction will increase positive labor market integration effects.

5.5. Robustness checks

In order to ensure the reliability of our approach and the accuracy of our findings, we conducted two different specifications for our initial analysis.

In the first alternative specification, we classified counties with RUCC 1–4 as metropolitan and counties with RUCC 5–9 as non-metropolitan. We considered that counties classified as RUCC 4 (with an urban population of 20,000 or more, adjacent to a metropolitan area) may seem more metropolitan than non-metropolitan. With this new categorization, only two counties were reclassified. The results for this specification were similar to those presented in this paper using the OMB and USDA-defined classifications. We observed some differences between the sets of results regarding the metropolitan factor.

First, the metropolitan factor loadings between 2008 and 2015 are negative rather than positive. This indicates that including these two counties as metropolitan led to the conclusion of more insulated metropolitan areas during recessionary periods. Second, we find a difference in the median percent variance contribution of the metropolitan factor. This alternate specification attributes more variance in LFPR volatility around the state capital to the metropolitan factor rather than the state common factor. Even with these differences, the overall results of this specification are very similar to those presented in Section 5.

The USDA has recently published the RUCC classifications for 2023. As a result, we used the latest RUCC classification as a robustness check instead of the 2013 classifications. In this scenario, two counties switched from metropolitan to non-metropolitan, and only one switched from non-metropolitan to metropolitan. The results closely resemble those presented in this paper, with the only statistical difference being in the average metropolitan factor loadings. In this specification, the factor loadings remain positive and non-zero from 2008 to the end of the sample. This implies that the increased volatility in metropolitan

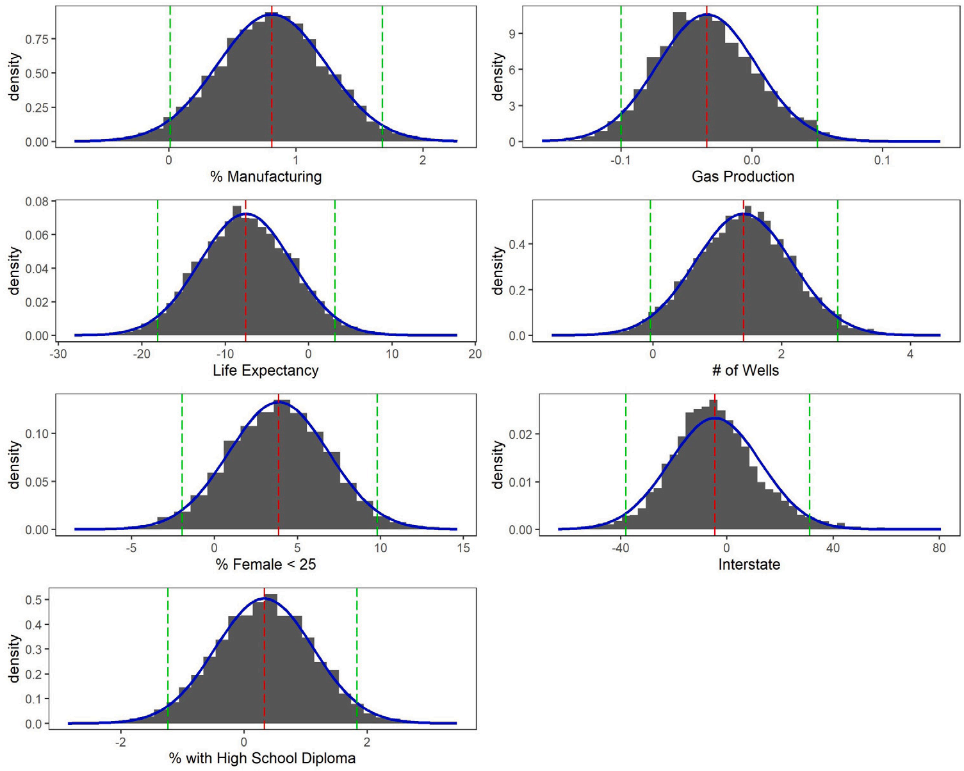

Fig. 12. Distribution of panel regression coefficients (County-specific factor variance contribution). Note: The variables reported display the strongest connection with the randomly-drawn variance contribution of the county-specific (idiosyncratic) factor, $\widetilde{\theta}_{it}$, as over 800 of p-values saved from the 5000 regressions are significant at the 5% level. The shaded bars present the distribution of coefficients from the 5000 regressions while the red lines denotes the mean of each distribution and blue lines represent the density curves associated with a normal distributions with the same mean and standard deviation as the collection of coefficients. The green dashed lines are the lower and upper bounds of the 95% Highest Posterior Density Interval (HPDI).

counties extended from the Great Recession through the 2020 COVID-19 recession. Considering the severity of the recession, the unusually sharp decline in LFPRs, and the slow recovery of the economy after 2010, our previous conclusion (Daly et al., 2009; Elsby et al., 2011; Taylor, 2016) is further supported. With these differences, our findings are consistent across all specifications, indicating their robustness. While we present the results for the original specification using OBM and USDA-defined RUCC classifications, the results for the alternative specifications are available upon request.

6. Conclusion

In this paper, we determine the degree of integration of county-level labor markets in West Virginia labor markets and identify the factors contributing to the volatility of the LFPR in these markets. By addressing these questions, we shed light on how labor market integration impacts economic activity and better understand the potential mechanisms through which shocks at the state, metropolitan/non-metropolitan, and county levels affect LFPR volatility. West Virginia was chosen as our case study due to the more considerable disparity in LFPRs within the state compared to other U.S. states, indicating economic inefficiencies that hinder growth. Previous literature has not fully explained these disparities, providing an opportunity to address potentially heterogeneous labor markets in a joint analysis framework. Furthermore, we decided to study metropolitan and non-metropolitan areas as our “regions” of interest because they are likely to provide more insightful findings than aggregated alternatives and highlight varied labor market responses.

In order to understand the level of integration in local labor markets in West Virginia and the factors affecting LFPR volatility, we decomposed LFPRs for West Virginia counties into state, county, metropolitan, and non-metropolitan latent factors using a Dynamic Factor Model with time-varying and stochastic volatility (DFM-TV-SV) parameters. This model allows us to determine the extent to which the estimated state, metropolitan, and non-metropolitan latent factors impact the observed county LFPRs. Additionally, we analyze the connection between county characteristics and the portion of variance explained by our estimated factors to identify which characteristics drive the state, metropolitan, and non-metropolitan influences on LFPR variation in West Virginia counties.

In this stage of our analysis, we found that the state and metropolitan factors have relatively weak influences on the LFPRs in West Virginia counties, especially outside of recessionary periods. This finding suggests that West Virginia has low labor market integration and significant county-specific behavior over the period studied. However, in recent years, we have observed a growing influence of a common state trend and increased synchronization of county LFPRs across the state. This increased integration in the labor market occurred before the COVID-19 pandemic and may have heightened West Virginia’s vulnerability to the negative economic impact. We also found strong and persistent evidence of non-metropolitan influences on LFPR volatility in all non-metropolitan West Virginia counties. This non-metropolitan influence contributes to labor market instability in rural areas and increases their vulnerability to labor market shocks. Additionally, we noted that the time frames for implementing effective policies following a labor market shock at the state, metropolitan, non-metropolitan, and county levels are relatively short.

In the second stage of our analysis, we identified several county characteristics that influence the change in county LFPRs. Our findings have significant implications for policymakers in West Virginia. Specifically, we found that total county personal income is the primary factor driving changes in county LFPRs. Given the historical and empirically negative relationship between non-wage income and LFPRs, we recommend implementing strategies to increase the wage-to-non-wage income ratio. Encouraging younger generations to stay and work in the state could be one such strategy, potentially reducing labor market instability and vulnerability associated with high non-wage income.

The LFPR in metropolitan areas is affected by higher education and the number of interstates in a county. Policymakers should take a nuanced approach to address changes in LFPRs. While investing in education is vital for long-term economic growth and skill development, aligning educational programs with local labor market demands and supporting workforce transition programs are also crucial to mitigate the disruptive effects of educational improvements on LFP. We also find that infrastructure development can affect LFPR volatility. However, prioritizing infrastructure projects that eliminate transportation barriers, provide better skill matching, and create access to education and broadband internet can lead to long-term employment growth.

In non-metropolitan areas, the agriculture industry, total personal income, and the natural gas industry play key roles. Increasing the stability of the agricultural and natural gas industries can benefit labor market integration. This could involve providing incentives for agricultural modernization, promoting responsible development of natural gas resources, and fostering entrepreneurship and innovation in rural communities. Policymakers can also enhance economic resilience and stimulate job creation outside urban centers by investing in human capital and strengthening these key sectors. Additionally, to promote income growth and stability for rural households, policymakers could support increased wages, improved access to employment benefits, and expanded social safety nets to boost consumer spending, support local businesses, and reduce reliance on volatile sources of income.

The manufacturing industry and the number of natural gas wells significantly influence the volatility of the LFPR volatility of individual counties. To address this issue, policymakers should prioritize diversifying the economy by promoting industries beyond manufacturing, such as healthcare, education, technology, and renewable energy. This diversification can enhance resilience and reduce vulnerability to industry-specific shocks. While the number of natural gas wells may drive LFPR volatility for individual counties, gas production can reduce volatility for non-metropolitan areas. Policymakers can involve stakeholders in collaborative decision-making processes to prioritize long-term growth and mitigate the adverse effects of economic fluctuations on employment and workforce stability in affected counties.

Lastly, the differences between metropolitan and non-metropolitan areas should be a primary concern for West Virginia policymakers in terms of employment and LFP growth in the state. Non-metropolitan counties demonstrate stronger signs of labor market integration, making them more vulnerable to economic and labor market shocks. The lack of statewide labor market integration and the persistent influence of non-metropolitan areas on county LFPR volatility highlights the need for policies tailored to rural areas and individual counties. Therefore, we recommend that West Virginia policymakers focus on long-term strategies to boost LFP in non-metropolitan and individual counties. This conclusion is also applicable to other states or countries. We demonstrate that even in a state with limited local/county control, there is significant heterogeneous labor market behavior at the county level and various mechanisms through which labor market integration benefits and vulnerabilities can manifest. Based on this, we suggest that "one-size-fits-all" statewide or countrywide policies may not be as effective and could have unintended effects on sub-state or sub-country economies and labor markets.

The findings in our paper elicit further examination of the relationship between economic indicators in West Virginia and the Appalachian Region. Specifically, it is crucial to study the connections between these economic indicators and the discouraged worker phenomenon, which refers to individuals dropping out of the labor force. This research is essential for promoting economic growth in the region, especially considering the historically high unemployment rates and low LFPRs in these areas. Ultimately, more research on labor market integration and the factors driving labor market volatility is needed to help break the cycles of economic despair in distressed areas in the U.S. and worldwide.

Table A.1
State LFP descriptive statistics.

Counties	Mean	Median	Minimum	Maximum	S.D.
Barbour County	63.03	62.98	57.30	70.87	2.47
Berkeley County[a]	71.90	72.00	66.00	77.25	2.47
Boone County[a]	53.29	54.67	45.30	58.17	3.36
Braxton County	59.72	60.22	54.13	63.84	2.36
Brooke County[a]	68.92	68.86	64.22	75.48	2.11
Cabell County[a]	67.27	67.44	64.13	71.38	1.80
Calhoun County	57.48	57.74	48.23	65.88	3.67
Clay County[a]	56.16	55.97	45.50	63.89	4.25
Doddridge County	61.79	62.80	50.52	72.16	5.90
Fayette County[a]	58.13	57.99	54.23	63.71	1.55
Gilmer County	51.02	53.11	40.97	63.32	5.96
Grant County	73.81	72.43	54.47	89.43	8.45
Greenbrier County	68.74	67.81	64.34	77.26	2.78
Hampshire County[a]	66.24	65.88	58.55	75.33	3.69
Hancock County[a]	70.78	70.63	65.71	76.17	2.29
Hardy County	75.67	77.41	59.73	93.53	9.15
Harrison County	72.29	71.11	67.47	82.56	3.89
Jackson County	68.57	66.57	61.43	97.80	5.97
Jefferson County[a]	74.69	74.03	66.39	82.34	3.23
Kanawha County[a]	73.30	72.58	69.88	80.08	2.13
Lewis County	66.80	66.91	60.66	73.45	2.53
Lincoln County[a]	52.82	53.85	45.71	59.09	3.14
Logan County	52.35	52.07	49.19	57.37	1.36
Marion County	68.54	69.36	62.25	72.92	2.91
Marshall County[a]	68.52	67.86	65.59	76.60	2.34
Mason County	59.22	59.51	50.28	64.74	3.00
McDowell County	42.35	41.47	38.82	51.13	2.59
Mercer County	62.42	61.63	56.70	69.63	3.91
Mineral County[a]	69.80	68.94	63.78	76.75	3.73
Mingo County	46.59	46.76	41.42	51.78	2.46
Monongalia County[a]	66.16	65.89	61.40	72.55	2.00
Monroe County	66.05	67.16	53.58	78.64	6.28
Morgan County	68.01	67.72	59.48	75.71	3.85
Nicholas County	61.45	61.42	57.53	65.68	1.58
Ohio County[a]	75.50	75.89	69.46	84.73	3.52
Pendleton County	77.15	75.02	69.42	94.68	6.22
Pleasants County	62.08	61.58	53.67	76.46	4.11
Pocahontas County	68.97	68.56	60.59	82.33	4.96
Preston County[a]	66.93	66.69	62.78	75.42	2.38
Putnam County[a]	73.40	73.55	69.52	79.35	1.99
Raleigh County[a]	62.61	62.21	58.84	67.92	1.89
Randolph County	66.86	67.04	61.52	72.47	2.55
Ritchie County	67.87	66.83	58.85	76.80	3.97
Roane County	58.94	58.72	52.90	66.13	3.21
Summers County	51.91	51.28	48.00	57.83	2.18
Taylor County	66.97	65.99	61.65	76.41	3.63
Tucker County	71.99	71.94	60.69	81.31	5.09
Tyler County	62.15	61.94	56.65	68.99	2.91
Upshur County	64.98	65.08	58.81	69.74	2.45
Wayne County[a]	61.22	61.14	58.39	65.52	1.58
Webster County	55.28	53.27	44.61	69.46	7.27
Wetzel County	65.14	63.44	57.32	76.42	5.36
Wirt County[a]	60.88	61.47	47.24	77.00	5.05
Wood County[a]	72.01	72.13	67.29	76.68	2.53
Wyoming County	49.57	49.98	41.92	56.49	3.81

Note: Statistics reflect the county-level labor force participation rates over the sample period January 1990–July 2020. S.D refers to the standard deviation.
[a] Denotes Metro Counties.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

https://doi.org/10.17632/njkymvxhgj.1.

Appendix

See Tables A.1–A.4 and Figs. A.1–A.5.

Table A.2
Descriptions of variables used in analysis.

	Variable	Description	Data source
1	% government jobs	Percentage of persons engaged in production in government industry.	Bureau of Economic Analysis (BEA)
2	% agriculture jobs	Percentage of persons engaged in production in agriculture industry.	BEA
3	% manufacturing jobs	Percentage of persons engaged in production in manufacturing industry.	BEA
4	% mining jobs	Percentage of persons engaged in production in mining industry.	BEA
5	% non-Farm jobs	Percentage of persons engaged in production in non-farming industry.	BEA
6	personal Income	Total personal income in thousands of U.S. dollars.[a]	BEA
7	Unemployment Rate	The number unemployed as a percentage of the labor force.	Bureau of Labor and Statistics (BLS)
8	Life Expectancy	Estimates for life expectancy at birth (in number of years).[b]	Institute for Health Metrics and Evaluation (IHME)
9	% black	Percentage of the population in each county that is black or African American.	U.S. Census Bureau
10	% female <25	Percentage of the working population that is female below the age of 25.	U.S. Census Bureau
11	% female 25–54	Percentage of the working population that is female between the ages 25–54.	U.S. Census Bureau
12	% female 54–65	Percentage of the working population that is female between the ages 54–65.	U.S. Census Bureau
13	% another race	Percentage of the working population that is neither white nor African American.	U.S. Census Bureau
14	% with HS diploma	Percentage of adults 25 years or older with a high school diploma or equivalent.[c]	United States Department of Agriculture (USDA) & U.S. Census Bureau
15	% with Some college	Percentage of adults 25 years or older with between 1–3 years of college.[c]	USDA & U.S. Census Bureau
16	Land area	Land area of each county in square miles.	U.S. Census Bureau
17	% receiving TANF	Percentage of families with related children who receive public assistance under the Temporary Aid to Needy Families (TANF) program.[d]	Kids Count Data Center – Annie E. Casey Foundation
18	Precipitation	Amount of rain in inches per county.	National Centers for Environmental Information
19	Gas production	Gas production measured in 1000s of cubic feet (Mcf).	West Virginia Geological and Economic Survey
20	Gas wells (#)	Number of gas wells in each county.	West Virginia Geological and Economic Survey
21	Coal production	Coal production in each county measured in tonnes.	West Virginia Office of Miners' Health Safety and Training
22	Interstate	A dummy variable for whether at least one interstate passes through each county.	Highway Performance Monitoring System (HPMS)

Notes: Unless otherwise stated, the data used correspond to census–years 1990, 2000, 2010, and 2020.
[a] Consists of the income received in return for labor, land, capital use, and other income such as transfer receipts.
[b] 2020 data are unavailable so we use data for years 2014 instead.
[c] Data for 1990, 2000, and 2015 are collected from the USDA. Data for 2020 however, is collected from the U.S. Census Bureau.
[d] 2020 data are unavailable so we use data for years 2015 instead.

Table A.3
County characteristic descriptive statistics.

Variable	Mean	SD	Min	Max
Metropolitan counties				
% government jobs	18.82	5.63	7.90	32.60
% agriculture jobs	3.64	4.47	0.20	20.20
% manufacturing jobs	8.41	8.03	0.00	47.20
% mining jobs	3.57	7.21	0.00	40.90
% non-farm jobs	17.51	5.41	7.80	31.70
Personal income('000s)	1,636,043.14	1,680,666.69	54,023.00	9,335,977.00
Unemployment rate (%)	8.00	2.74	3.30	17.80
Life expectancy(years)	75.47	1.56	72.17	79.15
% black	2.83	2.54	0.01	8.57
% female <25	15.41	1.81	11.90	20.65
% female 25–54	19.96	1.64	16.42	23.41
% female 54–65	34.67	25.03	6.31	64.87
% another race	1.87	1.44	0.19	8.47
% with HS diploma	39.57	5.55	26.70	52.70
% with some college	20.86	5.13	8.10	33.63
Land area (m^2)	394.35	206.66	82.61	903.17
% receiving TANF	0.06	0.07	0.01	0.32
Precipitation (inches)	44.96	6.14	33.71	57.84
Gas production (Mcf)	6,963,876.61	21,278,811.50	0.00	131,137,681.00
Gas wells (#)	532.48	691.02	0.00	3,295.00
Coal production (tonnes)	3,294,927.75	6,128,398.42	0.00	32,446,186.00
Non-Metropolitan counties				
% government jobs	18.74	4.96	9.30	35.70
% agriculture jobs	7.10	5.15	0.00	23.70
% manufacturing jobs	8.86	7.86	0.00	44.80
% mining jobs	4.98	7.12	0.00	26.20
% non-farm jobs	18.55	5.84	9.20	39.90
Personal income('000s)	515 765.63	498 031.13	76 819.00	3485 501.00
Unemployment rate (%)	9.36	2.75	3.90	19.40
Life expectancy(years)	75.24	1.86	69.45	79.34
% black	1.68	2.48	0.01	13.48
% female <25	14.52	1.82	9.48	19.82
% female 25–54	19.53	1.97	12.37	26.25
% female 54–65	35.18	24.76	6.11	66.14
% another race	1.44	1.03	0.24	7.48
% with HS diploma	43.13	4.98	28.20	51.70
% with some college	17.82	4.43	9.50	29.71
Land area (m^2)	464.08	205.88	130.10	1039.80
% receiving TANF	0.07	0.11	0.01	0.80
Precipitation (inches)	47.34	7.41	33.90	66.78
Gas production (Mcf)	19,261,843.14	75,540,908.33	0.00	5,97,800,583.00
Gas wells (#)	932.43	1077.23	0.00	5146.00
Coal production (tonnes)	2,013,393.13	4,142,730.23	0.00	21,840,363.00
Total				
% government jobs	18.77	5.23	7.93	35.70
% agriculture jobs	5.78	5.18	0.00	23.70
% manufacturing jobs	8.69	7.93	0.00	47.20
% mining jobs	4.44	7.19	0.00	40.90
% non-farm jobs	18.15	5.70	7.80	39.90
Personal income('000s)	943,507.95	123,6145.80	54,023.00	9,335,977.00
Unemployment rate (%)	8.84	2.82	3.30	19.40
Life expectancy(years)	75.33	1.75	69.45	79.34
% black	2.12	2.56	0.01	13.48
% female <25	14.86	1.87	9.48	20.65
% female 25–54	19.69	1.87	12.37	26.25
% female 54–65	34.99	24.87	6.11	66.14
% another race	1.60	1.22	0.19	8.47
% with HS diploma	41.77	5.49	26.70	52.70
% with some college	18.98	4.93	8.10	33.63
Land Area (m^2)	437.46	208.94	82.61	1039.80
% receiving TANF	0.07	0.09	0.01	0.80
Precipitation (inches)	46.43	7.05	33.71	66.78
Gas production (Mcf)	14,566,255.92	61,124,387.99	0.00	597,800,583.00
Gas wells (#)	779.72	968.21	0.00	5146.00
Coal production (tonnes)	2,502,706.35	5,033,593.19	0.00	32,446,186.00

Note: This table presents the descriptive statistics for the county characteristics used in the regressions outlined in Section 5.4. These statistics are aggregated and presented by metropolitan, non-metropolitan, and state totals, respectively. SD refers to standard deviation. See Table A.2 for a full description of the variables included.

Table A.4
Panel regression results.

Variable	Dependent variable			
	$\widetilde{\theta}_{it}^{S}$	$\widetilde{\theta}_{it}^{\mathcal{M}}$ Metro	$\widetilde{\theta}_{it}^{\mathcal{M}}$ Non-Metro	$\widetilde{\theta}_{it}$
% government jobs	0.317	−2.35**	−0.298	0.43
% agriculture jobs	1.927	0.98	−2.98**	0.85
% manufacturing jobs	−0.558	−0.75	−0.133	0.81***
% mining jobs	−0.176	−0.533	−0.299	0.39
% non-farm jobs	−0.078	−0.71	−0.387	0.67
Unemployment rate (%)	−1.753*	0.888	0.381	0.71
Life expectancy	7.204	−7.48	0.381	−7.54*
% black	0.044	−1.96	6.31	−1.09
% female <25	−4.559*	0.66	0.487	3.87*
% female 25–54	0.152	0.062	1.442	1.38
% female 54–65	−0.057	−0.225	−0.518	0.00
% another race	0.889	−1.35	−0.003	−0.18
Personal income	0.011***	0.003	−0.01***	−0.01
% with HS diploma	0.287	−0.838	−0.011	0.33***
% with some college	−1.375*	3.327**	−0.671	0.84
Land area	2.939	1.587	−0.296	−3.58
% receiving TANF	−13.359*	−26.733	1.75	10.48
Precipitation	−0.693	−0.023	1.131	0.35
Gas production	0.059**	0.009	−0.04***	−0.03*
Gas wells (#)	−0.0899*	−0.54	−0.039	1.41***
Interstate	−9.319**	25.53***	−0.202	−4.47**
Coal production	0.004	0.004	−0.003	−0.01
Regressions (total)	5000	5000	5000	5000
Average R^2	0.38	0.37	0.25	0.4

Note: This table reports the results of the mean average for each of the 5000 coefficients estimated in the panel regressions with the randomly drawn variance contributions, $\widetilde{\theta}_{it}^{S}$, $\widetilde{\theta}_{it}^{\mathcal{M}}$, $\widetilde{\theta}_{it}$, as the regressand. Each regression includes the county characteristics (column 1) and a county-specific intercept term as regressors. The mean of estimated coefficients of the latter was omitted for brevity. Our 5000 draws are random and evenly distributed over each month of the panel years (1990, 2000, 2010, 2020).

* Indicates variables with more than 800 (but less than 1500) associated p-values being statistically significant at the 5% level.

** Indicate statistical significance of more than 1500 (but less than 2000) p-values at the 5% level.

*** Indicate statistical significance of more than 2000 p-values at the 5% level.

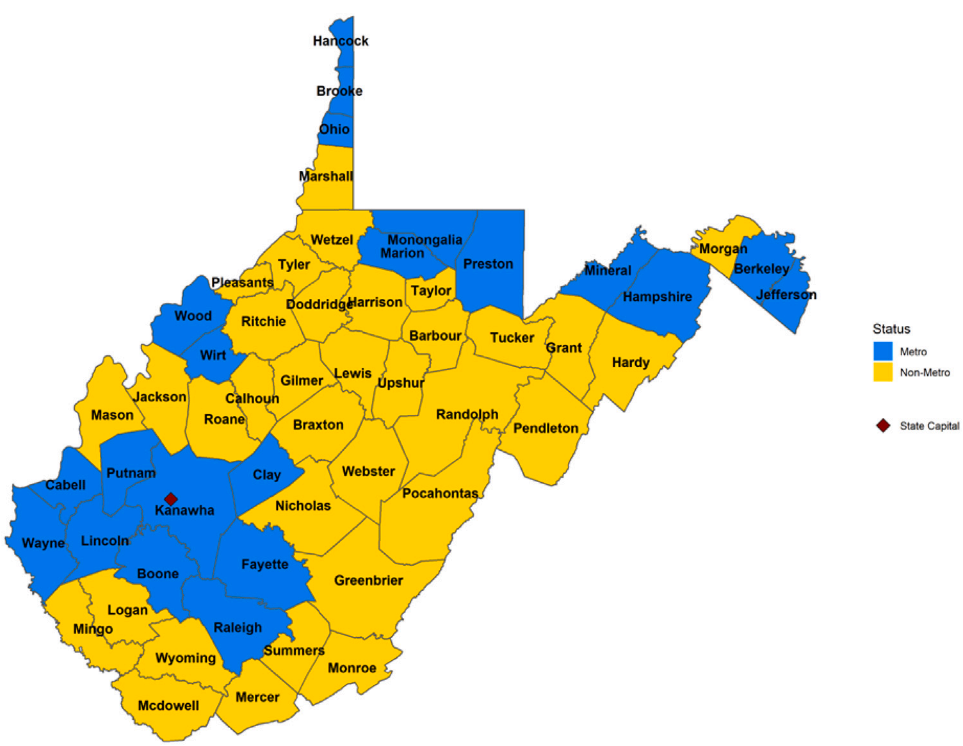

Fig. A.1. West Virginia counties by RUCC status. Note: The figure above shows the classification of counties in West Virginia by Metropolitan and Non-metropolitan region according to the USDA's Rural–Urban Continuum Code (RUCC) descriptions detailed in Table 1.

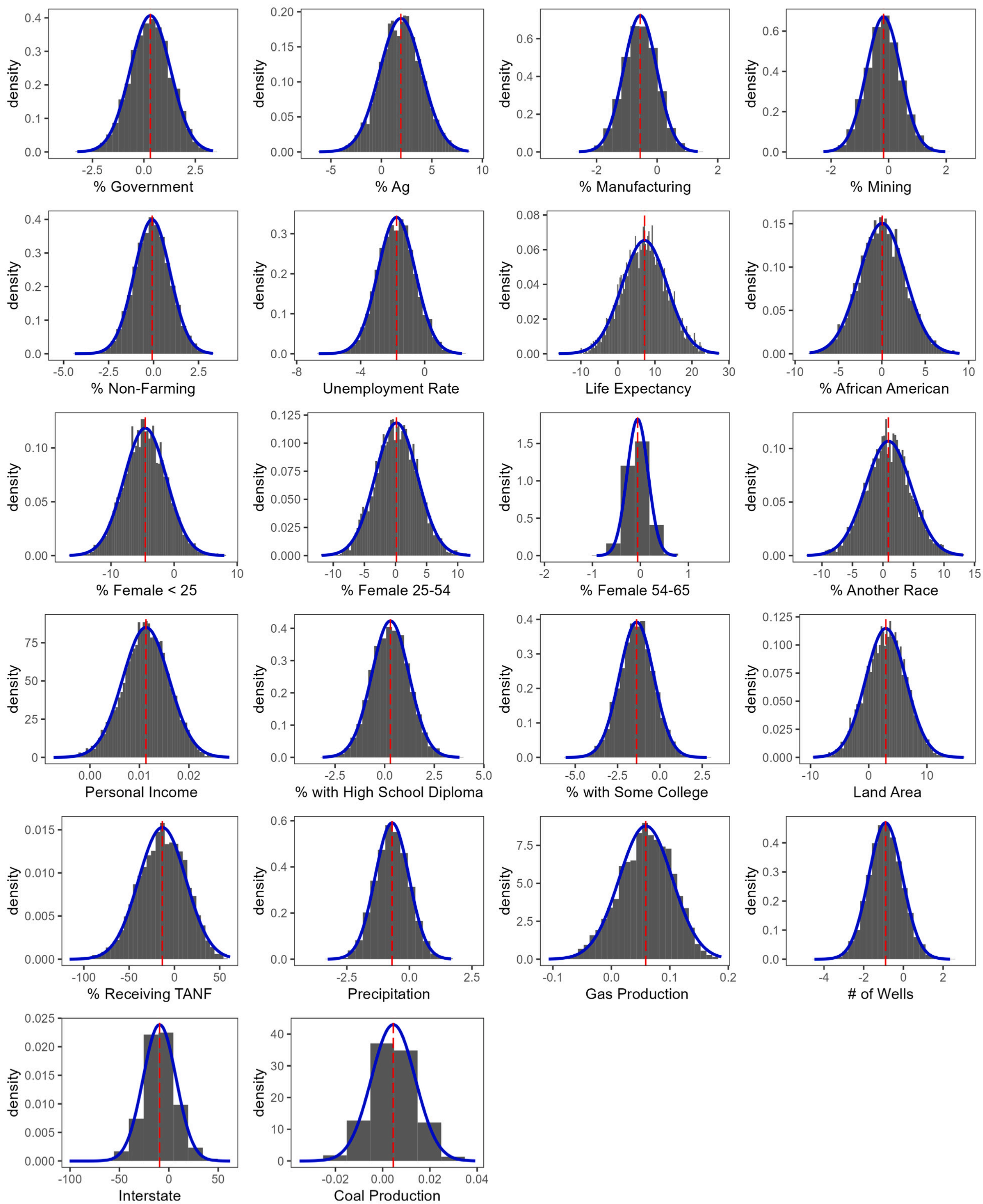

Fig. A.2. Distribution of panel regression coefficients (State factor variance contribution). Note: The dependent variable in all cases is the randomly-drawn variance contribution of the state factor, $\widetilde{\theta}^{S}_{it}$. The shaded bars present the distribution of coefficients from the 5000 regressions. The red lines denotes the mean of each distribution and blue lines represent the density curves associated with a normal distributions with the same mean and standard deviation as the collection of coefficients.

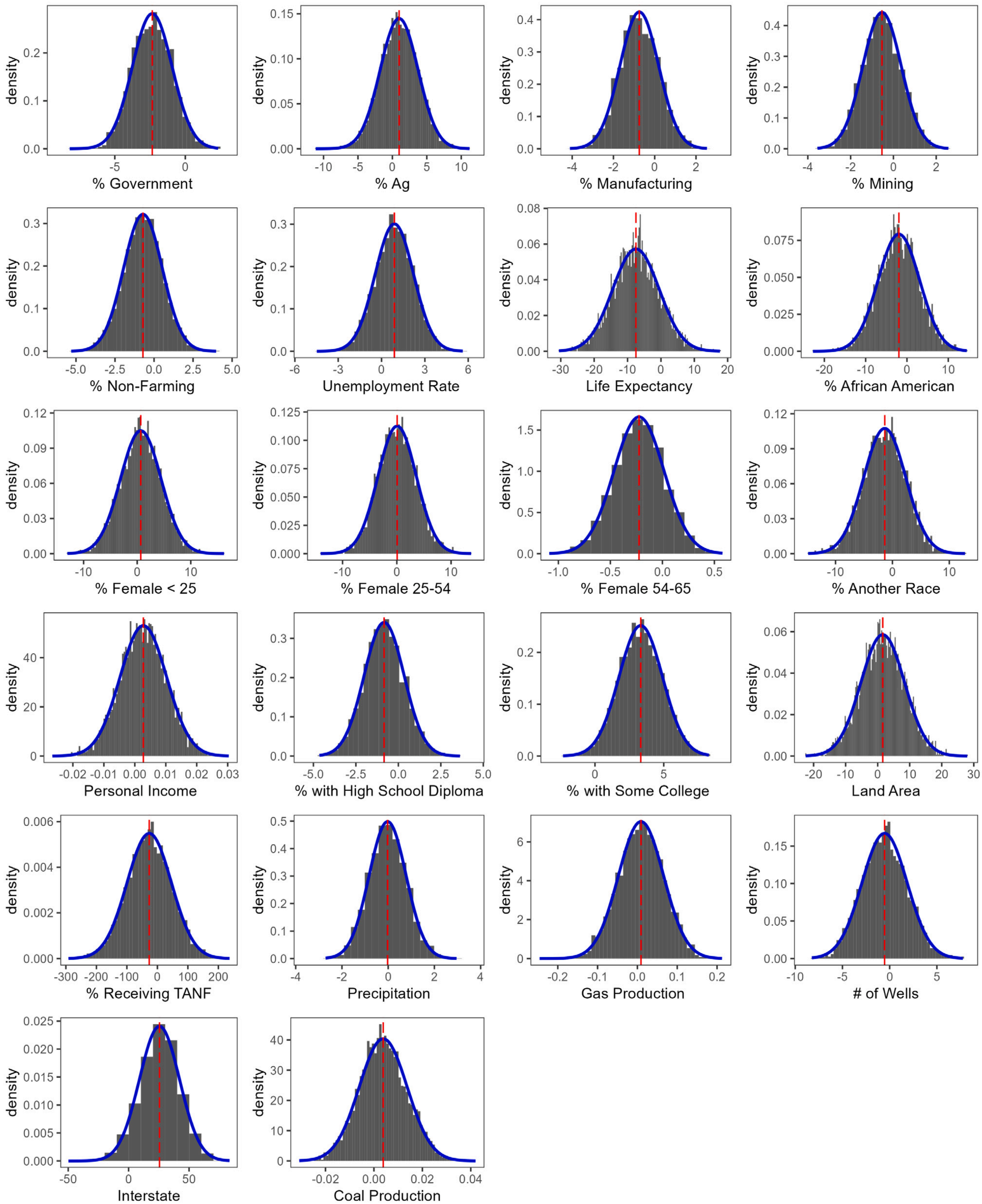

Fig. A.3. Distribution of panel regression coefficients (Metro factor variance contribution). Note: The dependent variable in all cases is the randomly-drawn variance contribution of the metropolitan factor. The shaded bars present the distribution of coefficients from the 5000 regressions. The red lines denotes the mean of each distribution and blue lines represent the density curves associated with a normal distributions with the same mean and standard deviation as the collection of coefficients.

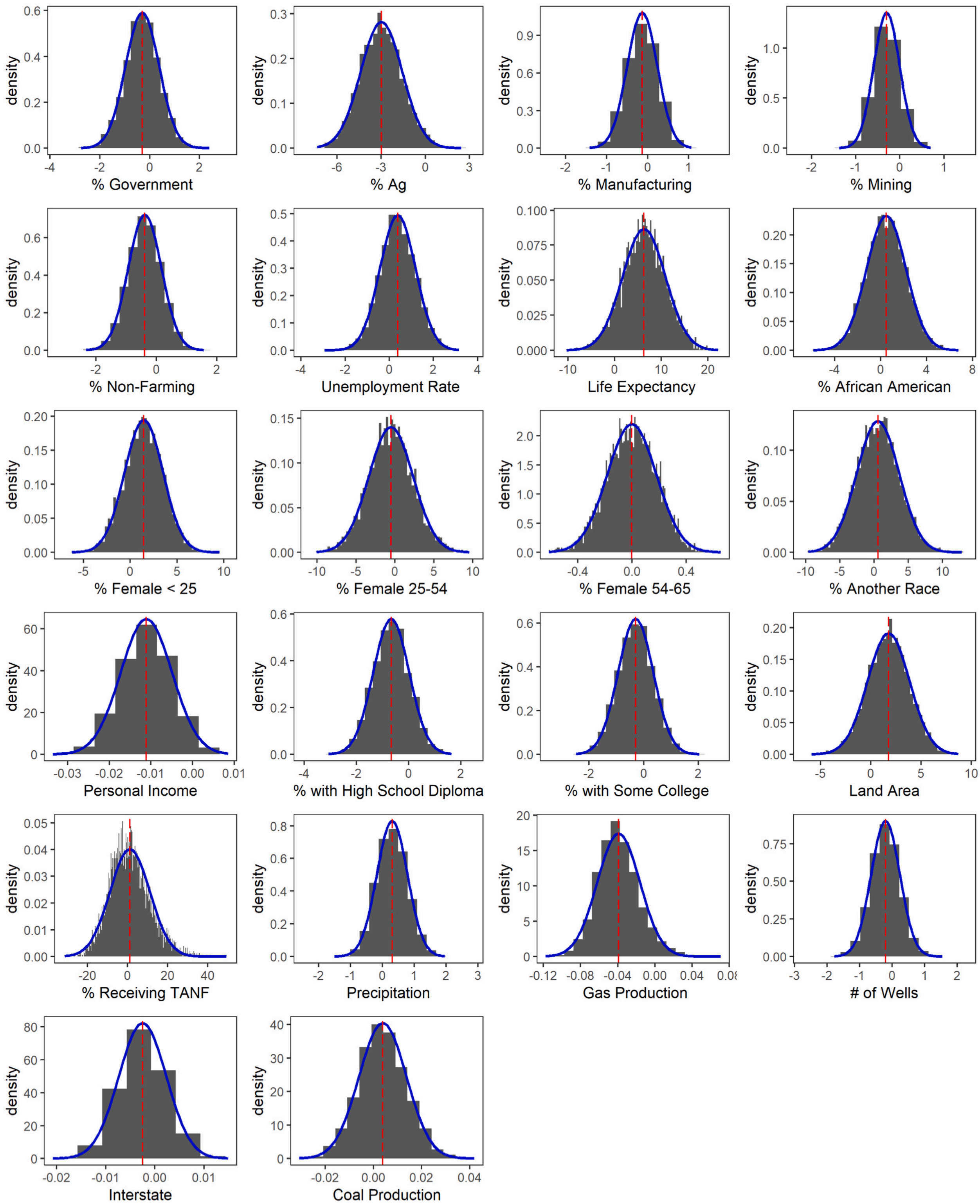

Fig. A.4. Distribution of panel regression coefficients (Non-Metro factor variance contribution). Note: The dependent variable in all cases is the randomly-drawn variance contribution of the non-metropolitan factor. The shaded bars present the distribution of coefficients from the 5000 regressions. The red lines denotes the mean of each distribution and blue lines represent the density curves associated with a normal distributions with the same mean and standard deviation as the collection of coefficients.

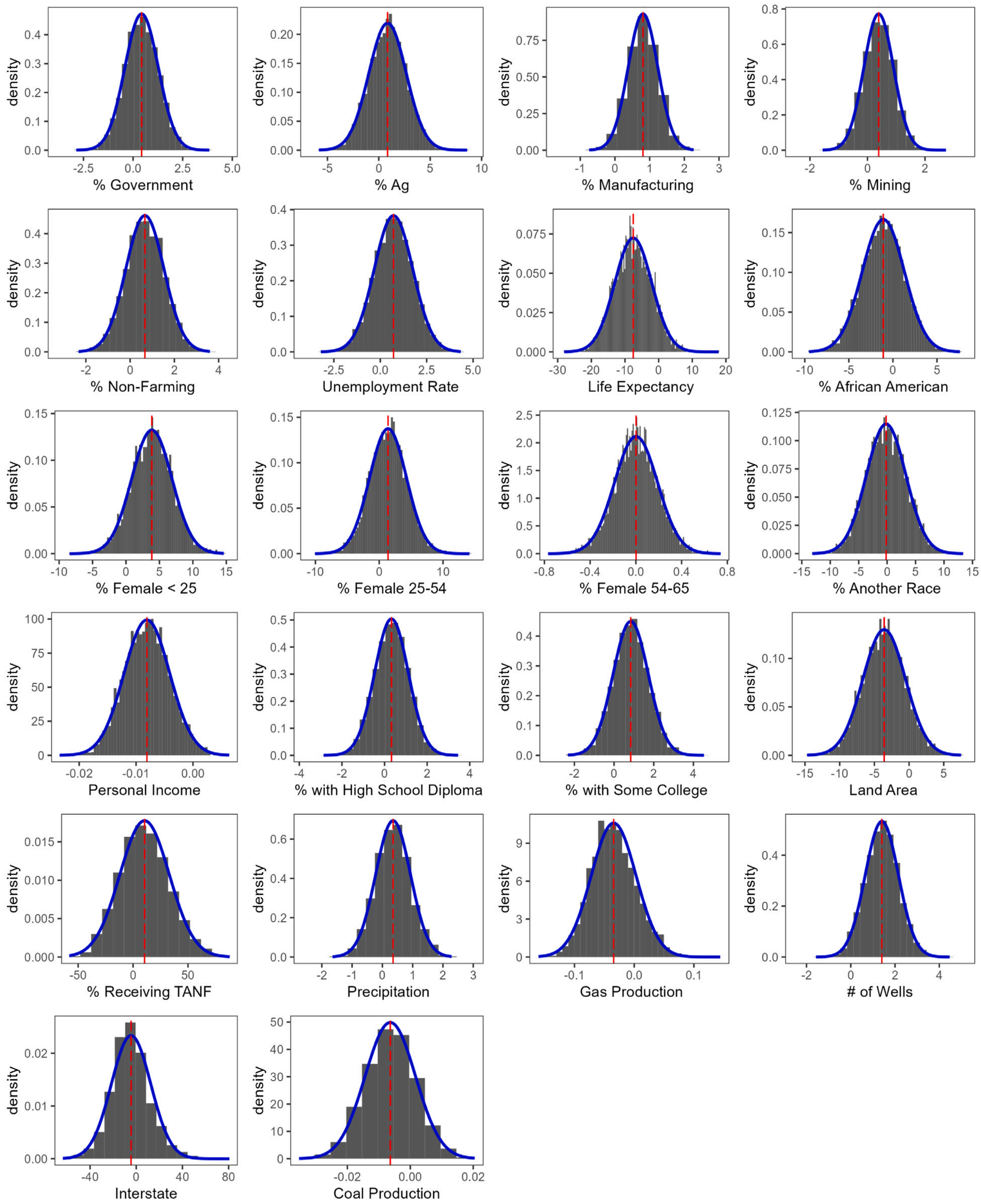

Fig. A.5. Distribution of panel regression coefficients (County-specific factor variance contribution). Note: The dependent variable in all cases is the randomly-drawn variance contribution of the county-specific (idiosyncratic) factor, $\widetilde{\theta}_{it}$. The shaded bars present the distribution of coefficients from the 5000 regressions. The red lines denotes the mean of each distribution and blue lines represent the density curves associated with a normal distributions with the same mean and standard deviation as the collection of coefficients.

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