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The turning point of regional deindustrialization in the U.S.: Evidence from panel and time-series data

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ABSTRACT

The phenomenon of deindustrialization may emerge in both developed and developing countries. Besides deindustrialization is observable in different regions of a country. This study analyzes inter-state deindustrialization trends in the United States (the U.S.) from 1977 to 2017 by dividing states into three income level groups (high, middle, and low). Instead of specifying the factors, we determine the turning points of inter-state deindustrialization and the difference in the rate of deindustrialization by applying both time-series and panel data methodology. The results suggest that the deindustrialization hypothesis is valid in 38 out of 50 states, DC, and the U.S. at the country level. Furthermore, our results show that deindustrialization curves in lower-income states reach a turning point at lower per capita income levels and at an earlier time-span compared to higher-income state groups. Our findings indicate that premature/early deindustrialization, which is commonly stated for developing countries in the literature is also valid for different regions in a developed country, the U.S. in our case.

1. Introduction

Deindustrialization is often defined as "the declining share of manufacturing in employment" (Rodrik, 2016). The literature has documented a recent trend of deindustrialization in all developed/industrialized countries, measured as the decreasing share of the manufacturing sector in total production or total employment (Nickell, et. al., 2008; Jorgenson and Timmer, 2011; Palma, 2014; Van Neuss, 2018). Studies on the deindustrialization processes of developing/less developed countries have also described the phenomenon of "premature deindustrialization", which is defined as decoupling from the deindustrialization experience of developed countries. On the other hand, premature deindustrialization indicates that the trend of deindustrialization, which has been observed historically in developed countries, sets at much lower per capita real income levels in developing countries (Dasgupta and Singh, 2006; Rodrik, 2016).

In many countries, there are large differences in the long-term performance of individual regions as economic activity is unequally and spatially distributed (Marshall, 1920; Jacobs, 1969; Krugman, 1980; Krugman,1991). Accordingly, the share of the manufacturing sector in the economy differs regionally and leads to regional deindustrialization. That is, manufacturing in some regions declines more rapidly than in others (Kiyota, 2020). The rapid decline of the manufacturing sector causes some regions to experience premature deindustrialization. Hence, premature deindustrialization might occur in some regions of a developed country. In this respect, this study examines the regional deindustrialization trend in the United States (the U.S.) from 1977 to 2017 with time-series and panel data analysis. Our main hypothesis is that despite the deindustrialization experience of the overall U.S. economy, the unfolding of deindustrialization might differ across states in the sample period. The paper adds to the existing literature on the deindustrialization nexus in three ways. First, albeit a very limited number of studies on regional deindustrialization of developed countries such as Japan and Germany (Murakami, 2015; Dauth and Suedekum, 2016), to our knowledge, this is the first study that empirically analyzes the regional deindustrialization heterogeneity by determining turning points of each state in the United States. Second, instead of specifying the factors for deindustrialization, we divide states into three income level groups (high, middle, and low) and attempt to reveal the difference in the rate of deindustrialization. Third, unlike previous literature, we apply both time-series and panel data methodology.

We find that there is an "Inverted-U shape" relationship, that is deindustrialization, between the share of the manufacturing sector in employment and real income per capita in the U.S. at both the

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country and state levels. The results indicate that the deindustrialization trend of the states in the U.S. differs from both the country and other states. Besides, at the state level, 38 of the 50 states and DC, and at the country level, the U.S. have experienced deindustrialization. A striking result of the study depicts that the deindustrialization curves at the country and state level in the U.S. reach their turning points at different income levels per capita, and as the income level increases/decreases, deindustrialization begins at higher/lower per capita income levels. Our results show that deindustrialization curves in lower-income states reach a turning point at lower GDP per capita income levels and at an earlier time-span compared to higher-income state groups. Also, the turning point of the deindustrialization curve at the country level in the U.S. is at a lower per capita income level than in high and middle-income states. Our findings show that premature/early industrialization, which is commonly stated for developing countries in the literature (Dasgupta and Singh, 2006; Rodrik, 2016), is also valid for different regions in a developed country, the U.S. in our case.

The remainder of the paper is organized as follows: Section 2 theoretically explains deindustrialization and elucidates premature deindustrialization and regional deindustrialization. Section 3 outlines the deindustrialization trend in the U.S. Section 4 describes the data and methodology. Section 5 explains the steps for testing the "Deindustrialization Hypothesis" at the country and state levels in the U.S. Section 6 summarizes and discusses the empirical results, and Section 7 concludes.

2. Deindustrialization

2.1. The concept of deindustrialization

Structural transformation and productivity are among the main determinants of economic growth (Kuznets, 1973). Productivity increases in the economy are driven by sectoral shifts, from low-productivity to high-productivity sectors. In this respect, productivity increase not only paves the way for economic growth but also structural transformation. Structural transformation or structural change is often defined as the process of redistributing economic activities across the agriculture, manufacturing, and service sectors (Van Neuss, 2019). In this framework, along with the economic development process, the weight of production and employment shifts, first, from the agricultural sector to the manufacturing sector (industrialization) and then from the manufacturing sector to the service sector (deindustrialization) (Kaldor, 1966; Kuznets, 1971; Maddison, 1980). With the structural transformation, the share of the manufacturing sector in production or employment increases until a certain per capita income level (turning point) and starts to decrease after that level. That is, there is a relationship between the share of the manufacturing sector in production or employment and real income per capita in the form of the "Inverted U-shape" (Dasgupta and Singh, 2006; Rodrik, 2016).

The literature generally defines deindustrialization as the decrease in the share of the manufacturing industry in total production or employment (Palma, 2014, Tregenna 2008). Besides, Bluestone and Harrison (1982), define deindustrialization as the widespread and systematic withdrawal of capital investments from a country or region to reduce the production capacity of capital investments.

Rowthorn and Coutts (2004) explain the causes of deindustrialization in developed countries with 4 factors. In this context, productivity is regarded as the primary source of deindustrialization (Rowthorn and Ramaswamy, 1998). By definition, productivity is the growth rate of labor productivity, expressed as the growth rate of output minus the growth rate of employment. Therefore, if output in the two sectors increases at the same rate, the sector with faster productivity growth would have slower employment growth or vice versa. Hence, deindustrialization occurs due to the increase in productivity in the manufacturing sector which is the main source of productivity gains in the economy and is described as the "engine" of economic growth (Kaldor, 1967). The second reason for deindustrialization is specialization such as design, catering, and transportation. Due to cost and quality advantages, the service sector starts to provide these activities which are mainly carried out by the manufacturing sector. Consumption is another factor for deindustrialization. As income per capita increases in poor countries in the industrialization process, the ratio of expenditures allocated to food decreases, and consumers tend to buy more manufacturing products. Accordingly, the share spent on manufacturing products increases in the first stages of economic development, and after a certain level of per capita income, this share decreases. In this respect, the income elasticity of services is greater than manufacturing. The fourth reason for deindustrialization is international trade which increases productivity by encouraging competition through efficient production.

As the definition and causes of deindustrialization are given above, the literature, also, makes a distinction between two types of deindustrialization, which are often referred to as positive and negative deindustrialization. First, positive deindustrialization, put forth by Rowthorn and Wells (1987), is accepted as a normal consequence of sustainable economic growth in developed countries at the full employment level. Accordingly, in the positive deindustrialization process, the decrease in employment in the manufacturing sector due to economic and rapid productivity growth in developed countries is compensated by the service sector. Hence, positive deindustrialization is regarded as a sign of economic success or as a natural effect of industrial dynamism. On the other hand, negative deindustrialization occurs due to the stagnation in production output and productivity in the manufacturing sector. Therefore, employment loss in manufacturing cannot be compensated by the service sector. Thus, negative deindustrialization is regarded as a problematic phenomenon (Alderson, 1997; Treganna 2009; Rowthorn and Wells, 1987). Another distinction of the types of deindustrialization might be expressed as premature and nonpremature deindustrialization. Structural transformation raises the question of the decrease in the share of manufacturing in developed countries at a certain stage. However, this stage can also occur at an earlier stage of development. This phenomenon usually occurs in developing countries. While the former type of deindustrialization is called nonpremature deindustrialization, the latter is known as premature deindustrialization (Du and Xie, 2019).

2.2. Premature deindustrialization

The deindustrialization experience of developed countries is often regarded as a natural result of a successful economic growth path (Rowthorn and Ramaswamy, 1997; Du and Xie, 2019). Yet, the deindustrialization experience of developed countries and developing countries differ. The problematic deindustrialization in developing countries is called "premature deindustrialization". Early/premature deindustrialization is defined as the insufficient maturity of the manufacturing sector which bypasses the industrialization phase of the structural transformation and inclines to leave its position to the service sector in developing countries (Rodrik, 2016). As the manufacturing sector is vital for economic growth and the service sector has a low potential to contribute to economic growth, employment, and productivity increase, early/premature deindustrialization is an important problem for developing countries (Rowthorn and Ramaswamy, 1997; Rodrik, 2016).

2.3. Regional deindustrialization

Regional deindustrialization, which is observable in different regions of a country, is another dimension of the deindustrialization trends in developed and developing countries. Deindustrialization at the regional level is one of the main driving forces of regional inequalities in, particularly, developed economies (Meçik and Aytun, 2018).

Economic activity and income are not evenly distributed in space Marshall (1920) and Jacobs (1969) highlight intra-industry and inter-industry externalities Krugman (1980,1991), on the other hand, emphasizes the importance of the unique historical characteristics of the regions. the New Economic Geography Theory, introduced by Krugman, is based on the economic growth in the manufacturing industry and investigates the interregional distribution of the companies in the manufacturing sector. The theory underlines that regions, not countries, are real units in economic analysis. According to the New Economic Geography Theory, most of the economic activities tend to be geographically concentrated in certain regions. These theoretical approaches have profound implications to comprehend the nature of the deindustrialization process and its impact on regional development and growth. The decline of the manufacturing sector in a given region inevitably leads to the deterioration of existing supplier, distribution, and information links, and requires all surviving firms in the production chain to seek new information and customers. The success rate in this process determines the survival of the remaining firms and the development prospects of the entire region. At the same time, the reduction of supply in the labor market might lead to an increase in unemployment and trigger migration trends. As a result, deindustrialization accelerates in the regions (Stojčić and Aralica, 2015).

In the literature, not so many studies focus on the dynamics of deindustrialization at the regional level.[1] Regional deindustrialization has both domestic causes such as an increase in per capita income, national/regional development policies, migration, and urbanization, etc., and foreign causes such as the global value chain, the Dutch disease, intensification of international competition, and international trade (Silva,2019; Dauth and Suedekum, 2016; Murakami, 2015; Kiyota, 2020).

3. The course of deindustrialization in the U.S.

Most of the developed countries followed a similar path in the course of economic development (Rowthorn and Coutts, 2004, 2013). Until the 18th century, agriculture was the most important sector by absorbing most of the workforce. Since the second half of the 18th century, most of the developed countries have experienced a successful industrialization wave. The industrial revolution that started in England, continued in continental Europe and North America. In the light of the New Economic Geography Theory, industrialization in the U.S., historically, has started in the Northern states (such as New England) of the country and has spread to other Northern states since the early 1800s. The fruitful mine and water resources, the widespread railway network in the region compared to other regions, and the high number of ports for foreign trade were the main factors for industrialization in the region (Stone, 2017). On the other hand, productivity was very low in the southern states where the agricultural sector was predominant. In the following period, California and Texas managed to attract some industrial investments thanks to the combination of climate conditions and energy resources with cheap labor (Rodwin, 1989). Later, the concentration of the automobile industry and Fordist-style production in the Northeast regions caused a huge industrialization gap between the North and South (Kollmeyer, 2018). Two factors stand out in the regional deindustrialization process of the U.S.: First, although the U.S. economy is well integrated, inter-state heterogeneity exists in the composition out and labor productivity. Second, the long-term performance of individual regions differs in the U.S. For example, cities in New York, Boston, or the Sun Belt have experienced phenomenal economic growth over the past decade, while industrial cities in the Rust Belt have declined over the same period. These (negative) developments are related to the local industrial structures of these regions: San Francisco or New York developed as they became more and more specialized in emerging sectors such as IT or finance. Detroit, on the other hand, has declined as it has traditionally specialized in heavy manufacturing industries (Glaeser et al., 2014).

Fig. 1 plots the regions where productivity growth was greater than 1% between 1978 and 2015. According to the figure, the Northeast regions are intensely industrialized and productive. Yet, the deindustrialization phenomenon becomes evident in the Northeast after 2004.

Table 1 shows the sectoral shares of employment by state income levels in the sample period. The table briefly describes the structural transformation process both in the whole country and in the state groups in the U.S. In other words, for both the country and the state groups, the share of the agriculture and manufacturing sector in total employment decreases and the share of the services sector increases in the sample period. While the economic development of the regions differs, the overall U.S. economy has experienced a positive deindustrialization process since the 1970s (Rowthorn and Ramaswamy, 1997).

Yet, the table itself does not explain how the deindustrialization phenomenon differs at states, or at which income per capita level deindustrialization begins. Therefore, the following section calculates the turning points of deindustrialization and deindustrialization curves at the state level. Accordingly, our main hypothesis is that despite the deindustrialization experience of the overall U.S. economy, the unfolding of deindustrialization might differ across states. Hence, premature deindustrialization might occur in a developed country such as the U.S.

4. Data and methodology

We attempt to compute and determine the deindustrialization at both state and country-level in the U.S. from 1977 to 2017. For this purpose, we divide our study into four steps to measure industrialization and calculate turning points. First, we analyze the variables in the literature, which theoretically and econometrically explain the “Inverted U-shape” deindustrialization hypothesis. We identify that, mostly, the ratio of employment in manufacturing to total employment (dependent), per capita income (independent), and the square of per capita income (independent) are used. Another commonly used dependent variable is the ratio of manufacturing value-added to GDP (Rodrik, 2016; Palma, 2014). Yet, the data of manufacturing value-added to GDP is limited for states in the U.S. for the sample period. Therefore, our only dependent variable is the ratio of employment in manufacturing to total employment. The data for 50 states, DC, and the U.S. is retrieved from the U.S. Department of Commerce and covers the period of 1977 -2017. Second, we apply the Engle-Granger time-series cointegration test for each state to measure deindustrialization. However, since the income level of the states is between 38,330$ and $174,572 based on 2017, we divide the states into three groups as high-income (HI), middle-income (MI), and low-income (LI) states and apply the Kao panel cointegration test. Therefore, this three-panel dataset allows us to measure deindustrialization according to income levels

[1] Refer to Wrobel (2008), (Sugrue, 1996), Crafts and Klein (2017), Dauth and Suedekum (2016), Kiyota (2020), Murakami (2015) Silva (2019), Doğruel (2013), Meçik and Aytun (2018) for the changing geography of the manufacturing industry at the regional level and deindustrialization in developed and developing countries.

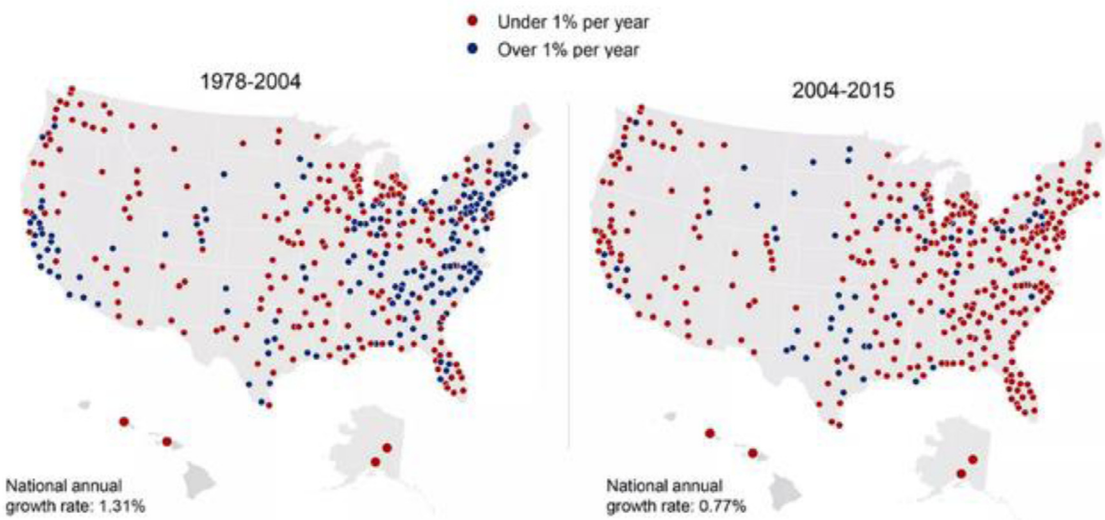

Fig. 1. Productivity Trends in the U.S.
Source: Brookings analysis of Moody's Analytics data. https://www.brookings.edu/research/understanding-us-productivity-trends-from-the-bottom-up.

Table 1
Sectoral shares of employment by state income levels (1977-2017).*

Industry	Low Income States 1977	Low Income States 2017	Middle Income States 1977	Middle Income States 2017	High Income States 1977	High Income States 2017
Farm employment	**0.70%**	**0.28%**	**1.51%**	**0.52%**	**1.38%**	**0.57%**
Nonfarm employment	13.30%	16.72%	21.83%	29.48%	48.35%	52.43%
Mining, quarrying, and oil and gas extraction	0.23%	0.09%	0.39%	0.24%	0.45%	0.44%
Construction	0.80%	0.98%	1.70%	1.58%	2.37%	2.81%
Manufacturing	**2.26%**	**1.02%**	**7.19%**	**2.64%**	**8.79%**	**2.91%**
Durable goods manufacturing	1.14%	0.66%	4.60%	1.68%	5.41%	1.80%
Nondurable goods manufacturing	1.12%	0.37%	2.58%	0.96%	3.39%	1.13%
Wholesale trade	0.65%	0.53%	1.56%	0.97%	2.77%	1.78%
Retail trade	2.24%	1.83%	5.42%	3.04%	5.92%	4.87%
Services	**3.73%**	**7.62%**	**9.38%**	**13.16%**	**16.29%**	**24.18%**
Transportation, warehousing and utilities	0.68%	0.72%	1.67%	1.25%	2.61%	2.39%
Finance insurance and real estate	1.01%	1.70%	2.33%	2.71%	4.53%	5.53%
Management of companies and enterprises	0.47%	0.17%	1.41%	0.49%	2.73%	0.62%
Educational services	0.14%	0.32%	0.44%	0.76%	0.81%	1.41%
Health care and social assistance	0.62%	1.87%	1.73%	3.56%	2.65%	6.06%
Arts, entertainment, and recreation	0.17%	0.42%	0.35%	0.64%	0.67%	1.30%
Accommodation and food services	0.43%	1.39%	0.95%	2.12%	1.25%	3.87%
Other services (except government and government enterprises)	0.22%	1.03%	0.50%	1.62%	1.03%	3.00%
Government and government enterprises	2.47%	2.05%	2.53%	3.77%	8.99%	6.56%
Other Industry	0.92%	2.60%	4.33%	-0.76%	5.04%	8.88%
Total Employment	**0.70%**	**0.28%**	**1.51%**	**0.52%**	**1.38%**	**0.57%**

Sources: Authors Constructed the table by utilizing St. Louis FED's FRED Database.
*Table indicates weighted averages of sectoral employment by states' income level.

and help us to identify deindustrialization trends based on income groups. Third, after analyzing deindustrialization with both panel data and the time-series method, following Shuai et. al. (2017), we use the derivative of the second-order functions of the hypothesis to calculate the turning points (TPs) of the deindustrialization hypothesis. Finally, we estimate the average annual growth rate, average years to reach turning year (TYs), or average years from the turning years with future value methodology.

4.1. Econometric model of deindustrialization

We hypothesize that deindustrialization differs across states. To gauge our hypothesis, we apply the purest form of industrialization that is frequently used in the literature (Rodrik, 2016; Du and Xie, 2019) as:

$$LnDe_{it} = \beta_0 + \beta_1 LnY_{it} + \beta_2 LnY_{it}^2 + \varepsilon_{it} \tag{1}$$

where t is the time, i indicates the state, De_{it} is the ratio of the employment in manufacturing to the total employment for each state, β_0 is the constant, Y_{it} is the per capita national income for each state. ${Y_{it}}^2$ shows the square of national income per capita for each state.

4.2. Calculation of turning years and turning points

After obtaining the deindustrialization equilibrium in Eq. (1), we calculate TPs by deriving the quadratic functions of equality.

The formula is as follows.

$$Let\ \frac{d}{d_{Yit}} LnDe_{it} = \frac{\beta_{1t}}{Y_{it}} + \frac{2\beta_{2t} Y_{it}}{Y_{it}} = 0 \tag{2}$$

Therefore, the TP of GDP per capita is:

$$Y_{it} = \exp\frac{-\beta_{1t}}{2\beta_{2t}}$$

We use the formula below to answer the question of whether related income groups have reached or yet to reach their turning points, we calculate the average growth rate for each state and panel group and find the average time for reaching or passing the threshold with each state's current GDP per capita level.

$$FV = PV*(1+r)n \tag{3}$$

where FV is the future value of GDP per capita, PV is the present value of GDP per capita, r is the interest rate, and n is the number of years.

5. Steps for testing deindustrialization hypothesis

We both apply panel and time-series methods to test the deindustrialization hypothesis. Both approaches have similar procedures.

5.1. Unit root test

Unit root tests are divided into two types as the first and second-generation depending on whether there is a cross-sectional dependency (CD) in the units forming the panel. In the first-generation panel unit root tests, it is assumed that all units are affected equally by the shock that occurs in one of the sections forming the series. Whereas, in the second-generation panel unit root tests, each unit is considered to be affected differently by the shock that occurs in one of the sections forming the series. In this context, in the case of CD, first-generation panel unit root tests may not yield consistent results (Hadri, 2000; Levin et al., 2002; Im et al., 2003; Breitung and Das, 2005). Thus, second-generation panel unit root tests should be used (Taylor and Sarno, 1998; Breuer, et al., 2002; Peseran, 2007; Hadri and Kurozumi, 2012; Gocer et al., 2012).

5.2. Cointegration test

Cointegration analysis tests the long-term relationship between variables Pedroni (1999) and Kao (1999) cointegration techniques are among the most commonly used tests in empirical research Pedroni (1999) test is based on error terms derived from the regression model. On the other hand, the Kao test uses the same general methodology, except that it defines cross-section-specific intercepts and homogeneous coefficients on the first-stage regressors. The fundamentals of Kao's (1999) cointegration tests are based on Dickey-Fuller (DF) and Augmented Dickey-Fuller (ADF) tests. In Kao (1999) panel cointegration test, the null hypothesis is "there is no cointegration" and the alternative hypothesis is defined as "there is cointegration between or among variables". ADF test is used to evaluate the null hypothesis. If the ADF test statistic is significant, the null hypothesis is rejected. Under this assumption Kao (1999) cointegration test is based on a panel regression model as follows:

$$y_{it} = x'_{it}\beta + z'_{it}\gamma + \varepsilon_{it} \tag{4}$$

In Eq. (4), y_{it} and x_{it} are stationary at the level of I (1) and a cointegrated relationship does not exist.

5.3. Long-run interaction estimation

The last step is to estimate the parameters of the variables in Eq. (1). We apply the Dynamic Common Correlated Effects (DCCE) technique to estimate the parameters of the variables of long-run interaction in Eq. (1).

Table 2
CDs cross dependency test result.

Panel	Variable	Results	Prob.
ALL	$Ln(De_{it})$	116.18 [a]	0,000
PANEL	$Ln(Y_{it})$	204.71 [a]	0,000
	$Ln(Y_{it})^2$	190.34 [a]	0,000
HI	$Ln(De_{it})$	29.270 [a]	0,000
	$Ln(Y_{it})$	58.880 [a]	0,000
	$Ln(Y_{it})^2$	58.860 [a]	0,000
MI	$Ln(De_{it})$	33.070 [a]	0,000
	$Ln(Y_{it})$	70.530 [a]	0,000
	$Ln(Y_{it})^2$	56.800 [a]	0,000
LI	$Ln(De_{it})$	51.680 [a]	0,000
	$Ln(Y_{it})$	72.100 [a]	0,000
	$Ln(Y_{it})^2$	71.480 [a]	0,000

6. Empirical analysis

6.1. Panel data method and results

Before applying the model estimations in panel data studies, it is necessary to investigate CD in the series/model cointegration equation and determine the unit root and other successive tests to be used in the analysis. When this situation is neglected, the tests may not yield reliable results (Peseran, 2004; Menyah, et al., 2014). Besides, one should consider the time and cross-sectional dimensions of the series together when investigating the cross-sectional dependency in panel data. The CD test developed by Peseran (2004) can be used in all situations where the time dimension of the series is larger (T> N), smaller (T <N) than or, equal to (T = N) the unit size. CD test mathematically is expressed as follows:

$$CD = \sqrt{\frac{2}{N(N-1)}} \sum_{k=1}^{N-1} \sum_{l=k+1}^{N} T_{kl}\partial_{kl} \rightarrow N(0,1) \tag{5}$$

The CD test analyzes the existence of cross-sectional independence with an alternative hypothesis that "there is no cross-sectional dependency in the series or model" compared to the null hypothesis of "there is a cross-sectional dependency in the series or model." If the null hypothesis is rejected, the CD test, which is assumed to have a standard normal distribution asymptotically, concludes that CD exists in the series or model. We also examine the existence of cross-section dependency in the series and the cointegration equation of the model with the CD test Table 2 tabulates the results.

Table 2 depicts that the probability values of all variables of the model and the CD test statistics of the cointegration equation are less than 0.05. In this case, we reject the null hypotheses for the variables in the HI, MI, and LI panel data models and the cointegration equation. These results show that there is a cross-sectional dependency between the units of the panel in the related income-level groups. Still, the results indicate that the following stage of analysis requires the application of the next generation of panel data methodology testing methods, which take the existence of CD into account (Baltagi, 2008). For this reason, we use a second-generation panel unit root test called the Cross-Sectional Augmented Dickey-Fuller test (CADF). CADF is developed by Pesaran (2007) and considers cross-sectional dependency. CADF calculates the test statistics of all cross-sectional units in the panel then finds Cross-Sectionally Im–Pesaran–Shin (CIPS) unit-root test statistics of the panel by taking the arithmetic average of CADF test statistics. CADF test statistics that are designed for N> T condition and which can give meaningful results in N <T condition is calcu-

Table 3
CIPS Panel Unit Root Test Results.

Panel	Variable	Intercept	Intercept and Trend	Order of Integration
ALL PANEL	$Ln(De_{it})$	-4.033[a]	-4.179[a]	1
	$Ln(Y_{it})$	-4.766[a]	-4.932[a]	1
	$Ln(Y_{it})^2$	-4.764[a]	-4.922[a]	1
HI	$Ln(De_{it})$	-4.55[a]	-4.678[a]	1
	$Ln(Y_{it})$	-4.458[a]	-4.662[a]	1
	$Ln(Y_{it})^2$	-4.476[a]	-4.673[a]	1
MI	$Ln(De_{it})$	-3.819[a]	-3.987[a]	1
	$Ln(Y_{it})$	-4.865[a]	-5.039[a]	1
	$Ln(Y_{it})^2$	-4.938[a]	-5.074[a]	1
LI	$Ln(De_{it})$	-3.91[a]	-4.182[a]	1
	$Ln(Y_{it})$	-4.906[a]	-5.121[a]	1
	$Ln(Y_{it})^2$	-5.022[a]	-5.073[a]	1
Critical Value	1%	5%	10%	
Intercept	-2.25	-2.11	-2.03	
Intercept & Trend	-2.76	-2.62	-2.54	

Table 4
Kao Cointegration Test Results.

Panel	t-Statistics	Prob.
High Income	-2.32[a]	0.010
Middle Income	-2.01[a]	0.022
Low Income	-4.03[a]	0.000

lated as follows:

$$t(N,T) = \frac{\Delta y_i' \overline{M_i} y_{i-1}}{\overline{\sigma^2}(\Delta y_{i-1}' \overline{M_i} y_{i-1})^{1/2}} \tag{6}$$

Eq. (7) shows the formula for CIPS statistical value which is obtained by averaging the CADF test statistical values,

$$CIPS = N^{-1} \sum_{i=1}^{n} t(N,T) \tag{7}$$

CADF and CIPS test statistics values are compared with critical table values created with Monte-Carlo simulations, and hypotheses are tested for stability. As a result of the test, if the absolute CADF and CIPS test statistic values are higher than the critical values, the null hypothesis (there is a unit root in the series) is rejected, and the alternative hypothesis (there is no unit root in the series) is accepted for the overall unit-panel (Peseran, 2007).

Table 3 tabulates the stationarity of the variables in the model examined by the CIPS Panel Unit Root Test.

Table 3 displays that all variables in the model are not stationary at the 5% significance level. When we take the first differences of variables, all variables become stationary at the 1% significance level. Here, constant positive (+) trended forms CIPS statistics values are larger than critical table values at the % 1 significance level.

Table 4 indicates the results of the cointegration tests. Accordingly, for all three-panel groups, the deindustrialization hypothesis is not rejected in the long term.

After finding the long-term interaction between series for HI, MI, and LI groups with the cointegration test, we need to determine how to estimate the long-term coefficients. Since CD exists in our model, we use estimators that take CD into account among independent and dependent variables. In this context, we apply the DCCE estimator, which is developed by Chudik and Peseran (2015). The authors suggest that although the DCCE estimator is resistant to CD, unit roots, and heterogeneity, it is not resistant to lagged values of the dependent variable and the existence of exogenous variables in the panel. The DCCE estimator addresses this gap by including these variables in the analysis. The DCCE estimator includes cross-sectional averages of the variables as the unobserved factors in the model. The mathematical equation of the dynamic heterogeneous panel data model is as follows:

$$y_{it} = c_{yi} + f_i y_{i,t-1} + b_{0i}' x_{\prime t} + b_{1i}' x_{i,t-1} + \mu_{it} \tag{8}$$

$$\mu_{it} = \gamma_i' f_t + \varepsilon_{it} \tag{9}$$

where y_{it} is the dependent variable, i = 1,2,..., N and t = 1,2,..., T, is x_{it} independent variable. c_{yi} is the fixed effects for each cross-sectional unit, x_{it} is the *kx1* vector for independent variables specific to the cross-section units, f_t is the *mx1* vector of the unobserved common factors, and ε_{it} is the error term.

Table 5 tabulates the DCEE results for our model. According to Table 5, the coefficients of the GDP per capita and SQRGDP per capita are positive and negative, and statistically significant at the level of 1% and 5%, respectively, in all panel groups. Also, we calculate TPs and TYs for each panel group in Table 5. States with high-income level reach at $57,835, states with middle-income level reach at $35,594, and lastly, states with low income reach their turning points at $28,978. Besides, along with the turning points level, the states reached their turning points on different dates: HI states 15.48 years ago, MI states 22.88 years ago, and LI states 25.58 years ago.

Fig. 2 below shows the deindustrialization curves of the state groups classified as high, middle, and low-income states. There are relative differences in the turning points of the industrialization curves of the three income groups. According to the figure, the turning points are relatively lower GDP per capita levels in lower-income states than in higher-income states. Moreover, the turning years of lower-income states start at an earlier time-span than that of higher-income states.

Table 5
Panel Dynamic Common Correlated Effects (Long Run Results).

Panel	Deindustrialization Model	TYs	TPs ($)	Growth Rate
HI	$Ln(De_{it})$=-288.7646 +54.7341 $Ln(Y_{it})$-2.495774$Ln(Y_{it})^2$	15.481	57,835	0.015
MI	$Ln(De_{it})$= -201.3263 + 40.43493 $Ln(Y_{it})$- 1.914377$Ln(Y_{it})^2$	22.885	35,594	0.016
LI	$Ln(De_{it})$= -289.3895 + 58.69628 $Ln(Y_{it})$- 2.856459$Ln(Y_{it})^2$	25.587	28,978	0.015

Table 6
ADF Unit Root Test Results.

State	Variable	Constant	Constant and Trend	Order of Integration	State	Variable	Constant	Constant and Trend	Order of Integration
USA	Ln(De_{it})	-4.0966[a]	-3.99110[b]	1	Missouri	Ln(De_{it})	-3.80133[a]	-6.88908 [a]	1
	Ln(Y_{it})	-4.5432[a]	-4.49247[a]	1		Ln(Y_{it})	-5.37152[a]	-5.59211 [a]	1
	Ln(Y_{it})^2	-4.5136[a]	-4.45689 [a]	1		Ln(Y_{it})^2	-5.36969[a]	-5.58610 [a]	1
Alabama	Ln(De_{it})	-3.6429[a]	-7.23064 [a]	1	Montana	Ln(De_{it})	-3.84370[a]	-5.88127 [a]	1
	Ln(Y_{it})	-5.1440[a]	-5.32112 [a]	1		Ln(Y_{it})	-5.65374 [a]	-5.66389 [a]	1
	Ln(Y_{it})^2	-5.11026[a]	-5.26848 [a]	1		Ln(Y_{it})^2	-5.62810 [a]	-5.64150 [a]	1
Alaska	Ln(De_{it})	-3.53177[b]	-6.65552 [a]	1	Nebraska	Ln(De_{it})	-4.30259 [a]	-7.0722 [a]	1
	Ln(Y_{it})	-5.05195[a]	-5.07014 [a]	1		Ln(Y_{it})	-7.66164 [a]	-7.68291 [a]	1
	Ln(Y_{it})^2	-5.07145[a]	-5.08997 [a]	1		Ln(Y_{it})^2	-7.65378 [a]	-7.64878 [a]	1
Arizona	Ln(De_{it})	-4.45305[a]	-4.27930 [a]	1	Nevada	Ln(De_{it})	-3.85065 [a]	-7.24571 [a]	1
	Ln(Y_{it})	-4.28989[a]	-4.2539 [a]	1		Ln(Y_{it})	-4.13554 [a]	-4.06595[b]	1
	Ln(Y_{it})^2	-4.06272[a]	-4.46252 [a]	1		Ln(Y_{it})^2	-4.11298 [a]	-4.04418[b]	1
Arkansas	Ln(De_{it})	-3.0644[b]	-6.73418 [a]	1	New Hampshire	Ln(De_{it})	-4.40875 [a]	-5.69250 [a]	1
	Ln(Y_{it})	-5.5924[a]	-5.75624 [a]	1		Ln(Y_{it})	-3.80996 [a]	-3.57187[c]	1
	Ln(Y_{it})^2	-5.53524[a]	-5.67910 [a]	1		Ln(Y_{it})^2	-3.82279 [a]	-3.98333[b]	1
California	Ln(De_{it})	-3.9101[a]	-17.1610 [a]	1	New Jersey	Ln(De_{it})	-3.56424 [b]	-6.68669 [a]	1
	Ln(Yit)	-3.71045[a]	-3.68352[c]	1		Ln(Y_{it})	-3.83104 [a]	-3.96606 [a]	1
	Ln(Yit)2	-3.69112[a]	-3.67454[c]	1		Ln(Yit)^2	-3.87006 [a]	-4.48732 [a]	1
Colorado	Ln(De_{it})	-3.58274[a]	-7.32620 [a]	1	New Mexico	Ln(De_{it})	-3.86701 [a]	-7.38994 [a]	1
	Ln(Y_{it})	-3.75170[a]	-3.68445[c]	1		Ln(Y_{it})	-4.95517 [a]	-4.89614 [a]	1
	Ln(Y_{it})2	-3.71694[a]	-3.64829[c]	1		Ln(Y_{it})^2	-4.97584 [a]	-4.91603 [a]	1
Connecticut	Ln(De_{it})	-3.67707[a]	-6.73640[a]	1	New York	Ln(De_{it})	-3.75914 [a]	-7.54584 [a]	1
	Ln(Y_{it})	-3.73525[a]	-4.34919[a]	1		Ln(Y_{it})	-5.29248 [a]	-5.21964 [a]	1
	Ln(Y_{it})^2	-3.76184[a]	-4.34892[a]	1		Ln(Y_{it})2	-5.31730 [a]	-5.23904 [a]	1
Delaware	Ln(De_{it})	-4.07181 [a]	-6.93581 [a]	1	North Carolina	Ln(De_{it})	-3.16200[b]	-6.86295 [a]	1
	Ln(Y_{it})	-5.17234 [a]	-5.75943 [a]	1		Ln(Y_{it})	-4.95703 [a]	-5.28903 [a]	1
	Ln(Y_{it})^2	-5.20709 [a]	-5.77527 [a]	1		Ln(Y_{it})^2	-4.95503 [a]	-5.27063 [a]	1
DC	Ln(De_{it})	-3.65079 [a]	-7.26288 [a]	1	North Dakota	Ln(De_{it})	-4.21866 [a]	-6.14551 [a]	1
	Ln(Y_{it})	-4.22679 [a]	-4.27827 [a]	1		Ln(Y_{it})	-6.68130 [a]	-6.69925 [a]	1
	Ln(Y_{it})^2	-4.22982 [a]	-4.27790 [a]	1		Ln(Y_{it})2	-6.48427 [a]	-6.45539 [a]	1
Florida	Ln(De_{it})	-3.52821[b]	-6.42785[a]	1	Ohio	Ln(De_{it})	-3.80656 [a]	-7.14863 [a]	1
	Ln(Y_{it})	-3.29083[b]	-3.32933[c]	1		Ln(Y_{it})	-5.24396 [a]	-5.19900 [a]	1
	Ln(Y_{it})^2	-3.25838[b]	-3.29229[c]	1		Ln(Y_{it})2	-5.23294 [a]	-5.18402 [a]	1
Georgia	Ln(De_{it})	-3.22051[b]	-6.67444 [a]	1	Oklahoma	Ln(De_{it})	-5.32470 [a]	-3.24997[c]	1
	Ln(Y_{it})	-3.07432[c]	-3.21974[c]	1		Ln(Y_{it})	-6.13762 [a]	-6.33171 [a]	1
	Ln(Y_{it})^2	-3.50485[b]	-3.41686[c]	1		Ln(Y_{it})^2	-6.05994 [a]	-6.28119 [a]	1
Hawaii	Ln(De_{it})	-3.81908 [a]	-5.07594 [a]	1	Oregon	Ln(De_{it})	-4.34044 [a]	-3.27417[c]	1
	Ln(Y_{it})	-3.53592[b]	-3.48359 [a]	1		Ln(Y_{it})	-4.06846 [a]	-4.04275 [b]	1
	Ln(Y_{it})^2	-3.54086[b]	-3.48759 [a]	1		Ln(Y_{it})^2	-4.09817 [a]	-4.07722[b]	1
Idaho	Ln(De_{it})	-3.88512[a]	-7.48215 [a]	1	Pennsylvania	Ln(De_{it})	-3.89440 [a]	-6.69149 [a]	1
	Ln(Y_{it})	-4.85287 [a]	-4.78874 [a]	1		Ln(Y_{it})	-5.24726 [a]	-5.16978 [a]	1
	Ln(Y_{it})^2	-4.84585 [a]	-4.78128 [a]	1		Ln(Y_{it})^2	-5.27251 [a]	-5.19293 [a]	1
Illinois	Ln(De_{it})	-3.92797 [a]	-6.19738 [a]	1	Rhode Islands	Ln(De_{it})	-3.61109 [a]	-6.67889 [a]	1
	Ln(Y_{it})	-4.75014 [a]	-4.73399 [a]	1		Ln(Y_{it})	-3.65174 [a]	-3.85726[b]	1
	Ln(Y_{it})^2	-4.72467 [a]	-4.70304 [a]	1		Ln(Y_{it})^2	-3.66891 [a]	-3.85726[b]	1
Indiana	Ln(De_{it})	-3.81033 [a]	-5.76608 [a]	1	South Carolina	Ln(De_{it})	-3.61948 [a]	-7.22637[a]	1
	Ln(Y_{it})	-6.00602 [a]	-5.94480 [a]	1		Ln(Y_{it})	-4.95703 [a]	-5.28903[a]	1
	Ln(Y_{it})^2	-6.03384 [a]	-5.96992 [a]	1		Ln(Y_{it})^2	-4.95503 [a]	-5.27063[a]	1
Iowa	Ln(De_{it})	-4.07621 [a]	-6.79689 [a]	1	South Dakota	Ln(De_{it})	-3.33892 [a]	-3.27550[c]	1
	Ln(Y_{it})	-6.0263 [a]	-4.85287 [a]	1		Ln(Y_{it})	-6.89861 [a]	-6.95173[a]	1
	Ln(Y_{it})^2	-6.01293 [a]	-4.78128 [a]	1		Ln(Y_{it})^2	-6.83734 [a]	-6.86082[a]	1
Kansas	Ln(De_{it})	-4.79108 [a]	-6.61694 [a]	1	Tennessee	Ln(De_{it})	-3.9406 [a]	-3.85704[b]	1
	Ln(Y_{it})	-5.99311 [a]	-5.95753 [a]	1		Ln(Y_{it})	-4.84813 [a]	-4.94106 [a]	1
	Ln(Y_{it})^2	-5.94449 [a]	-5.89839 [a]	1		Ln(Y_{it})^2	-4.82726 [a]	-4.90618 [a]	1
Kentucky	Ln(De_{it})	-3.53226[b]	-6.57689 [a]	1	Texas	Ln(De_{it})	-4.97585 [a]	-4.87219 [a]	1
	Ln(Y_{it})	-5.52187 [a]	-5.57087 [a]	1		Ln(Y_{it})	-5.09089 [a]	-5.04509 [a]	1
	Ln(Y_{it})^2	-5.50645 [a]	-5.55005 [a]	1		Ln(Y_{it})^2	-5.03242 [a]	-4.9935 [a]	1
Louisiana	Ln(De_{it})	-4.50844 [a]	-6.91247 [a]	1	Utah	Ln(De_{it})	-4.98126 [a]	-4.92162 [a]	1
	Ln(Y_{it})	-5.28521 [a]	-5.2379 [a]	1		Ln(Y_{it})	-4.32018 [a]	-4.26731 [a]	1
	Ln(Y_{it})^2	-5.28259 [a]	-5.23568 [a]	1		Ln(Y_{it})^2	-4.30588 [a]	-4.25050 [a]	1
Maine	Ln(De_{it})	-3.84272 [a]	-6.27935 [a]	1	Vermont	Ln(De_{it})	-4.73962 [a]	-4.66048 [a]	1
	Ln(Y_{it})	-3.54141 [a]	-3.64750[c]	1		Ln(Y_{it})	-5.0321 [a]	-5.22063 [a]	1
	Ln(Y_{it})^2	-3.52141 [a]	-3.60244[c]	1		Ln(Y_{it})^2	-5.0231 [a]	-5.18411 [a]	1
Maryland	Ln(De_{it})	-3.87997 [a]	-7.58527 [a]	1	Virginia	Ln(De_{it})	-3.5567 [a]	-3.49097 [a]	1
	Ln(Y_{it})	-3.67403 [a]	-3.65071[c]	1		Ln(Y_{it})	-3.13428[b]	-3.40927 [a]	1
	Ln(Y_{it})^2	-3.67458 [a]	-3.64444[c]	1		Ln(Y_{it})^2	-3.14031[b]	-3.39886[c]	1
Massachusetts	Ln(De_{it})	-3.82181 [a]	-6.56936 [a]	1	Washington	Ln(De_{it})	-4.47396 [a]	-4.41378 [a]	1
	Ln(Y_{it})	-3.66974 [a]	-3.74624[c]	1		Ln(Y_{it})	-5.04912 [a]	-4.98607 [a]	1
	Ln(Y_{it})^2	-3.71043 [a]	-3.77099[c]	1		Ln(Y_{it})^2	-5.02352 [a]	-4.96749 [a]	1
Michigan	Ln(De_{it})	-3.63045 [a]	-7.32816[a]	1	West Virginia	Ln(De_{it})	-4.47396 [a]	-4.41378 [a]	1
	Ln(Y_{it})	-5.23113 [a]	-5.15817 [a]	1		Ln(Y_{it})	-4.88952 [a]	-4.83469 [a]	1
	Ln(Y_{it})^2	-5.22503 [a]	-5.15244 [a]	1		Ln(Y_{it})^2	-4.89423 [a]	-4.83766 [a]	1

(continued on next page)

Table 6 (*continued*)

State	Variable	Constant	Constant and Trend	Order of Integration	State	Variable	Constant	Constant and Trend	Order of Integration
Minnesota	$Ln(De_{it})$	-4.30741 [a]	-5.02927 [a]	1	Wisconsin	$Ln(De_{it})$	-4.26662 [a]	-4.17554 [a]	1
	$Ln(Y_{it})$	-3.98896 [a]	-5.85726 [a]	1		$Ln(Y_{it})$	-4.3724 [a]	-4.37084 [a]	1
	$Ln(Y_{it})^2$	-3.95873 [a]	-5.8358 [a]	1		$Ln(Y_{it})^2$	-4.35537 [a]	-4.34576 [a]	1
Mississippi	$Ln(De_{it})$	-3.32534[b]	-7.42235 [a]	1	Wyoming	$Ln(De_{it})$	-5.32736 [a]	-5.24384	1
	$Ln(Y_{it})$	-5.6008 [a]	-5.94882 [a]	1		$Ln(Y_{it})$	-4.42752 [a]	-4.36173 [a]	1
	$Ln(Y_{it})^2$	-5.58624 [a]	-5.91634 [a]	1		$Ln(Y_{it})^2$	-4.3867 [a]	-4.32157 [a]	1

Note: a denotes the rejection of null nonstationary at the level of %1 significance, b denotes the rejection of null nonstationary at the level of %5 significance, and c denotes the rejection of null nonstationary at the level of %10 significance.

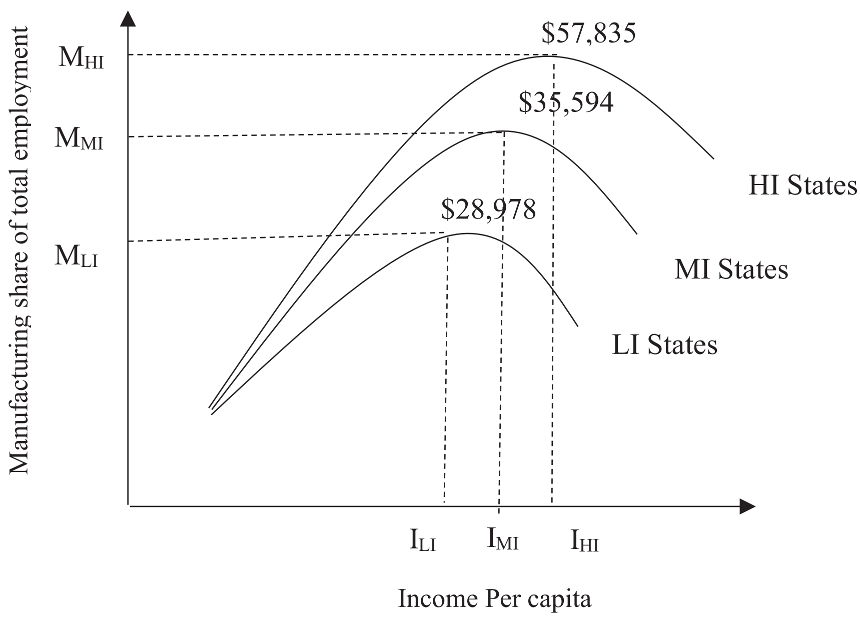

Fig. 2. Different pPaths of Deindustrialization for High, Middle, and Low Income States.

6.2. Time- Series Method and Results

The data is required to be stationary in time-series analysis. Non-stationarity generally causes a spurious regression problem (MacKinnon, 1991; Gujarati, 1995). We first, apply the Augmented Dickey-Fuller (ADF) unit root test to select the right model in our study Table 6. shows the ADF unit root test results. All series are stationary at 1% and 5% significance levels.

In the next step, we apply the two-stage Engle-Granger (E-G) Cointegration test to the deindustrialization hypothesis for each state. In the first stage of the E-G test, the error term is estimated with the Ordinary Least Squares (OLS) method. In the second stage, the unit root test is performed. Consequently, if there is stationarity, cointegration exists. Besides, if two series are stationary at the I (0) level, they are most likely to be cointegrated. So their level values and regressions would be significant. In this case, there is a long-term equilibrium. The results of E-G cointegration tests for each state are in Table 7.

In 40 out of 50 states, DC and the U.S. at the country level, there is a cointegration relationship among variables at 1% or 5% significance levels. Hence, we reject the null hypothesis. In other words, there exists a long-term equilibrium among the variables in these states. Finally, we analyze the long-term coefficients of the states from the E-G test with the OLS method. According to the results in Table 8, 38 of the 40 states support the deindustrialization hypothesis, while the deindustrialization hypothesis is not valid in Georgia and Arizona. Coefficients of both states in the regression do not have an "Inverted U-shape". Therefore, we cannot determine the turning points and test the deindustrialization hypothesis. According to Table 8, turning points and turning years of states differ. Although initial income per capita is vital for determining turning points, the growth rate is crucial for calculating the turning year. As stated in Section 2, many factors have an impact on the growth rate. Hence, a state with a higher growth rate has a chance to reach higher peak levels (turning points) than the one with a lower growth rate. That is, a high productive poorer state might experience a higher turning point than a relatively low productive richer state. For instance, in our sample, Iowa, Minnesota, and Ohio have a GDP per capita of $25,109, $27,085, and $27,687 in 1977, respectively. Their growth rates are 0.19%, %0,19, and 0.15%, respectively, despite the higher initial income per capita level of Ohio, Iowa, and Minnesota reaching their turning points at $35,974 and $38,971. Yet, Ohio reaches its peak level at $29,371. This pattern can be seen also in inter-state groups. For instance, Massachusetts as a higher-income state with an initial income per capita level of $26,848 in 1977 has a lower turning point than Iowa which has a $25,109 initial income per capita level in 1977. In sum, the growth performance of states is an important factor for reaching their turning point levels and years. As deindustrialization is a crucial determinant for growth performance, it inevitably affects the turning points of the states.

Fig. 3 displays the share of states' manufacturing jobs to total U.S. manufacturing jobs. Along with our empirical results, Fig. 3 suggests that the deindustrialized states have the most

Table 7
Engle-Granger (EG) Cointegration Test Results.

High Income States			
States	Tau Stat.	States	Tau Stat.
D.C.	-3.669[a]	New York	-3.208[b]
Massachusetts	-3.145[b]	Alaska	-3.127[b]
Connecticut	-2.674[c]	Delaware	-1.467
North Dakota	-2.777[c]	Wyoming	-3.441[a]
California	-3.586[a]	Washington	-4.132[a]
New Jersey	-2.359	Maryland	-3.594[a]
Illinois	-3.171[b]	Colorado	-2.878[c]
Nebraska	-2.681[c]	Texas	-4.267[a]
Hawaii	-2.018	USA	-3.495[a]
Middle Income States			
States	Tau Stat.	States	Tau Stat.
Virginia	-3.163[b]	Pennsylvania	-3.062[b]
Iowa	-3.728[a]	Minnesota	-2.664[c]
South Dakota	2.858[c]	Kansas	-4.118[a]
Ohio	-2.654[c]	Rhode Islands	-3.404[a]
Wisconsin	-3.119[b]	Oregon	-3.699[a]
Louisiana	-2.672[c]	Georgia	-3.245[a]
Utah	-3.941[a]	Oklahoma	-4.173[a]
Indiana	-2.734[c]	New Hampshire	-3.179[b]
Nevada	-1.972		
Low Income States			
States	Tau Stat.	States	Tau Stat.
Vermont	-3.461[a]	North Carolina	-2.279
Tennessee	-2.619[c]	Michigan	-2.340
Missouri	-2.192	New Mexico	-2.953[b]
Florida	-3.710[a]	Arizona	-3.016[b]
Montana	-3.641[a]	Maine	-2.638[c]
Kentucky	-2.661[c]	South Carolina	-2.185
Alabama	3.433[a]	Idaho	-3.364[a]
West Virginia	-2.788[c]	Arkansas	-2.323
Mississippi	-2.514		

Note: a denotes the rejection of null nonstationary at the level of %1 significance, b denotes the rejection of null nonstationary at the level of %5 significance, and c denotes the rejection of null nonstationary at the level of %10 significance.

Fig. 3. Rankings of States by Industrial Subsector Jobs- Share of Manufacturing Employment to Total Employment in the U.S.
Source: constructconnect.com

Table 8
Turning Points (TPs) and Turning Years (TYs) of Different Income Level States

States	TPs	GDP per capita	Growth Rate	TYs	Deindustrialization Model (DM)	Exists DM or not
High-Income Level						
District of Columbia	119,739	174,572	0.013	29	$Ln(De_{it})=-272.825+335.362Ln(Y_{it})-14.3402Ln(Y_{it})^2$	√
New York	25,512	71,831	0.018	59	$Ln(De_{it})=-131.316+28.7316\ Ln(Y_{it})-1.41578Ln(Y_{it})^2$	√
Massachusetts	26,848	71,153	0.024	40	$Ln(De_{it})=-100.966+22.4341\ Ln(Y_{it})-1.09993Ln(Y_{it})^2$	√
Alaska	72,138	70,956	0.002	-8	$Ln(De_{it})=-309.892+57.1354Ln(Y_{it}-2.55380Ln(Y_{it})^2$	√
Connecticut	32,018	67,121	0.020	38	$Ln(De_{it})$=-143.127+30.0983$Ln(Y_{it})$-1.45065$Ln(Y_{it})$2	√
North Dakota	57,336	66,099	0.027	5	$Ln(De_{it})=-89.1483+18.1386\ Ln(Yit)-0.827741Ln(Y_{it})^2$	√
Wyoming	58,638	66,083	0.011	11	$Ln(De_{it})=-193.886+37.0309Ln(Yit)-1.68642Ln(Y_{it})^2$	√
California	36,301	65,675	0.019	32	$Ln(De_{it})=-148.5494+31.06467Ln(Y_{it})-1.479325Ln(Y_{it})^2$	√
Washington	45,506	64,529	0.015	23	$Ln(De_{it})=-259.339+50.6361Ln(Y_{it})-2.35575Ln(Y_{it})^2$	√
Maryland	28,804	60,091	0.018	41	$Ln(De_{it})=-132.677+28.2520\ Ln(Y_{it})-1.37569Ln(Y_{it})^2$	√
Illinois	32,918	58,513	0.016	37	$Ln(De_{it})=-193.720+39.9254\ Ln(Y_{it})-1.91916Ln(Y_{it})^2$	√
Colorado	40,592	57,894	0.016	22	$Ln(De_{it})=-279.818+55.0436Ln(Y_{it})-2.59362Ln(Y_{it})^2$	√
Nebraska	41,833	57,639	0.020	16	$Ln(De_{it})=-114.843+23.7666\ Ln(Y_{it})-1.11670Ln(Y_{it})^2$	√
Texas	41,151	57,373	0.014	24	$Ln(De_{it})=-147.116+30.3036\ Ln(Y_{it})-1.42605Ln(Y_{it})^2$	√
USA	32,613	55,515	0.017	32	$Ln(De_{it})=-180.754+38.0238Ln(Y_{it})-1.82939\ Ln(Y_{it})^2$	√
Middle-Income Level						
New Hampshire	28,079	54,810	0.025	27	$Ln(De_{it})=-120.661+25.8477\ Ln(Yit)-1.26175Ln(Y_{it})^2$	√
Virginia	36,259	54,745	0.016	26	$Ln(De_{it})=-341.564+67.5493Ln(Yit)-3.21711Ln(Y_{it})^2$	√
Pennsylvania	21,854	54,508	0.017	53	$Ln(De_{it})=-94.0359+21.6470\ Ln(Yit)-1.08320Ln(Y_{it})^2$	√
Iowa	35,974	53,547	0.019	21	$Ln(De_{it})=-84.4956+18.4780Ln(Yit)-0.880697Ln(Y_{it})^2$	√
Minnesota	38,971	52,235	0.019	21	$Ln(De_{it})=-186.137+37.6698\ Ln(Y_{it})-1.78182Ln(Y_{it})^2$	√
South Dakota	39,759	51,832	0.019	38	$Ln(De_{it})=-156.693+31.6208\ Ln(Yit)-1.49287Ln(Y_{it})^2$	√
Kansas	32,774	51,335	0.015	30	$Ln(Deit)=-158.478+50.2980Ln(Yit)-1.53971Ln(Y_{it})^2$	√
Ohio	29,371	50,658	0.015	36	$Ln(Deit)=-192.033+40.0565\ Ln(Yit)-1.94680Ln(Y_{it})^2$	√
Rhode Islands	25,180	50,549	0.018	40	$Ln(Deit)=-223.853+46.5063\ Ln(Yit)-2.29461Ln(Yit)^2$	√
Wisconsin	34,751	50,496	0.017	22	$Ln(Deit)=-170.329+35.1231Ln(Yit)-1.67957Ln(Y_{it})^2$	√
Oregon	31,860	49,851	0.015	24	$Ln(De_{it})=-134.044+28.2459\ Ln(Y_{it})-1.36202Ln(Y_{it})^2$	√
Louisiana	33,096	48,959	0.007	56	$Ln(De_{it})=-115.593+24.5601Ln(Y_{it})-1.17996Ln(Yit)^2$	√
Georgia		48,921			$Ln(De_{it})=6.55136-0.00107749\ Ln(Y_{it})+0.0382201Ln(Y_{it})^2$	X
Utah	42,137	48,593	0.016	1	$Ln(De_{it})=-213.480+42.3085\ Ln(Y_{it})-1.98656Ln(Y_{it})^2$	√
Oklahoma	29,070	48,204	0.015	34	$Ln(De_{it})=-86.4147+19.1686\ Ln(Y_{it})-0.932555Ln(Y_{it})^2$	√
Indiana	31,601	48,060	0.015	28	$Ln(De_{it})=-147.896+31.1403\ Ln(Y_{it})-1.50277Ln(Y_{it})^2$	√
Low-Income Level						
Vermont	25,840	47,467	0.023	27	$Ln(De_{it})=-123.406+26.4394Ln(Y_{it})-1.30119Ln(Y_{it})^2$	√
Tennessee	29,752	46,741	0.018	26	$Ln(De_{it})=-237.330+48.6462\ Ln(Y_{it})-2.36131Ln(Y_{it})^2$	√
New Mexico	32,971	43,465	0.014	20	$Ln(De_{it})=-455.398+89.6321\ Ln(Y_{it})-4.30783Ln(Y_{it})^2$	√
Florida	31,976	42,233	0.013	21	$Ln(De_{it})=-1950.95+55.1360\ Ln(Y_{it})-2.65773Ln(Y_{it})^2$	√
Arizona		42,164			$Ln(Deit)=-12.06881-1.167138Ln(Y_{it})+0.096696Ln(Y_{it})^2$	X
Montana	32,226	42,158	0.011	25	$Ln(De_{it})=-260.235+52.1021\ Ln(Y_{it})-2.50960Ln(Y_{it})^2$	√
Maine	26,150	41,659	0.015	31	$Ln(De_{it})=-347.492+70.6235Ln(Y_{it})-3.47159Ln(Y_{it})^2$	√
Kentucky	31,056	41,215	0.013	21	$Ln(Dei_{t})=-247.503+32.4210Ln(Y_{it})-2.431371Ln(Y_{it})^2$	√
South Carolina	25,298	39,730	0.017	27	$Ln(De_{it})=247.317+51.3299\ Ln(Y_{it})-2.53109Ln(Y_{it})^2$	√
Alabama	27,261	39,600	0.015	25	$Ln(De_{it})=-281.435+57.6378Ln(Y_{it})-2.82172Ln(Y_{it})^2$	√
Idaho	30,121	39,072	0.016	16	$Ln(De_{it})=-221.966+45.2254\ Ln(Y_{it})-2.19264Ln(Y_{it})^2$	√
West Virginia	24,108	38,330	0.013	37	$Ln(De_{it})=--330.572+67.8141Ln(Y_{it})-3.36035Ln(Y_{it})^2$	√

shares of manufacturing employment share of all the states in the U.S.

7. Conclusion

The deindustrialization experiences of developed countries emerge as a natural result of a successful economic growth process. Studies on the deindustrialization processes of developing/less developed countries reveal the phenomenon of "premature deindustrialization", which is considered as decoupling from the industrialization experience of developed countries. Unlike previous studies that focus on deindustrialization at the country level, this study analyzes the deindustrialization trends at the regional level in the United States by applying panel and time series analysis. The results of the empirical analysis suggest that the deindustrialization hypothesis is valid in 38 out of 50 states, DC, and the U.S. at the country level. That is, there is an "Inverted U-shape" form relationship between the share of manufacturing in employment and the real income per capita. In 10 states (Arkansas, Delaware, Hawaii, Michigan, Mississippi, Missouri, Nevada, New Jersey, North Carolina, and South Carolina) there is no relationship between the share of the manufacturing industry in employment and real GDP per capita. Moreover, despite the existence of cointegration between variables, deindustrialization does not occur in Georgia and Arizona.

A striking result in this study is the relative differences between the deindustrialization tendencies in the state groups classified as high, middle, and low-income states. Our results show that deindustrialization curves in lower-income states reach a turning point at lower GDP per capita income levels and at an earlier time-span compared to higher-income state groups. Also, the turning point of the deindustrialization curve at the country level in the U.S. is at a lower per capita income level than in middle and high-income states. A possible interpretation of our results is that a state with a higher growth rate has a chance to reach higher peak levels (turning points) than the one with a lower growth rate. That is, a high productive poorer state might experience a higher turning point than a relatively low productive richer state. Despite several factors for deindustrialization such as historical background, heterogeneity of states, uneven distribution of income, trade, etc., the growth rate seems to be the crucial factor for states to experience a natural deindustrialization process.

Consequently, we suggest that the phenomenon of premature deindustrialization, which is historically observed in developing countries at a very lower GDP per capita income levels than developed countries, might exist at the regional level even in a developed country, the U.S. Further research might refer to the regional deindustrialization hypothesis in other countries.

CRediT authorship contribution statement

Sekip Yazgan: Methodology, Software, Data curation. **Cumali Marangoz:** Conceptualization, Visualization, Investigation. **Emre Bulut:** Writing – original draft, Conceptualization, Writing – review & editing.

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