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Dualism and payroll shares across US states

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ABSTRACT

This paper analyses US payroll share and components across states for the period 1977–2017. Findings include that spatial clustering in payroll shares decreased until the year 2000. States are clustered in low and high productivity groups. We relate this phenomenon to *dualism*. High labour productivity states featured high payroll shares early on, but now feature low payroll shares. We label this phenomenon *decoupling* of labour productivity from real wages. A Divisia Decomposition documents that Rust Belt states dominated the decline in US payroll share in the 1980s, whereas more recently large (coastal) states dominated. While we do not explain (potentially different) mechanisms, *decoupling* is apparent throughout.

KEYWORDS

labour share; US states; Divisia decomposition; mixture models

JEL D33, J31, J42, O51

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INTRODUCTION

The labour share of income is equivalent to the ratio of real wage and labour productivity. Its precipitous decline has led to a growing literature investigating underlying causes, not least since it illuminates interactions between labour incomes and technology. This paper provides novel evidence on the sources of the decline with a focus on *spatial* dimensions. We decompose the aggregate US payroll share – which excludes income from self-employment from compensation – by states for the period 1977–2017 and analyse its components from several angles. These state payroll shares are driven by the sectoral composition of each state's economy, and therefore related to geographical factors and agglomeration effects. The former include endowments – a bay facilitating a port and transportation hub; the Bakken Formation facilitating an extractive boom – but the focus of the latter has been on the returns to density. These ideas build on Smith (1776), Marshall (1890) and Krugman (1991, 2011) and have been categorized as related to (1) reduced transportation costs, and improved flows of (2) labour and (3) ideas. More recently, such *agglomeration economies* have been critically examined in light of the ubiquity of information technology (Ellison et al., 2010; Giuliano et al., 2019; Glaeser & Gottlieb, 2009). The evidence suggests that agglomeration still matters in manufacturing, albeit less today than earlier; and that certain service activities crucially benefit from agglomeration due to (2) and (3). Throughout our analysis, we distinguish between (1) progressive and stagnant sectors and (2) states with (predominantly) progressive or stagnant sectors. In his seminal paper, Baumol (1967, p. 415) defines 'technologically *progressive* activities in which innovations, capital accumulation, and economies of large scale all make for a cumulative rise in output per man hour' (emphasis added). In this research, we will refer to sectors as either progressive or stagnant along these lines, and refer to states with relatively high labour productivity growth as *states with progressive sectors*. A key observation is that stagnant sectors – such as healthcare and education – tend to have relatively high and increasing labour shares, whereas progressive sectors have lower labour shares and have also seen the most pronounced *decoupling*, that is, a

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pronounced decline in real wages relative to labour productivity (Mendieta-Muñoz et al., 2020). While our analysis here does not focus on sectors *per se*, this context is crucial for the assessment of results, and connects it to the literature on agglomeration economies: throughout the 1980s, Rust Belt states with heavy concentrations of manufacturing are a dominant source of the decline in the labour share. Subsequently, large (coastal) states (New York, California) with important progressive service sectors (information technology (IT), finance) take the lead in driving down the labour share. Crucially, these states with progressive activities appear increasingly disconnected from predominantly stagnant states. We label this phenomenon as an emerging *dualism*, drawing on terminology from development literature. Importantly, this emerging dualism appears to not have a strong regional or spatial dimension. The next section discusses literature and our contribution. Subsequently, we present time trends of US and state payroll shares, and assesses spatial segregation. The following section puts forth mixture models for real wages, labour productivity and payroll shares across states to investigate clustering. Next, we present results from a Divisia decomposition of the US payroll share across states. The last section concludes. Across all of it, we observe (1) decoupling of growth rates of real wage and labour productivity, specifically in states with progressive sectors; and (2) an emerging dualism in state economic performance. Decoupling occurs in all activities with high productivity growth, but appears to be dominated pre-2000 by spatially clustered states with heavy concentrations of manufacturing, and post-2000 by geographically disjoint states with heavy concentrations of progressive service activities. The latter process seems to be at the root of emerging dualism.

OVERVIEW

Here we discuss the literature and our contribution in more detail. We begin by considering several important studies that investigate the decline of the labour share on the basis of sectoral and firm-level data.

Rognlie (2016) associates the majority of the rise in the profit share with mark-ups over the user costs of capital in the real-estate sector, and thus views it as a reflection of imputed rents, on the one hand, and rising real estate prices, on the other. Karabarbounis and Neiman (2014) link the fall in the labour share to the decline in the relative price of investment goods. This implies a rise in the capital–output ratio and, under the assumption of an elasticity of substitution greater than unity, a rise in the capital share. Autor et al. (2020) focus on the rise in within-industry market shares of highly productive firms. These 'superstar' firms hold acute technological advantages over their competitors, which they use to expand market shares and, in the process, drive down the labour share. Importantly, similar patterns are discernible across six sectors, and no sector emerges as an outlier.

Other studies highlight the importance of traded versus non-traded activities. Elsby et al. (2013) maintain that increased foreign competition and subsequent offshoring of labour-intensive activities have been critical factors in the decline of the labour share since the 1980s. Manufacturing is most obviously affected in this manner, whereas the service sector is largely spared due to the generally non-tradable nature of its outputs. Utilizing a Divisia index decomposition of the labour share into four components (real wage, employment structure, labour productivity and relative prices) in 14 sectors, Mendieta-Muñoz et al. (2020) complement and extend these findings. Their results indicate that manufacturing, and specifically the large and growing gap between the sector's labour productivity and real wage contributions, plays an important role in the overall decline of the labour share.

However, so do other progressive *service* sectors, particularly finance, information technology and wholesale trade – which is also an important result in Taylor and Ömer (2019). While employment shares in these progressive sectors are falling, those of less progressive sectors – health, education, entertainment – are rising. Importantly, these latter activities have relatively high labour shares, but low real wages. This is an interesting finding for two reasons. First, it suggests that the story in Autor et al. (2020) of intra-industry productivity driven decline is perhaps incomplete given its focus on a few selected sectors. Second, it indicates a divergence in meaning between two important macro variables: the real wage and the labour share. Structural shifts of this type may in fact raise the share of income going to labour – but workers are worse off than before, since real wages are now lower.

We add to this literature a systematic and novel analysis of the labour share by states, including its spatial dimensions, and state-level components (real wages, labour productivity, relative prices and employment shares). The labour share measures the portion of total income flowing to persons for labour effort in a given time period. Since we exclude income of proprietors and the self-employed from labour compensation, we refer to our measure as the payroll share rather than the labour share. We investigate the US payroll share at the state level, and find that, on the one hand, spatial dependence has declined, likely with a diminishing role of manufacturing, and, on the other, dualism in labour productivity appears to have taken hold.

The concept of dualism is particularly relevant to our analysis. We define dualism as an increasing divide between states with (predominantly) progressive or stagnant sectors. The concept originates in development economics, and refers to the coexistence of modern high-growth and 'backward' stagnant activities. In the former, output per worker can be increased consistently via innovation, capital accumulation or economies of scale, whereas the latter see only sporadic and small gains in productivity (Bhaduri & Skarstein, 2003; Lewis, 1954). Dualism situates our research within another growing strand of the literature that investigates its emergence in recent decades in developed economies (Mendieta-Muñoz et al., 2020; Temin, 2016). Importantly, dualism in productivity performance *might* have a geographical component (i.e., be spatially clustered), or not: our findings indicate that spatial clustering of state payroll shares has decreased (largely in the 1980s), whereas dualism has increased (largely after 2000), likely associated with 'winner-take-all' activities within a small number of geographically distinct states. The remainder of this section discusses our contribution in more detail.

We implement several empirical exercises to draw out profiles of state economies, particularly in terms of their contributions to changes in the US payroll share. First, we investigate state-level payroll share, its two main components (real wage and labour productivity), and sectoral employment shares, across time and space. We employ a spatial Gini index to qualify if changes are clustered geographically, or not. Second, we utilize mixture models to further investigate the data for these distributive variables. Mixture models are useful in assessing whether a distribution is likely to be generated by one or more data-generating processes. While the method does not speak to the underlying mechanism(s) itself, it can powerfully illustrate degrees of heterogeneity and tendencies of convergence or lack thereof, and changes therein over time. Third, we use a Divisia index decomposition of US state-level data. This method provides exact contributions of four critical components (real wages, employment structure, labour productivity and relative prices) to the change in the aggregate index of the payroll share over the chosen period.

Our analysis covers the period from 1977 to 2017. We provide results for the entire period, as well as for the four major business cycles contained in this sample. Our focus on business cycles is not an enquiry into the role of market fluctuations, but rather into how US and state payroll shares vary across time. Indeed, to deemphasize cyclical narratives, we report peak-to-peak changes. These peak-to-peak sub-periods are roughly similar in length: 1979–89, 1989–2000, 2000–07 and 2007–17. Of course, the first of these brushes over the double-dip in the early 1980s, and the endpoint of the last is not a peak, but as discussion further below illustrates, relevant patterns do emerge.

We start the following section with a discussion of spatial segregation indexes for state-level real wages, labour productivity and employment shares. Trends in these variables define the trend in state payroll shares and therefore in the aggregate. Observed dynamics are heterogeneous. Between-state variability and the degree of spatial clustering in payroll shares have declined over the first two cycles. These tendencies began to reverse in 2000, which, incidentally, marks the acceleration in the decline of the US payroll share, and a pause (or even reversal) of income convergence (Ganong & Shoag, 2017; Kinfemichael & Morshed, 2019; Young et al., 2008). Labour productivity shows a similar behaviour over time as the payroll share, but exhibits higher variability (inequality) between states relative to the US mean. Between-state real wage variability remains on a downward trend throughout the entire period, suggesting a decline in wage inequality across regions. Differences in the behaviour of labour productivity and the real wage are found in other empirical exercises in this paper also, and in combination all point to decoupling of real wage growth from labour productivity growth as one of the key mechanisms behind the decline in payroll shares.

Next, we explore between-state variations in employment shares for manufacturing, progressive and stagnant sectors. We find that manufacturing is unequally distributed, spatially and otherwise, between states. Progressive sectors are more equally distributed across states compared with manufacturing, but more unequally distributed than stagnant sectors. In light of recent literature on sectoral differences in payroll shares, these findings reflect another dimension of state heterogeneity that can explain observed trends in state payroll shares.

In line with these findings, univariate mixture models indicate that the distribution of state-level real wages is generated by a single mechanism, whereas that of labour productivity is generated by two distinct mechanisms. This result pertains to the entire period. Labour productivity displays a mixture of distributions in two of the four cycles (1989–2000 and 2000–07), whereas real wages feature a single distribution across all four sub-periods. While our disaggregation remains at the state-level, and does not provide sectoral detail, these findings do indicate that *dualism* in terms of state labour productivities might have taken hold. Economic dualism could manifest geographically if certain regions are more conducive to progressive (or stagnant) economic activities, due to historical, social, institutional or political factors.[1]

Subsequently, bivariate analysis investigates the joint distribution of states' productivity performance and payroll shares across the four sub-periods. We find that two different mechanisms generate these joint distributions, reinforcing the idea of economic dualism across US states. Specifically, the difference between distributional means is initially relatively high for payroll shares, but more recently high for productivity performance. Further, the first two cycles exhibit a positive correlation between performance and payroll share, whereas the latter two suggest a negative correlation.

In essence, a widening gap between productivity and real wage growth specifically in states with progressive sectors is driving the aggregate payroll share down. This finding echoes those identified by others (Autor et al., 2020; Kehrig & Vincent, 2018; Mendieta-Muñoz et al., 2020; Taylor & Ömer, 2019). These studies document such downward decoupling in the most progressive units – either in large and innovative firms or in dynamic, high productivity sectors. Indeed, states with progressive sectors appear more likely to have experienced a decline in their payroll shares.[2] Preliminary sector-based evidence also shows that these states have, on average, a relatively higher share of employment in progressive or high productivity sectors.

Decoupling of real wages and labour productivity is the main process at work here. The Divisia decomposition presented in the next section further suggests (1) that changes in the US payroll share are dominated by these two components; and (2) that contributions of the latter outweigh the former. This is broadly consistent with previous findings that within-unit changes overwhelm across-unit (reallocation) effects. The decline in the aggregate payroll share implies that downward decoupling – growth of productivity exceeding that of real wages – in some states eclipses upward decoupling in others.

We also observe an evolving geography of state contributions to the US payroll share and their economic fundamentals. Thus, the Divisia decomposition results complement the findings regarding spatial dynamics. A regional cluster of *deindustrializing* states plays a central role in the decline of the payroll share in the early period of our sample. Our disaggregation provides no detail on sectoral issues *per se*. However, Rust Belt states, including Ohio, Indiana and Pennsylvania, drive the fall in the payroll share from 1979 to 1989. Subsequently, a *large state* effect that eschews geography emerges. New York, California and Texas show significant negative contributions, while positive contributions by Florida (and Louisiana, a middling state by size) provide a small buffer on the overall decline of payroll share. We conjecture that the decline in spatial dependence is related to the rise of finance, information and other dynamic services in select but geographically disjoint regions. One reason might be that these type of economic activities do not require local backward linkages to the extent that manufacturing does, or at least used to. Though these results should be checked at a finer level of disaggregation, they do suggest that contributions to the aggregate payroll share are less spatially clustered in more recent decades. Overall, our analysis is in line with recent work on the rise of superstar ecosystems characterized by (limited) geographically clustered superstar firms in superstar sectors (Manyika et al., 2018).

In summary, changes in state-level payroll shares are far from uniform. Instead, they differ across time and space: the Rust Belt states matter early, likely because of deindustrialization, and this period shows significant spatial correlation. Several large (coastal) states are in the driver's seat later, with a pronounced decrease in spatial dependence. The latter half of the sample shows striking heterogeneity in state-level productivity distributions and, to an extent, in sectoral composition. Across all of it, the unifying feature is a decoupling of growth rates of real wage and labour productivity, specifically in states with progressive sectors.

PAYROLL SHARE, REAL WAGE AND LABOUR PRODUCTIVITY OVER TIME AND SPACE

This section provides a profile of the US payroll share and its two main components: the real wage and labour productivity. We examine time trends in these variables, their variability between states, and include an assessment of spatial segregation. Before delving into these issues, a subsection describes our data set on US state-level payroll shares from 1977 to 2017. Subsequently, we discuss spatial characteristics of state payroll shares. Crucially, the spatial dependence of payroll shares has decreased, which appears to be due to the decline of manufacturing. Employment in this sector is more strongly clustered than employment in either progressive or stagnant service sectors.

Data: US state-level payroll shares, 1977–2017

Our measure of the payroll share is simply the ratio of employee compensation (wages and salaries plus supplements) to value added net of taxes (compensation plus gross operating surplus). We include only private industries, and hence exclude all government activities. By definition, the public sector does not have operating surpluses, and would thus not add substantially to the analysis. We also exclude real estate activities from our dataset. A large portion of income in this sector comes in the form of imputed rent, whereby owners of real estate are presumed to have paid rent to themselves. This obscures the meaning of income at the heart of this paper, and we thus exclude it from our analysis. Further, in light of Rognlie (2016), we guard against bias in the labour share decline due to relative price increases in the real estate sector. For comprehensive discussions on issues that arise with measurement of the labour share, see Elsby et al. (2013), Mućk et al. (2018) and Mendieta-Muñoz et al. (2020).

The data used consist of five state-level annual panels: compensation, gross operating surplus, nominal gross domestic product (GDP), real GDP and employment. All data were obtained via the Bureau of Economic Analysis (BEA), which compiles data from a variety of sources including the Bureau of Labor Statistics (BLS), US Department of Labor, and various other federal and state government agencies.[3]

Figure 1 depicts the time series of the thus obtained US payroll share together with state payroll shares, as well as the labour share and employee share. The latter two are headline measures issued by the BLS. The labour share is the ratio of total labour compensation (employee and proprietor) to output. The employee share excludes proprietor labour compensation. Thus, the payroll share is similar in that it excludes proprietor labour compensation, but also removes compensation of those who are self-employed as well as real estate and rental and leasing activities (compensation and output).

In general, the movements of the three aggregate series are quite similar, despite the difference in levels which we attribute to the exclusion of self-employed income, real estate sector and gross taxes in the case of the payroll share. Like other measures of the functional distribution of income, business cycle fluctuations are clearly visible. Nevertheless, a clear downward trend is observed in all three series. Over the entire period, the US payroll share declined 3.1 percentage points. Notice also that declining payroll shares are not uniformly observed across all states (see additionally Figure F1 in Appendix F in the supplemental data online). The payroll share rose in about a third of the states, while it declined or remained constant in the rest. Very roughly, coastal states have seen more pronounced declines in payroll shares.[4]

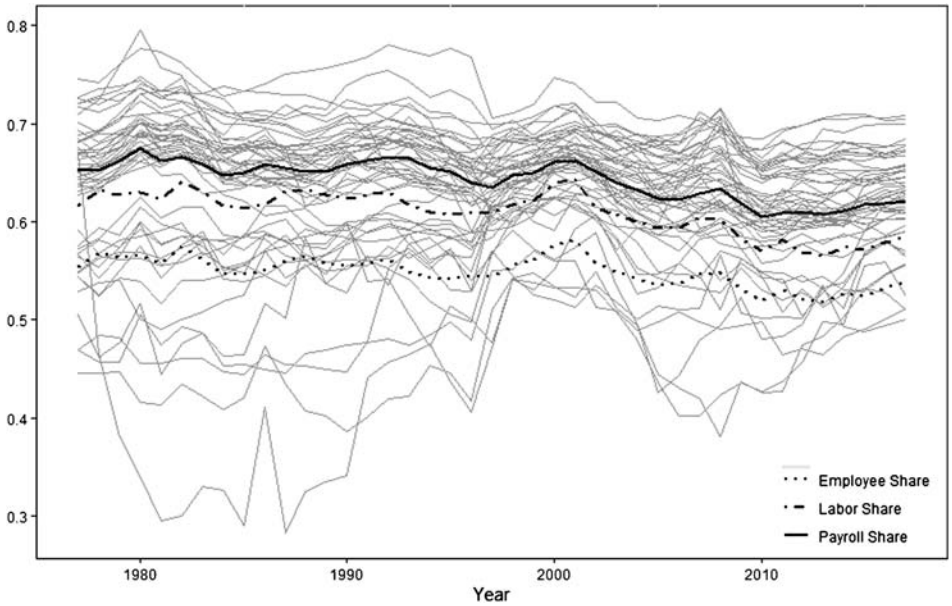


Figure 1. US aggregate and state payroll shares (1977–2017).

Spatial characteristics of the payroll share and its components

This section reports spatial characteristics of the payroll share, the real wage and labour productivity across US states, as well as employment shares by sectors. The sectoral employment composition describes the state economies' 'fundamentals' and thus elucidates relevant connections. Following Dawkins (2007) and Panzera and Postiglione (2020), we employ a spatial Gini index analysis and present three findings. First, we observe a decline in between-states differences for most variables we study until about 2000. Since then, trends suggest a shift towards divergence, especially for the payroll shares and labour productivity. Second, the largest between-state differences are found for employment shares, and specifically for manufacturing, followed by progressive services. This underscores the fundamental importance of sectoral composition. Nevertheless, and third, new sectors deemed as progressive such as information, wholesale trade and finance appear to be less regionally clustered.

To begin, Figure 2 provides evidence of payroll share heterogeneity and its spatial dimension for the US states.[5] It shows time series for three indicators: G_B is a Gini index of variability or payroll share segregation between states; G_r represents a spatial Gini index that measures how much of this variability is due to spatial arrangements; and γ, the ratio of the two Gini indices, measures the degree of spatial dependence (see Appendix B in the supplemental data online for technical details). Spatial dependence is an important feature of state payroll shares early on, but, over time, its significance has diminished quickly. Equally important, the G_B index remains low suggesting relatively low payroll share inequality. This is not entirely unexpected. After all, the payroll share is the real unit labour cost which is expected to adjust as a result of fluctuations in the real wage and labour productivity, both of which exhibit different dynamics as discussed next.

US states labour productivity and real wage data relative to the national average are shown in Figure 3. In 2017, productivity and real wages were significantly higher in large populous states such as Texas, California, New York and Illinois, and coastal states such as Massachusetts, Connecticut, Delaware and Washington. Results presented below indicate that these are also the states that have dominated the negative contributions to the aggregate payroll share. Other states display much lower levels of labour productivity and real wage and, as found by the Divisia decomposition, positive contributions to the US payroll share. Alaska and Wyoming are outlier states because of their extremely high productivity due to mining and oil extraction activities combined with very low populations.[6] Louisiana and Oklahoma also have higher than average labour productivity due to the importance of extractive industries, but their economies are significantly more diverse than Alaska and Wyoming.

Compared with the payroll share, we find more between-states variability for both labour productivity and the real wage (Figure 4). The Gini indexes G_B for both are around 0.10. Although wage segregation (G_B) is declining, a small uptick in spatial inequality (G_r) is sufficient to indicate an increase in the spatial dependence γ for the real wage in the right panel. The spatial Gini index G_r remains low also for labour productivity, suggesting the absence of *regional* dualism; see also the right panel for spatial dependence of this variable. As we will learn next, and as suggested by Figure 3, labour productivity is characterized by dualism but which is not necessarily, or as strongly, regionally clustered. We connect this observation to changes in the economic structures of states over the past decades. Our conjecture is that progressive services do not need to be regionally clustered as has traditionally been the case with manufacturing. Hence, we observe non-neighbouring states such as California, New York or Washington with higher than average labour productivity.

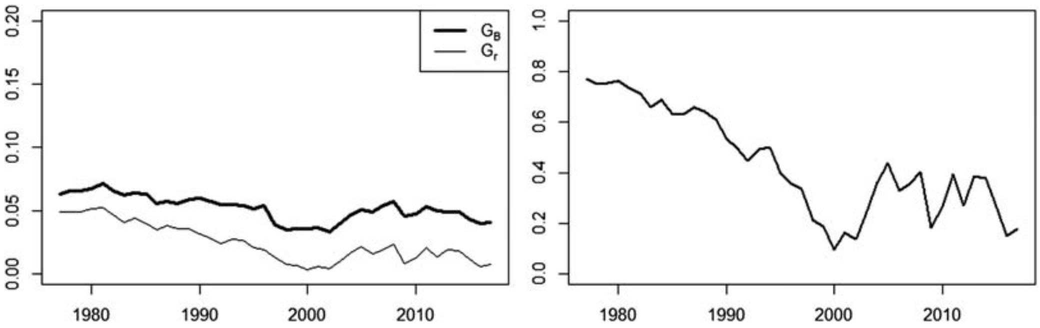


Figure 2. Spatial analysis of state payroll shares ψ (1977–2017).
Note: G_B (left) is a Gini index of between-state variability or segregation of state payroll shares; G_r (left) is a spatial Gini index of segregation of state payroll shares; and (right) the index of spatial dependence, $\gamma = G_r/G_B$.

Nevertheless, regional patterns emerge with respect to the economic structure of US states as discussed next.

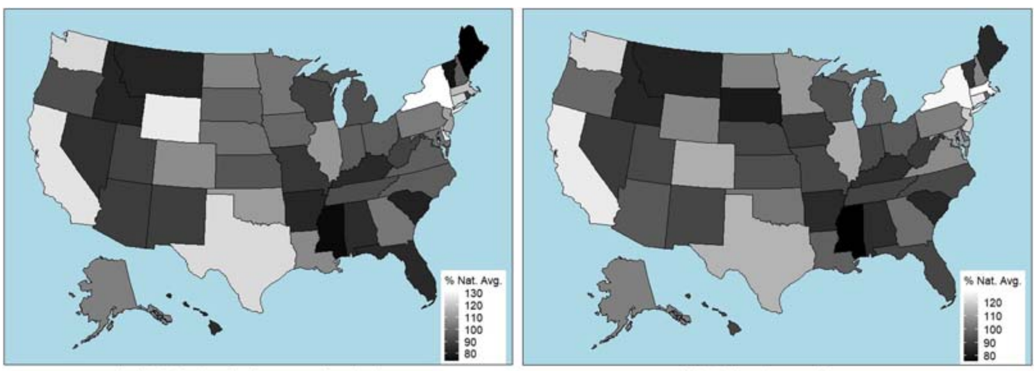
Figure 5 compares the spatial Gini index for employment shares of manufacturing, progressive and stagnant sectors. Following Mendieta-Muñoz et al. (2020), the progressive sector group consists of finance, information and wholesale trade, while the stagnant sector group covers the rest of the economy excluding agriculture, mining, utilities, transportation and warehousing. These sectors are excluded because they tend to be highly volatile and, generally, represent a small share of state economies.

Clearly, manufacturing remains unequally distributed, spatially and otherwise. Among the three groups of sectors, manufacturing exhibits the highest Gini (G_B). There is significantly less and declining between-state variability of stagnant sector employment shares. Regional clustering of stagnant sectors also appears to have diminished over time (G_r). Lastly, the progressive sector group is more segregated compared with stagnant sectors (its G_B is considerably larger), but more equally distributed compared with manufacturing. At the same time, progressive sectors have become more spatially clustered than stagnant sectors, although they remain more dispersed than manufacturing. These patterns are confirmed in the right panel, which shows high spatial dependence of manufacturing, followed by stagnant services and then progressive services. Services are, in general, less tradeable than manufactures and have increased their share of employment across all states. This is especially true of stagnant services that cover large sectors such as retail trade, education, health, social services, recreation, arts and entertainment.

These observations are relevant for understanding trends in state and aggregate payroll shares. In particular, stagnant service sectors tend to have higher payroll shares, and manufacturing and progressive services tend to have experienced the largest declines in payroll shares (Elsby et al., 2013; Mendieta-Muñoz et al., 2020). While we do not provide a complete answer regarding sectoral disaggregation, the following section offers preliminary evidence for a significant association between economic structure and the payroll share especially in the more recent period.

MIXTURE MODELS OF THE PAYROLL SHARE AND ITS COMPONENTS

This section discusses results from Gaussian mixture models for real wages, labour productivity and payroll shares across states. A mixture model is, in short, an algorithm that provides evidence on whether a distribution features significant clusters of data. The following subsection briefly circumscribes the methodology as applied here. Next, we report univariate mixture models. Results



(a) Relative labor productivity (b) Relative real wage

Figure 3. State labour productivity and real wage (2017); 2012 state chained dollars.
Note: Excludes Alaska and Washington, DC, for clarity.

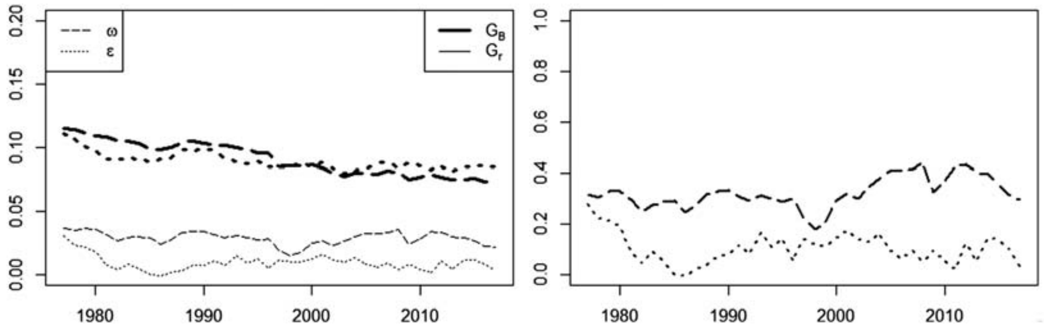


Figure 4. Spatial analysis of real wage ω and labour productivity ε (1977–2017).
Note: G_B (left) is a Gini index of between-state variability or segregation of ω and ε; G_r (left) is a spatial Gini index of segregation of state ω and ε; and (right) the index of spatial dependence, $\gamma = G_r/G_B$.

indicate that the distribution of labour productivity across states is generated by two distinct mechanisms; we label this phenomenon *dualism*. We further illustrate this dualism with bivariate mixture models of payroll shares versus labour productivity in the next subsection. Results indicate *decoupling*: states with relatively high labour productivity used to also have high payroll shares, but now feature low payroll shares. In other words, (1) states are clustered into high and low labour productivity groups; and (2) in the high productivity group, real wages have the hardest time keeping up.

Methodology: a note on mixture models

A mixture model is a probabilistic method to identify latent sub-populations in data based on one or more observed variables. Unlike other clustering methods such as *K-means*, mixture models do not perform 'hard assignment' where observations are unambiguously placed in particular groups. Rather, mixture models construct one or more probability distributions aimed at capturing the underlying data generating process.

Hence, it is assumed that the data is generated by sampling from some continuous function, also referred to as the generative model. Observations can then be sorted based on the their probability of belonging to each sub-population, thus creating a new 'latent' categorical variable for each observation in the data. The ability of mixture models to serve not only as a clustering method but also a means for identifying latent or missing variables is a primary reason for their use in both machine learning as well as applied statistics. For documentation and references, see Appendix C in the supplemental data online as well as Scrucca et al. (2016); for further discussion, see McLachlan et al. (2019). A Gaussian mixture model is a model for which each sub-population is assumed to follow a normal distribution.[7]

The process of computing a Gaussian mixture model utilizes the expectation maximization (EM) method for obtaining parameter estimates for mean(s) $\hat{\mu}$ and variance(s) $\hat{\sigma}$. EM follows a two-step process:

(1) Expectation: given the current values of vectors $\hat{\mu}$ and $\hat{\sigma}$ of length K, what is the most likely parent distribution for each observation?
(2) Maximization: given the new grouping of observations from the previous step, update $\hat{\mu}$ and $\hat{\sigma}$.

The EM process is repeated until $\hat{\mu}$ and $\hat{\sigma}$ converge. These final parameter values thus make up the optimal mixture for a model consisting of K distinct distributions. When the preferred value of K is unknown, the EM process is repeated several times with different values of K. The default range of values in the *Mclust* package used in this paper is $K \in [1, 9]$. The optimal model for the preferred value of K is selected among candidate models according to the Bayesian information criterion (BIC).

As mentioned previously, the method does *not* provide evidence on the specific mechanism(s) that generate these distributions, but powerfully illustrates statistical support for significant heterogeneity within the population. Subsequent discussion confirms such heterogeneity, and confirms *dualism* in labour productivity as well as *decoupling* of real wages from labour productivity specifically in high-performing states.

Univariate mixtures: dualism in labour productivity

We first apply the mixture model to real wage and labour productivity distributions across states for the entire sample, 1977–2017. Figure 6 reports the results. The left panel indicates that the data-generating process of (log) real wage is the same across all states. In contrast, (log) labour productivity appears to be driven by different phenomena across groups of states. More specifically, the resulting distribution for the real wage over the entire period remains unimodal. The mixture model for labour productivity produces a bimodal distribution, indicating the existence of two distinct clusters of states: one each with relatively low and high productivity levels. The states determined by the model to belong to the rightward 'progressive' distribution for labour productivity are: California, Connecticut, Delaware, Illinois, Louisiana, New Jersey, New York, Texas, Washington and Wyoming. With the exception of Wyoming and Louisiana, these are largely the same states identified above as having higher than average labour productivity and, as discussed below, significant negative contributions to the US payroll share over the period.

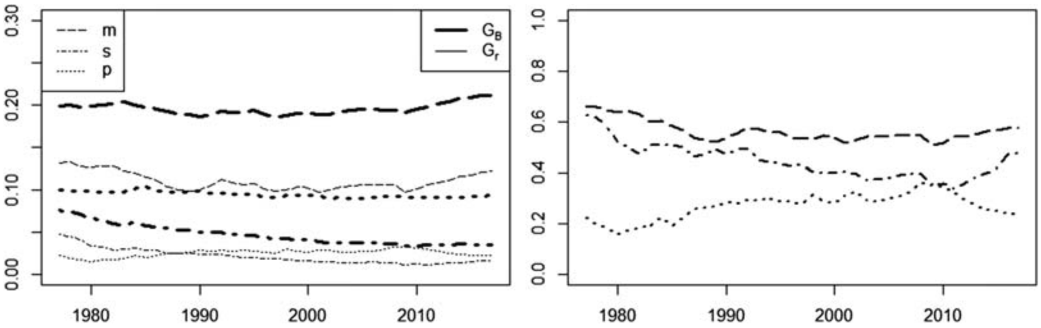


Figure 5. Spatial analysis of employment shares of manufacture (m), progressive (p) and stagnant (s) sectors (1977–2017).
Note: G_B is a Gini index of between-state employment share variability or segregation; G_r is a spatial Gini index of segregation; and (right) the index of spatial dependence $\gamma = G_r/G_B$.

The real wage continues to exhibit a unimodal distribution throughout all cycles, albeit the distribution becomes more skewed towards the right especially in the last two cycles (see Figure F2 in the Appendix F in the supplemental data online). In contrast, the productivity mixture appears to change over time. In the initial cycle (1979–89), productivity is unimodal. However, in the following two cycles (1989–2000 and 2000–07) productivity exhibits a bimodal mixture.[8] The distribution of labour productivity returns to unimodal in the most recent business cycle, but with a pronounced shoulder on the right. On balance, the evidence here clearly suggests that labour productivity levels across states appear to be the result of two distinct processes: one relatively progressive, one rather stagnant.

We posit two crucial insights. First, the bimodal distribution for labour productivity renders *dualism* a distinct possibility. Though this dualism is not regionally clustered, Figures 6 and F2 in Appendix F in the supplemental data online provide illustrative evidence.

Extensive evidence of dualism at the *sectoral* level is presented by Storm (2017), Taylor and Ömer (2019) and Mendieta-Muñoz et al. (2020). The latter connects Baumol's (1967) analysis of dualism to the observed decline in the US payroll share. Baumol's cost disease presumes that nominal wages in progressive and stagnant sectors are determined by progressive sector labour productivity. Due to a lack of productivity growth in stagnant sectors, prices have to rise to ward off a profit squeeze. The key finding is that while the terms of trade of stagnant sectors have indeed risen, a pronounced and simultaneous decoupling of wages and productivity especially in progressive sectors occurred – calling into question the very heart of Baumol's mechanism. In summary, results at the sectoral level indicate that there have been strong negative contributions to the aggregate payroll share from progressive activities (i.e., manufacturing, wholesale trade, information and finance) and positive contributions from stagnant sectors.

A similar pattern seems to arise at the *state* level, which leads to the second insight. We hypothesize that the relationship between real wages and productivity in states with predominantly progressive versus stagnant activities differs. Evidence we present in this paper confirms that decoupling has not been uniform across states. Of course, decoupling *per se* does not require multimodal mixtures, but the pertinent question is how *decoupling* and *dualism* interact.

Bivariate mixtures: dualism and decoupling

This section considers the joint distributions of payroll shares and labour productivity across states. Before we present and discuss evidence, we briefly motivate this approach with the help of Figure 7.

A state's average payroll share is shown on the horizontal axis. A move over time to the left represents a decline in the state's payroll share as its real wage falls behind labour productivity growth ($\hat{\omega} < \hat{\varepsilon}$) – thus reflecting downward decoupling. Analogously, a move to the right describes

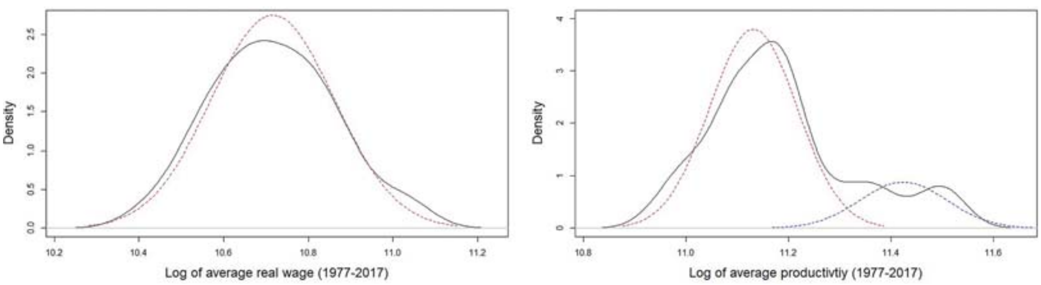


Figure 6. Result of mixture model: densities of log average annual real wage and labour productivity (2012 state chained dollars) by component for the whole period.
Note: Bold lines indicate the kernel density of the entire data, while dashed lines indicate the distributions selected by the mixture model. Excludes Alaska and Washington, DC. BIC model selection plots are available from the authors on request.

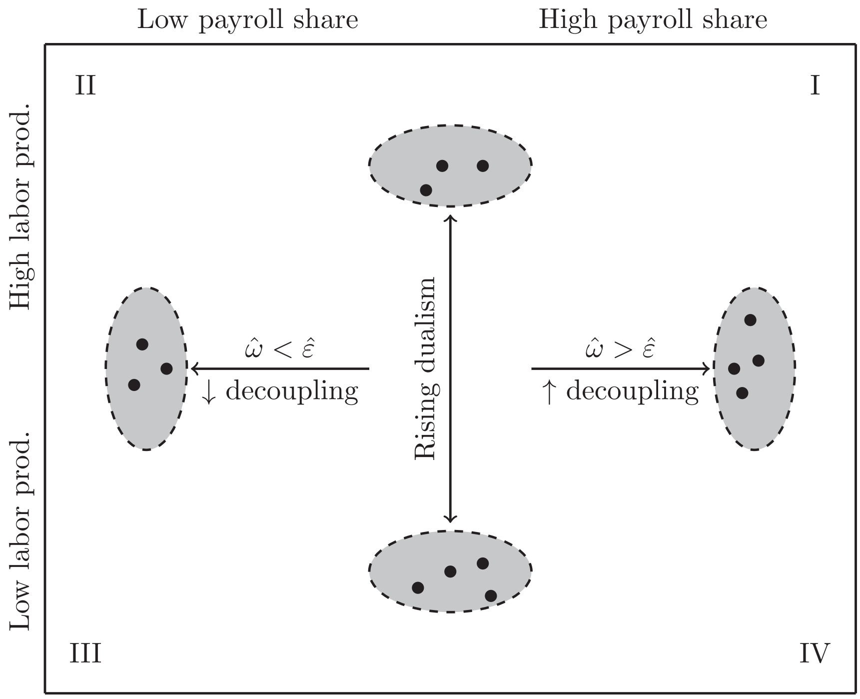


Figure 7. Decoupling and dualism: a conceptual framework.

upward decoupling, that is, an increase in the payroll share as real wages grow faster (or falls less) than labour productivity. On the vertical axis, relative labour productivity is a proxy for differences across states. It is calculated as the state's labour productivity over the unweighted population average. A vertical move reflects a widening gap between the state's economic performance and the average for the US economy.

A state can belong to one of four quadrants: high payroll share and labour productivity in quadrant I; low payroll share/high productivity in quadrant II; low payroll share and labour productivity in quadrant III; and high payroll share/low productivity in quadrant IV. Below, we apply a bivariate mixture model for each of the four business cycles. Our discussion focuses on two issues. First, emphasis is placed on the scatter and its movement over time: if groups of states move towards the left across the four cycles, we observe downward decoupling. Similarly, if some states move up while others move down over time, we observe rising dualism. Second, the mixture model lends further support to dualism *if significantly different distributional means are found to be separated along the vertical axis*.

Figure 8 features the average payroll share over the relevant subperiod, and relates these to relative labour productivity levels.[9] Following our proposed conceptual representation, all graphs are divided into quadrants by the unweighted average payroll share on the horizontal axis, and the line crossing at unity on the vertical axis representing the point where the state *j*'s level of labour productivity is the same as the unweighted average labour productivity.

We make three broad observations. First, the bivariate mixture model detects two distinct distributions across three of the four periods.[10] In short, the algorithm finds significant differences of the joint distributions of payroll share and labour productivity across states, and hence indicates distinct clusters. The distributional means differ along both vertical (productivity) and horizontal (payroll share) axis. In other words, each cycle features relatively low and high productivity and payroll share distributions. However, the location of these distributions has changed significantly over time. Crucially, the low payroll share distribution has migrated upwards towards a higher relative labour productivity, while the distribution to the right of centre has moved downwards. Dualism is apparent in that the distance between distributions increases over time. Moreover, the distribution with relatively good productivity performance had an above average payroll share initially, but the states constituting this cluster now have below average payroll shares.

Second, we highlight movements of particular states across quadrants and distributions over the four business cycles. We focus here on a comparison of first and last cycle. To begin, only states from quadrant IV (low labour productivity but high payroll share) have managed to move to quadrant I (high payroll share and high labour productivity).[11] Furthermore, the large states of California, New York and Washington, initially in quadrant I, transitioned to quadrant II by the end of the period, driving much of the decline in the US payroll share – as seen in results from the Divisia decomposition, too.

Of particular relevance are changes within the high payroll share distribution. In the first cycle, this distribution included most states aside of those with important primary activities, and the large state of Texas. In the last cycle, California, New York, Washington and Connecticut, Illinois and New Jersey had shifted left as they maintained their labour productivity rank but experienced

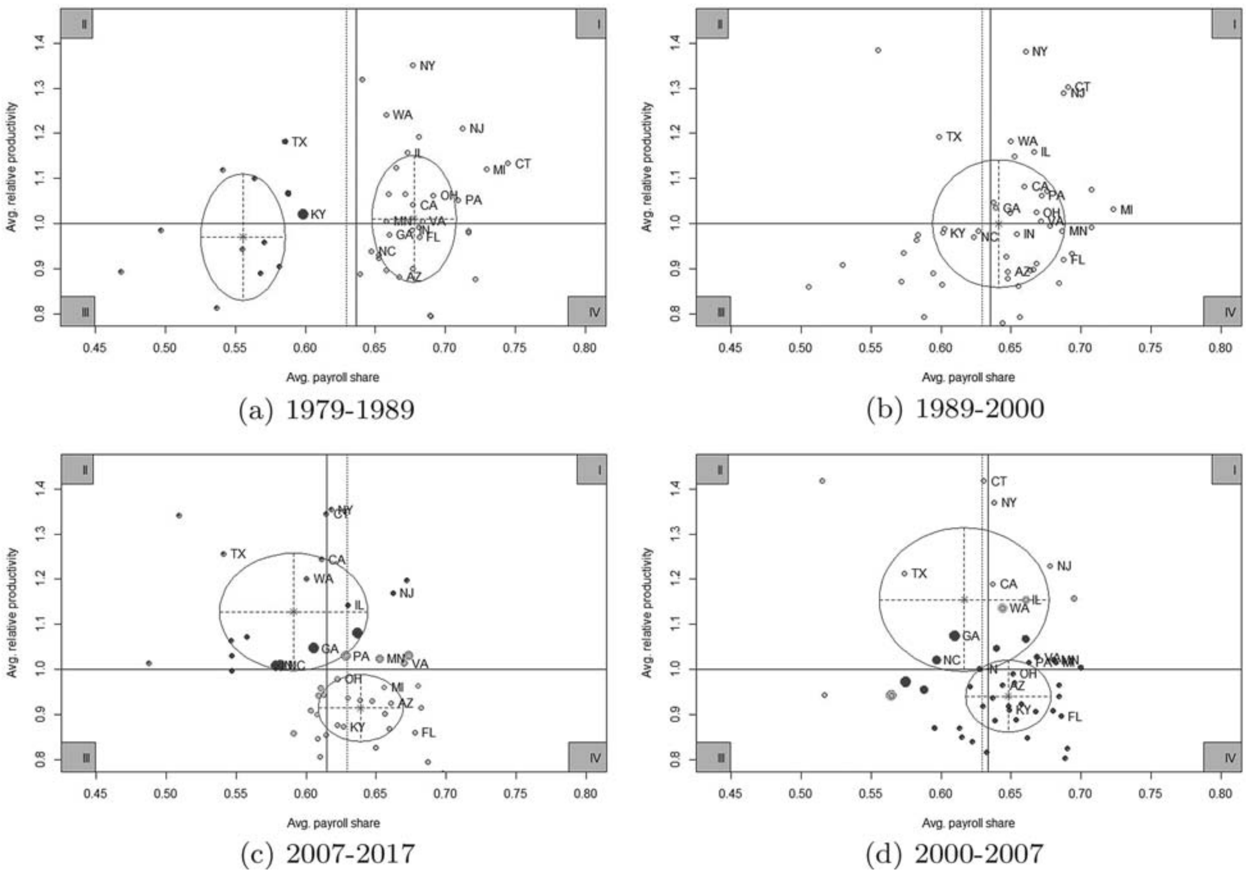


Figure 8. Bivariate mixture model analysis of the payroll share and relative labour productivity across business cycles.
Note: Dot colour indicates grouping based on the most likely generative distribution; dot size indicates the degree of classification uncertainty. For reference, the average payroll share over the entire period (1977–2017) is shown with the dashed vertical line. Excludes Alaska, Washington, DC, Louisiana and Wyoming due to their outlier nature. We label only states that, based on the Divisia exercise in next section, have contributed more than twice the (absolute) average contribution to the change in the payroll share over the entire period. The average contribution to the US payroll share between 1977 and 2017 was −0.06 percentage points. According to Table E1 in Appendix E in the supplemental data online, the states that have contributed more than twice the absolute value of the average contribution are: New York, California, Pennsylvania, Texas, Ohio, Michigan, Illinois, Indiana, North Carolina, Georgia, Connecticut, New Jersey and Washington on the negative side; and Minnesota, Arizona, Kentucky, Virginia, Louisiana and Florida on the positive side of contributions. However, as explained above, we exclude Louisiana from the analysis. BIC model selection plots are available from the authors on request.

downward decoupling. In contrast, Michigan, Ohio, Pennsylvania and Virginia remained in the distribution with low relative productivity, reinforcing the emergence of dualism suggested by the univariate analysis above.[12]

Third, and last, we connect these results to one basic indicator of economic structure. We focus on the degree of sectoral segregation between states, which we define as the ratio of progressive to stagnant sector employment. We find that, between 1979 and 2017, this ratio has declined as stagnant sector employment has expanded in relative terms in all states (with the exception of Delaware). Presumably, stagnant sectors absorbed declining manufacturing employment. More importantly, we find a negative correlation between the sectoral segregation ratio and the payroll share for peak-to-peak sub-periods. In other words, a relatively higher ratio of *progressive* services is associated with a lower payroll share. This association becomes stronger in the last two periods.[13]

We also perform *t*-tests for the segregation ratio and the payroll share means for the distributions identified in panels (a), (c) and (d) of Figure 8.[14] Statistically significant differences for the average segregation ratio of the two groups of states emerge for the last two sub-periods. Crucially, the high-productivity states' average segregation ratio is 3.5 and 4.5 percentage points higher over the 2000–07 and 2007–17 periods, respectively, compared with the average ratio for the low-productivity states. And, in line with the preceding paragraph, the same statistical test suggests that average payroll shares are different between the two distributions for the first and the last business cycle. Mean differences are −12 percentage points between the two distributions in the first cycle, and −5.4 percentage points in the last cycle.

DECOMPOSITION OF THE US PAYROLL SHARE BY STATE

This section presents a Divisia index decomposition of the aggregate US payroll share by state payroll shares and their main components (real wages, labour productivity, relative prices and employment shares). Index decomposition analysis dates back to the 1970s, when it was used to assess the effect of changes in the structure of industrial production on energy demand. Decomposition techniques have since been refined and applied widely across disciplines including economics. For an example on growth and structural change, see Dietzenbacher and Los (1998), and Mendieta-Muñoz et al. (2020) for an application to the labour share. Next, we outline details on the methodology. Subsequently, we present results for the entire period as well as the four sub-periods therein, defined by peak-to-peak business cycles. Key findings are (1) that payroll share declines in Rust Belt states dominate the 1980s, and (2) whereas large (and predominantly coastal) states matter most in the more recent period. Further, (3) across states and periods, the decoupling of real wage from labour productivity contributions stands out as the key issue.

Methodology: Divisia index decomposition

Critically, the Divisia index decomposition has the desirable theoretical property of being a symmetric and additive indicator of relative change (Ang, 2004). Its discrete representation as a Törnqvist index is also a good approximation of the Fisher ideal index; for a discussion, see Dumagan (2002). We build here especially on Diewert (2010).

The payroll share in an economy is generally defined as the ratio of nominal values of the wage bill and value added. If there are N regions or states the payroll share can be written as the ratio of the sum of state level nominal wage bill and the sum of state level nominal value added:

$$\psi = \frac{\sum_{i=1}^{N} w_i L_i}{\sum_{i=1}^{N} P_i X_i} \qquad (1)$$

where w_i, L_i, P_i, X_i are the nominal wage, employment, price level and quantity of output of state i. Multiplying (1) by PL/PL the general price level and aggregate employment, and after simple algebraic manipulations, we rewrite aggregate payroll share as follows:[15]

$$\psi = \frac{\sum_{i=1}^{N} p_i \omega_i \lambda_i}{\sum_{i=1}^{N} p_i \varepsilon_i \lambda_i} \qquad (2)$$

where $\omega_i = w_i/P_i$, $\varepsilon_i = X_i/L_i$, $\lambda_i = L_i/L$, $p_i = P_i/P$ indicates real compensation or the nominal wage deflated by the *state* price level P_i, labour productivity, employment share and terms of trade at the state level.

The following are the discrete format terms following from the decomposition:

$$D_{comp} = \exp\left[\sum (\phi_{i,t} + \phi_{i,t-n})/2 \ln(\omega_{i,t}/\omega_{i,t-n})\right] \qquad (3)$$

$$D_{prod} = \exp\left[\sum (\theta_{i,t} + \theta_{i,t-n})/2 \ln(\varepsilon_{i,t}/\varepsilon_{i,t-n})\right] \qquad (4)$$

$$D_{empl} = \exp\left[\sum [(\phi_{i,t} + \phi_{i,t-n})/2 - (\theta_{i,t} + \theta_{i,t-n})/2] \ln(\lambda_{i,t}/\lambda_{i,t-n})\right] \qquad (5)$$

$$D_{pric} = \exp\left[\sum [(\phi_{i,t} + \phi_{i,t-n})/2 - (\theta_{i,t} + \theta_{i,t-n})/2] \ln(p_{i,t}/p_{i,t-n})\right] \qquad (6)$$

where ϕ_i and θ_i are the weights, defined as the state's share of the aggregate nominal wage bill and the state's share of nominal value added, respectively. The ratio between the two weights ϕ_i/θ_i represents payroll share of state i relative to the US aggregate payroll share. The index for the change in the aggregate payroll share over the interval $[t-n, t]$ is then given by:

$$D = D_{comp} D_{empl} D_{pric} D_{prod}^{-1} \qquad (7)$$

where D is simply the ratio of end-year value of the payroll share over the first-year value ψ_t/ψ_{t-n}, or the growth rate plus one, $D = g_\psi + 1$.[16]

A positive change in state i's real wage contributes to a rise in the US payroll share, while a positive change in the state's labour productivity lowers the payroll share. The interpretation of the structural and the terms-of-trade components (equations 5 and 6) are more nuanced. The $ln(\lambda_i)$ term is negative if the employment share of state i declines. However, if the state's payroll share is below the aggregate payroll share, the weight in equation (5) is negative since $\phi_i - \theta_i = \psi_i/\psi - 1$. It follows that the aggregate payroll share increases when employment shares decline in states with lower-than-average payroll shares. This apparent improvement in the payroll share is not necessarily a positive development if the state that sheds labour (in either relative or absolute terms) is a state with higher-than-average real wage and labour productivity. In this case the change in the regional structure of the economy takes place towards states with higher payroll shares, yet a lower productivity and therefore a lower real wage in absolute terms.

The last component of the decomposition is the contribution from changes in terms of trade, equation (6).

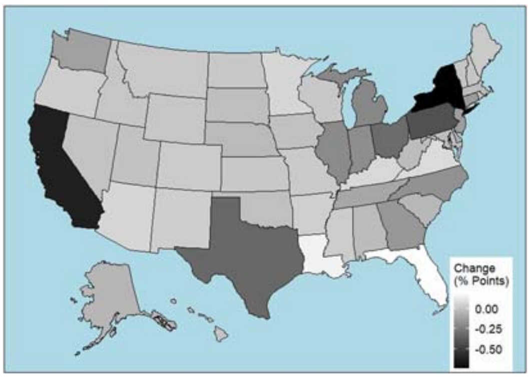


Figure 9. State contributions to aggregate labour share change (1977–2017).
Note: The map shows state contributions to the aggregate payroll share change over the entire sample period from a Divisia decomposition by state. See the fifth section for a discussion. Table 1 reports the same data in the first column (1977–2017).

The term $\ln(p_i)$ is positive if the state price level grows faster than the general price level. The final effect on the change in the aggregate payroll share depends, once again, on the state's relative payroll share. Positive changes in relative prices will add to the aggregate payroll share in states with higher relative payroll shares. The reason is that a relative price increase will increase the weight of states with higher payroll shares, driving up the aggregate payroll share.

Last but not least, the contributions from *empl* and *pric* are expected to be smaller, on average, than contributions from *comp* and *prod*. There are two reasons for this. First, by construction, *empl* and *pric* are weighted averages of growth rates of state employment shares and relative prices, respectively. Their mean in the aggregate is bound to be close to zero, for example, employment shares cannot all grow from one period to the next (Diewert, 2010). Second, the weights attached to the terms in equations 3 and 4 are likely to have a different order of magnitude – they are likely smaller for *empl* and *pric* since they represent the difference between two terms, the state's share in nominal wage bill and value added, that should be in the same range.

Results: Rust Belt versus large states, and decoupling of real wages from productivity

We begin with the total contribution of each state (Figure 9 and Table 1). New York had the greatest negative contribution of –0.74 percentage points followed by California (–0.62), Pennsylvania (–0.41) and Texas (–0.33) (see also Table E1 in Appendix E in the supplemental data online). Connecticut, Indiana, Michigan, New Jersey and Ohio also contributed significantly to the decline, as did North Carolina, Georgia and, in the north-west, Washington state. At the other end of the spectrum, Florida exhibited the greatest positive contribution of 0.20 percentage points, followed by Louisiana with 0.16, and Virginia, Kentucky, Arizona and Minnesota with about 0.07 percentage points on average each.

To illustrate the importance of weighting in the decomposition, consider Texas in more detail. Its overall payroll share increased between 1977 and 2017 by 2.2 percentage points: real wages grew faster than labour productivity in all but the third cycle. However, its total contribution to the aggregate is negative. The reason is that its share in nominal value added is much larger than its share of the national wage bill. In other words, its payroll share is below the US average, and this in turn amplifies the (negative) effect of Texas' labour productivity growth on the national payroll share.[17]

Next, we turn to aggregate component contributions. The key finding is that compensation and productivity dominate; employment structure and relative price changes are relatively minor factors. Real wages show a positive contribution of 33.6 percentage points, and labour productivity a negative contribution of 36.6 percentage points (see Table E1 in Appendix E in the supplemental data online).[18] This finding is consistent with Mendieta-Muñoz et al. (2020), who argue that changes in the payroll share are primarily due to differences between real wage and labour productivity growth. Put differently, we find that the fall in the payroll share is driven by intra-state decoupling of compensation and productivity, not shifts in state employment shares or changing relative prices. Texas is the only state that stands out with a negative contribution of −0.20 from the structural component. The reason is – again – that Texas' payroll share remains below the nation's average. As a consequence, the observed increase in the share of employment of more than 2 percentage points has an overall negative impact.

Let us now consider the four major business cycles contained in the sample. These are 1979–89, 1989–2000, 2000–07 and 2007–17. At the beginning of the period, we lose two years of data.[19] However, comparing periods peak to peak when possible is preferable. Further, and as mentioned previously, the last cycle indeed does not end in a peak, and the first brushes over the second downturn at the onset of the 1980s. Nevertheless, clear patterns emerge.

During the 1979–89 business cycle, the payroll share declined by 1.15 percentage points (Table 1). The greatest negative contributors were from Michigan, Ohio, Pennsylvania, Illinois, North Carolina and Indiana (−0.19, −0.17, −0.16 and −0.10 in each of the last three states, respectively). These states experienced strong *downward* decoupling as the real wage lagged productivity growth (see Table E2 in Appendix E in the supplemental data online). These dynamics mirror profound changes in economic structures and industrial sector activities. This is especially the case with manufacturing. The sector's payroll and employment shares dropped while, at the same time, techniques of production became more automated and regional economies faced stiff import competition leading, according to the literature, to downward pressures on wages (Acemoglu & Restrepo, 2020; Elsby et al., 2013). An equally consequential development is the emergence of monopsony in the labour markets and, hence, wage markdowns especially in manufacturing (Hershbein et al., 2019). With manufacturing concentrated spatially, it is no surprise that the Rust Belt states dominated changes in the aggregate labour share early on. In contrast, Florida and Texas, states known for the predominance of services and extractive industries respectively, stand out with relatively strong *upward* decoupling, and therefore contributed positively at 0.05 and 0.10 percentage points.

The 1989–2000 business cycle saw an increase in the national payroll share of 1.1 percentage points. Significant negative contributions arise in New York, Georgia and California (−0.19, −0.10 and −0.08).[20] Moreover, we observe a greatly diminished impact of Rust Belt states that previously drove the decline (Table 1). Louisiana, Texas and Florida remained the greatest positive contributors at 0.19, 0.14 and 0.10 percentage points, respectively. It should be noted that while positive contributions from Texas and Florida came primarily from strong compensation growth, Louisiana's contribution is due mostly to a dramatic decrease in productivity. Labour productivity in the state actually *fell* by 5.3% (see Table E3 in the Appendix E in the

Table 1. State contributions in percentage points over the entire period and cycles.

	State	1977–2017	1979–89	1989–2000	2000–07	2007–17
1	Alabama	−0.02	−0.02	0.04	−0.04	0.00
2	Alaska	−0.05	−0.04	0.10	−0.06	0.05
3	Arizona	0.07	0.03	−0.02	0.00	0.03
4	Arkansas	0.04	−0.01	0.03	−0.01	0.01
5	California	−0.62	−0.04	−0.08	−0.53	−0.11
6	Colorado	0.03	0.01	0.04	−0.09	0.03
7	Connecticut	−0.14	−0.02	−0.09	−0.14	0.06
8	Delaware	−0.07	−0.03	−0.04	−0.01	0.00
9	District of Columbia	0.03	0.03	0.00	−0.01	0.01
10	Florida	0.20	0.05	0.10	−0.03	0.01
11	Georgia	−0.15	−0.03	−0.10	−0.05	−0.03
12	Hawaii	0.00	−0.01	0.01	−0.01	0.01
13	Idaho	0.01	−0.01	0.00	0.02	−0.01
14	Illinois	−0.20	−0.10	0.08	−0.11	−0.09
15	Indiana	−0.19	−0.10	0.00	−0.12	−0.01
16	Iowa	−0.01	0.02	0.05	−0.08	0.01
17	Kansas	0.02	0.01	0.07	−0.05	−0.01
18	Kentucky	0.07	−0.04	0.10	−0.03	0.00
19	Louisiana	0.16	−0.02	0.19	−0.17	0.14
20	Maine	0.02	0.00	0.00	0.01	0.00
21	Maryland	−0.02	−0.03	0.05	0.00	−0.06
22	Massachusetts	−0.02	0.00	0.07	−0.07	−0.04
23	Michigan	−0.21	−0.19	0.00	−0.14	−0.04
24	Minnesota	0.06	0.01	0.10	−0.05	−0.02
25	Mississippi	0.03	−0.01	0.05	−0.03	0.01
26	Missouri	0.03	−0.04	0.03	0.01	−0.01
27	Montana	0.02	0.01	0.02	−0.01	0.01
28	Nebraska	−0.03	0.00	0.05	−0.04	−0.02
29	Nevada	0.00	−0.02	0.00	−0.01	0.00
30	New Hampshire	0.01	0.01	0.00	0.01	−0.01
31	New Jersey	−0.13	−0.05	−0.01	−0.02	−0.08
32	New Mexico	0.04	0.02	−0.03	0.01	0.02
33	New York	−0.74	0.00	−0.19	0.18	−0.59
34	North Carolina	−0.17	−0.10	−0.01	−0.11	−0.01
35	North Dakota	0.02	0.02	0.01	−0.01	0.01
36	Ohio	−0.31	−0.17	−0.02	−0.06	−0.12
37	Oklahoma	−0.01	0.02	0.06	−0.10	0.02
38	Oregon	0.04	0.00	0.02	−0.01	0.00
39	Pennsylvania	−0.41	−0.16	−0.03	−0.09	−0.13
40	Rhode Island	−0.01	−0.01	−0.01	0.00	0.00
41	South Carolina	−0.04	−0.05	0.02	0.00	−0.02
42	South Dakota	−0.01	0.01	0.01	−0.02	0.00
43	Tennessee	−0.10	−0.03	0.01	−0.02	−0.07
44	Texas	−0.33	0.10	0.14	−0.92	0.28
45	Utah	0.00	0.00	0.01	−0.05	0.02
46	Vermont	0.01	−0.01	0.01	0.00	0.00
47	Virginia	0.08	0.00	0.02	0.01	0.00
48	Washington	−0.12	−0.08	0.08	−0.14	−0.03

(*Continued*)

Table 1. Continued.

	State	1977–2017	1979–89	1989–2000	2000–07	2007–17
49	West Virginia	−0.02	−0.04	0.02	−0.01	−0.01
50	Wisconsin	0.02	−0.05	0.10	−0.03	−0.04
51	Wyoming	0.01	0.01	0.03	−0.05	0.03
Total		−3.13	−1.15	1.08	−3.26	−0.78

supplemental data online). Thus, while the direction of the contribution is the same for all three states, the reason behind Louisiana's positive contribution is not encouraging.

The payroll share declined most precipitously during the 2000–07 business cycle by a total of 3.26 percentage points. Texas (−0.92), previously a positive contributor to the aggregate payroll share, and California (−0.53) had the largest negative effect. High productivity growth relative to wages appears to be the source of the decline in these states (see Table E4 in Appendix E in the supplemental data online). New York, on the other hand, bounced back and had a positive contribution of 0.18 percentage points: New York's productivity contribution in these years is considerably lower relative to previous cycles, but while the state's real wage contribution decreased as well, it did so by less.

In the current business cycle, the payroll share has continued its downward trend, falling by 0.78 percentage points. California contributed −0.11 percentage points as its productivity growth continued to dominate that of compensation (see Table E5 in Appendix E in the supplemental data online). Pennsylvania, Ohio and Illinois also followed their previous downward trend with −0.13, −0.12 and −0.09 percentage points. Texas has seen compensation rebound relative to productivity, resulting in a positive total contribution of 0.28. The most striking development, however, is the dramatic reversal in New York's contribution. In the previous business cycle New York was the greatest positive contributor, but now the state has been leading the decline with a −0.59 percentage points. This shift appears to be due to a dramatic collapse in New York's contribution from compensation.

The shift in importance from Rust Belt states to large states (in terms of value added) with regards to payroll share dynamics is an important finding derived from the Divisia method. To strengthen this claim, we run simple rank correlations between states' contribution to payroll share change in absolute terms, and their average value-added share for each period. Unsurprisingly, positive and statistically significant correlation coefficients are observed for all four periods: 0.492, 0.405, 0.560 and 0.618, respectively. This correlation becomes stronger in the later two periods, indicating a strengthening in the relationship between the size of a state's economy and its contribution to changes in the payroll share.

It is further apparent that aggregate component contributions across the four business cycles differ starkly. During the last period (2007–17), the aggregate contribution from productivity growth amounts to only −4.13 percentage points, or −0.4 percentage points on an annual basis. The aggregate contribution from real compensation growth *per annum* is 0.3. In contrast, the corresponding averages across the preceding three cycles are 0.9 and −1.1 for compensation and productivity components, respectively.

In summary, we broadly identify three major results. First, the Rust Belt states of Ohio, Michigan, Indiana and Pennsylvania contributed significantly and negatively in the earliest cycle of 1979–89, but developments there have since lost their potency. Second, in the ensuing years, a large state effect has emerged: California, Florida, Illinois, New York and Texas consistently dominate contributions to the aggregate payroll share. Third, the gap between contributions from compensation and labour productivity drive changes in the payroll share. More specifically, upward decoupling between the real wage and productivity growth in states such as Florida, Louisiana, Arizona, Virginia or Kentucky have buffered the negative effects of downward decoupling in, among others, California, Michigan, New York, Illinois, Indiana, Ohio or Pennsylvania. The latter group dominated overall and, as a result, the aggregate payroll share declined.

CONCLUSIONS

This paper investigates the decline of the US labour share by states. We conduct three exercises. First, a spatial Gini index illuminates regional patterns in payroll share changes. A key result is that spatial dependence of payroll shares decreased throughout the 1980s and 1990s. Further, spatial dependence is highest for manufacturing employment shares. The decline in spatial dependence occurs simultaneously with deindustrialization in (spatially clustered) Rust Belt states. Future research could investigate whether these results are robust to further disaggregation.

Second, uni- and bivariate mixture models indicate that the distribution of labour productivity – but not that of real wages – across states has become increasingly dislocated. Our results support the hypothesis that labour productivity in US states differs in a statistically significant manner. Particularly bivariate mixture model results show that during the last two periods, states with higher labour productivity feature relatively low payroll shares, and vice versa. In the earlier periods, states with high labour productivity featured high payroll shares. This emerging dualism does not feature strong spatial clustering *at the level of the state*. Nevertheless, results appear consistent with recent literature on agglomeration economies

(Ellison et al., 2010; Giuliano et al., 2019; Glaeser & Gottlieb, 2009).

Third, Divisia index decomposition provides detailed contributions of real wages, employment structure, labour productivity and relative prices across states to aggregate change in the labour share. These results confirm that the decrease in the labour share is driven by within-unit changes, not reallocation. Specifically, the gap between productivity and real wage growth within states dominates.

Future research should investigate this pattern and the underlying mechanisms in more detail. One route forward concerns the sectoral composition of state economies: Florida, California, and Michigan all differ significantly. A second is to explicitly link relevant patterns to the hypothesis of a race to the bottom. According to our results, private business in high labour productivity states pays relatively high wages, but *apparently does not need to offer wage increases in accordance with labour productivity growth to attract labour*. Hence, the relevant hypothesis – as argued by Taylor (2020) – is that wage suppression represents the key mechanism. Indeed, meaningful associations between factors such as globalization (or offshoring) and the rate of de-unionization, and the decline in the labour share and rising income inequality both at country and regional levels have been found (Florida & Mellander, 2016; Rada & Kiefer, 2016). In our view, these observations are inconsistent with explanations that merely focus on product market structure and technological change. The prevailing climate of low inflation is consistent with firm's increasing pricing power only if employees have none.

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NOTES

1. Dualism in labour productivity could also correspond to a lack of income convergence (Magrini et al., 2015; Ganong & Shoag, 2017; Kinfemichael & Morshed, 2019).
2. There are important differences at the firm level where reallocation of value added to firms with low labour shares is an important source of the decline in the aggregate labour share, and the observed decoupling. While Autor et al. (2020) clearly document the importance of such reallocation, they further interpret it as a largely benign facet of technological change. Such claims appear premature.
3. In 1997, the BEA and BLS transitioned from the Standard Industrial Classification (SIC) system to the North American Industry Classification System (NAICS). Thus, our complete panels are constructed by linking the 1977–97 SIC and 1998–2017 NAICS data. To exclude real estate activities, we take the 'private industry' observation for the given series and subtract 'real estate and rental and leasing' for NAICS data and the corresponding activities for SIC data based on the concordance tables supplied by the BLS. For employment data, the 'private industry' observation must first be constructed by summing 'private nonfarm wage and salary employment' and 'farm wage and salary employment' before subtracting the real estate term. See Appendix A in the supplemental data online for more details. Because we do not consider sectoral data in more detail, we are not concerned with the general change in industry classification.
4. However, and as will be seen further below, changes in state payroll shares do not always reflect states' contributions to changes in the national payroll share. This is due to the importance of a state's weight, in terms of wage bill and value added, in the decomposition method – which is the topic of section on the Divisia decomposition.
5. Heterogeneity in this context can be quantified by a first-order moment such as the mean and, consequently, explored further through differences in means of groups of states. Spatial dimension and, importantly, spatial dependence 'reflects a situation where values observed at one location depend on the values of neighboring observation' (Basile et al., 2014, p. 229).
6. We exclude Alaska and Washington, DC, from the analyses throughout this section. Wyoming is also excluded from the bivariate mixture model analysis. For details, see the descriptions accompanying each figure.
7. In this regard, our approach differs from other applications of mixture models to – usually – personal income distribution data. The critical question in that literature is to identify shapes, thresholds and potentially mechanisms that define different quantiles of a distribution. For a discussion, see Schneider and Scharfenaker (2020).
8. The states in the rightward distributions in both cycles are Connecticut, Delaware, Louisiana, New Jersey, New York, Texas, Washington and Wyoming. California, Illinois and Massachusetts join the distribution in the 2000–07 cycle.
9. For reference, the average payroll share over the entire period (1977–2017) is shown with the dashed vertical line. Figure F3 in Appendix F in the supplemental data online presents the same exercise but compares the average payroll share relative with average labour productivity growth rates. Relative average labour productivity is calculated as the ratio of state i annual average labour productivity over the annual unweighted average labour productivity for all states. Average relative labour productivity growth is simply calculated as the ratio of state i percentage change in peak-to-peak labour productivity over the unweighted

average of peak-to-peak change in labour productivity for all states. The analysis covers 47 states. In addition to Washington, DC, we have excluded the resource-intensive states of Alaska, Louisiana and Wyoming which are outliers and would have distorted the analysis and data visualization significantly.

10. The exception is panel (b) of Figure 8, which shows average relative labour productivity levels vis-à-vis the payroll share in the cycle 1989–2000. In subsequent discussion, recall that the members of each distribution might be different. Note that Figure F3 in Appendix F in the supplemental data online, which does the same exercise but for average labour productivity growth rates, finds two distinct distributions across all four periods.

11. Between the first and the last business cycle, three (five) states have transitioned to quadrant I in Figure 8 (see Figure F3 in Appendix F in the supplemental data online). These were Colorado, Maryland and Massachusetts, and Colorado, Ohio, Oregon, Pennsylvania and Wisconsin, respectively.

12. As previously alluded to, our results appear to be in line with a growing empirical literature regarding the lack of income convergence between US states in recent decades. Note the simple yet pertinent argument that diverging bimodal cross-sectional distributions as in our uni- and bivariate mixture models are inconsistent with the neoclassical model of balanced growth (Quah, 1993).

13. We perform simple correlation analysis of peak-to-peak values of the segregation ratio and the payroll share. We exclude Louisiana and Wyoming due to their strong outlier status. The correlation coefficient was −0.13 in the 1979–89 cycle, and −0.05, −0.26 and −0.49 in the three subsequent periods. Note that disaggregated industry employment data under the SIC classification (1977–2001) is available only for full- and part-time employment, including proprietors and individual general partners. See Appendix A in the supplemental data online for further data sources and definitions.

14. Because the sample variances are unequal, we use the Welch approximation t-test, with a threshold p-value of 0.05.

15. Appendix D in the supplemental data online provides more detail on the specific decomposition here.

16. The time interval $[t - n, t]$ can be defined on an annual basis, over a specific period or over peak-to-peak business cycles.

17. journal reviewer summarized this to imply that states with growing labour shares can contribute negatively to the total. This is indeed the case: suppose there were two states that are identical in all variables except nominal wages; call them low-wage TX and high-wage NY. Now suppose that nominal wages rise in TX but remain below wage levels in NY, and that employment shifts to TX. Then the labour share rises in TX, but falls in the aggregate, because the shift to the lower level of wages continues to dominate growth of wages until TX wages exceed NY wages.

18. An aggregate real-wage component contribution of 33.6 percentage points implies – *ceteris paribus* – an increase in the payroll share of 33.6 percentage points. Other components are interpreted analogously.

19. Given its pro-cyclical behaviour, the payroll share increased by about 1 percentage point between 1977 and 1979. Adding up changes in the aggregate payroll shares across the four cycles leads to an overall decline in the payroll share of 4.1 percentage points between 1979 and 2017.

20. These states have sizable information and finance sectors. In the previous section we provide suggestive evidence of a negative relationship between the presence of such *progressive* sectors and the labour share. In line with this hypothesis, but approaching the topic from a micro-data angle, Dube et al. (2020) find significant wage markdowns in online labour markets for high productivity/high wage sectors; while Macaluso et al. (2019) identify a robust association between concentration in the labour markets and upskilling and wage compression, although they speak against a significant association between labour market concentration and the decline in the labour share.

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