Still Growing Together? The Spatial Distribution and Industrial Composition of U.S. County GDP since 1870*

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Abstract

We construct the first estimates of U.S. county nominal and real GDP by broadly defined industrial sectors from 1870 to 2018. Counties tended to converge from 1870 until 1970, but subsequently grew apart. Falling inequality between states explains most of the fall in county inequality from 1870 to 1970. After 1970, increasing inequality within states explains most of the overall inequality increase. Before 1970, more productive states were more equal, after 1970 more productive states were more unequal. U.S. geographic inequality is no longer primarily about differences between regions or states, but instead about differences within them. We show how the changing industrial composition affects inequality. The path to riches has changed from manufacturing to tradable services. From 1870 to 1950, manufacturing became increasingly concentrated in the richest counties. The manufacturing share is now the highest in middle income counties, while the richest counties increasingly produce tradable services. Manufacturing's contribution to inequality is the largest before 1960 and its decline is the main explanation for the fall in inequality from 1930 to 1970, while the growth of tradable services and their concentration in top metropolitan areas contribute to the nominal inequality increase after 1970. Agriculture used to be the primary activity of the poorest counties. Now, the poorer the county, the larger the share in government, education, and health. Government services decrease county inequality. We show that population growth and education used to be strongly pro-convergence, but after 1970 became neutral or anti-convergence. At the same time, agglomeration effects in manufacturing and tradable services appear to have increased.

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1 Introduction

Rough stone walls cross the woods through upstate New York, Vermont, New Hampshire, and Massachusetts. In the 1900s, New England was covered in prosperous farmland and farmers constructed the walls to move the stones from their fields. While some farms remain, for most of them the only remnants are these stone walls, a silent reminder of a past economy. Over the same period Las Vegas rose from the desert and the Atlanta economy approached New York City's. These changes, and many others, have reshaped U.S. economic geography.

Understanding how local economies grow together or apart, with their borders open to labor, capital, and trade goods gives insight into fundamental questions about growth, development, and regional inequalities. Further, the U.S. and other countries devote substantial resources to location-specific policies to help develop local economies. These policies' effectiveness rest in part on understanding how local economies have developed across time and industries.

This paper examines how U.S. counties' gross domestic product (GDP) has evolved from 1870 to 2018. We build a new data set that measures the production that takes place within each county by broad industrial sector since 1870. The data set allows for a breakdown between agriculture, manufacturing, mining, construction and many services, and makes it possible to analyze the local GDP's evolution and its industrial composition over a long period at a level of spatial disaggregation unavailable up to now. We also reconstruct, as consistently as possible, value added deflators for these broadly defined sectors. Combined with our measure of county GDP, these deflators allow us to construct measures of real county GDP and labor productivity by industry which take into account each county's sectoral composition and the relative price changes that occur over time across sectors.

Our approach, which builds on Fulford, Petkov, and Schiantarelli (2020), uses earnings and employment information contained in individual census records or in county employment records to reconstruct where services economic activity occurred in the past. We also use direct measures of output and inputs when they are available for manufacturing and agriculture. We thus contribute to a growing literature using innovative sources, such as satellite light density (Henderson, Storeygard, and Weil, 2012), to infer local GDP. We justify our approach using standard economic theory for allocating GDP using the wage bill. We show our estimates closely compare to the recent BEA estimates of county GDP after 2001. Yet our estimates are the only ones available for county GDP before 2001 and, aggregated up to states, the only estimates of state GDP before 1963, to our knowledge. In this sense, we follow in the footsteps of the efforts to produce the first National Income and Product Accounts at the National Bureau of Economic Research and what would become the Bureau of Economic Analysis within the Bureau of Commerce.

While our data can answer many questions, we focus on key results that characterize the distribution of county-level economic development since 1870.

> **Result 1**: U.S. counties tended to converge from 1870 until 1970, but subsequently grew apart.

We focus on the Theil inequality index for its attractive properties (Theil, 1967; Cowell, 2000), however, this result is robust to using other inequality measures. The same pattern holds both for real GDP per worker measured using a common GDP deflator and measured using industry specific deflators (which we discuss more below). The convergence and subsequent divergence also occurred when we limit the sample to metropolitan areas or to non-metropolitan areas.

> **Result 2**: Falling inequality between states explains most of the fall in county inequality from 1870 to 1970. After 1970, increasing inequality within states explains most of the overall inequality increase.

While in the late nineteenth century, the level of development of New York state and Georgia was very different, they converged until 1970 as Atlanta approached the GDP per worker of New York City. Meanwhile, Atlanta and New York City both diverged from their hinterlands and secondary metro areas. Rochester, NY had an identical GDP per worker to New York City from 1910 to 1970, but grew less quickly than New York City after that. Rochester has instead converged with Savannah, GA, which Atlanta passed in GDP per worker in 1960.

> **Result 3**: Since 1970, GDP per person inequality increases more than GDP per worker inequality. The difference is due to a growing inequality in the employment-to-population not due to changes in the dependency ratio.

With the growth of retirement oriented states such as Florida or Arizona, one hypothesis is that growing inequality in the dependency share is responsible for the difference between GDP per worker and GDP per person inequality. Instead, we show that inequality in the share of the population aged 25 to 54 appears constant since 1950, while growing employment-to-population ratio inequality—where some counties have far more people out of the labor force or unemployed—appears responsible for the difference.

> **Result 4**: Before 1970 there is a negative relationship between state GDP per worker and inequality; more productive states were more equal. The relationship becomes positive in the 1970s; more productive states were more unequal, particularly in recent years.

New York State, for example, had a fairly equal distribution of GDP per worker across counties from 1870 to 1970 characterized by productive upstate farms and smaller industrial cities, while Georgia was markedly more unequal and much poorer. In more recent decades, this relationship has flipped as the most productive metro areas in the richest states pull away from both rural areas and other cities.

Combining Results 1 through 4, we show that U.S. geographic inequality is no longer primarily about differences between regions or states, but instead about differences within them. This result complicates and enriches discussions about convergence (see Barro and Sala-i-Martin (1991) and Barro and Sala-i-Martin (2004) for a discussion of state convergence). On the one hand, U.S. states have converged over the long term. On the other, convergence has largely stopped, and there are growing inequalities within states, particularly in the highest GDP per worker states.

We next examine the contribution of different sectors to the evolution of inequality of county GDP per worker. Since 1870, there have been three important sectoral transitions: (1) the declining importance of agriculture; (2) the increasing and then decreasing importance of manufacturing; (3) the rise of services in general and, in particular, of what we refer to as "tradable" services such as finance, insurance, professional, scientific, and business services. These services are tradable in the sense that consumption and production can be geographically separated, unlike personal or recreational services, which generally must be consumed where they are produced. Our data uniquely capture services' importance and distribution which is crucial for understanding sectoral transitions because services have been more than 60 percent of GDP since 1880.

To understand what role different sectors play, we adapt Shorrocks (1982) and decompose the Theil index into components that show the contribution of each sector. The decomposition shows how two components help to determine an industry's inequality contribution: (1) its overall share, and (2) the correlation across counties between the industry share and county GDP per worker. Industries concentrated in rich counties will tend to increase inequality. Four major stylized facts stand out:

> **Result 5:** Agriculture used to be the primary activity of the poorest counties. Now, the poorer the county, the larger the share in government, education, and health.
>
> **Result 6:** The path to riches has changed from manufacturing to tradable services. From 1870 to 1950 manufacturing became increasingly concentrated in the richest counties. The manufacturing share is now the highest in middle income counties, while the richest counties increasingly produce tradable services.
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> **Result 7:** Manufacturing's contribution to inequality is the largest before 1960 and its decline is the main explanation for the fall in inequality from 1930 to 1970. Manufacturing's declining contribution to inequality is explained by both greater geographical diffusion and falling cross-county productivity inequality. As for other sectors, agriculture explains most of the increase in real GDP per worker inequality since 1970 and its rise is mostly due to increasing productivity inequality. Both agriculture and mining's contribution to inequality in nominal GDP per worker has large spikes associated with material prices fluctuations. Finance and professional services contribute to the rise in nominal GDP per worker inequality, mostly because they have become more concentrated.
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> **Result 8:** After 1950, government services reduce inequality. Before 1950, government services increased inequality.

Our results 5 through 8 describe the complex interaction between sectoral transitions and geographical inequality. Some changes—such as the spreading out and productivity homogenization of manufacturing—have reduced inequality. Others—such as the increasing concentration of tradable services—increase it. Meanwhile, government services reduce inequality directly and government transfers reduce inequality indirectly by supporting local non-tradable services that have come to dominate poor counties' economies.

We examine three changing factors that adversely affect convergence: declining population mobility to where it has the highest returns, decreasing education convergence, and an increase in agglomeration effects. We show that while the population of the highest GDP per worker counties used to grow much faster than other counties, they no longer grown much more rapidly. Indeed, during the 1980s and 1990s high GDP per worker counties' population grew *slower* than low GDP per worker counties. A decline in factor mobility to where it has the highest returns is a troubling development for long-term growth. Cross-country education inequality declined substantially from 1870 to 1970. Since then education convergence has slowed and the top metropolitan statistical areas (MSAs) have a growing advantage in attracting college educated workers. Finally, tradable services and manufacturing productivity in the MSAs with the highest GDP increased more quickly than in other MSAs and non-metro areas since 1970, suggesting growing agglomeration economies. We summarize these trends as:

> **Result 9:** Population growth and education used to be strongly pro-convergence, but after 1970 became neutral or anti-convergence. At the same time, agglomeration effects in manufacturing and tradable services appear to have increased.

Relationship with the literature. Our work touches on several research areas. First, there is the large literature on convergence within the U.S. (Barro and Sala-i-Martin, 1991, 1992, 2004; Barro, 2015) that typically is very supportive of relative β convergence, using 1880–2000 state level data on personal income per person.[1] There is similar evidence in favor of of β convergence for regions in Europe and prefectures in Japan. However, while absolute σ convergence for U.S. states was rapid until around 1960, it was approximately zero after. Using county level data for personal income per person for the period 1970-1998, Young, Higgins, and Levy (2008) show that there is evidence of significant absolute divergence for that period, but this is not true for county income inequality measured by the Gini coefficient. Higgins, Levy, and Young (2006) present evidence supporting β convergence for U.S. counties during the same period using personal income per person.

[1] See also Blanchard and Katz (1992) who discuss the general features of regional booms and slumps studying the behavior of U.S. state level employment, unemployment and wages over the last 40 years .

Second, a more recent literature is mostly concerned with the regional, state and city divergence after 1970 and its reasons. Moretti (2012) and Hsieh and Moretti (2015) emphasize the large and growing wage dispersion across U.S. cities since the 1960s. Hsieh and Moretti (2015) use an spatial equilibrium model to estimate that the lack of population mobility to the most productive cities has large economic costs. Ganong and Shoag (2017) focus on states and examine the importance of state housing regulations in slowing this mobility. Giannone (2019) focuses, instead, on the structural reasons for diverging productivity and analyzes the role of skill-biased technological change and agglomeration economies for wage convergence between 1980 and 2010. The importance of both agglomeration economies and housing supply factors in models of spatial equilibrium is emphasized and reviewed by Glaeser and Gottlieb (2009). Gennaioli et al. (2013) instead focuses on role of human capital in regional development. This literature relies mostly on wages or income per capita as an indicator of productivity dispersion and is mostly at the metropolitan level, while we rely on direct measures of labor productivity (real GDP per worker) in each sector at the county level calculated over a longer period of time. Our more granular data allow us to distinguish the role of inter-state and intra-state components in accounting for changes in inequality in a broad historical context. Finally, our data allows us to describe how the process of structural transformation interacts with the spatial evolution of income. A related literature examines where intergenerational mobility is the highest (Chetty et al., 2014).

Third, the emphasis on GDP per worker and its sectoral breakdown is shared by several empirical and theoretical contributions. On the empirical front, Bernard and Jones (1996) uses state level GDP data per worker and its sectoral breakdown for the period 1963–1989. They find evidence of σ and β convergence at the aggregate state level until the early 1980s, while sectors behave heterogeneously, with only manufacturing and mining displaying convergence in labor productivity. Most of the aggregate convergence is accounted for by manufacturing's productivity convergence. We also find a decrease manufacturing's dispersion and productivity inequality and we similarly emphasize manufacturing's role in accounting for changes in GDP per worker dispersion.

More generally, a broad literature uses theoretical models to understand overall growth through sectoral growth. Herrendorf, Rogerson, and Ákos Valentinyi (2014) and Comin, Lashkari, and Mestieri (2015) review this literature. In addition, Breinlich, Ottaviano, and Temple (2014) analyze regional growth and decline and discuss the role that structural transformation plays in it. Related theoretical work has emphasized the role of structural transformation for spatial growth and the process of regional convergence. Caselli and Coleman (2001) and Michaels, Rauch, and Redding (2012) focus on the transition between agriculture and manufacturing and how the movement out of agriculture helps explain the convergence of wages across regions and the process of urbanization. Desmet and Rossi-Hansberg (2009) and Desmet and Rossi-Hansberg (2014) focus on the transition between manufacturing and services and produce models that help explaining some of the stylized facts in the spatial growth distribution and its sectoral composition. In particular, Desmet and Rossi-Hansberg (2009) rationalize the negative correlation between employment growth and the initial level of employment in a model in which agglomeration economies decrease with the level of maturity of the industry. Desmet and Rossi-Hansberg (2014) instead develop a dynamic spatial model with endogenous innovation that can explain the reduction in manufacturing employment and the increasing spatial concentration of services. Our granular data covering a long period gives us a deeper understanding of sectoral transformation's role in affecting the county-level distribution of productivity. We document the relative role of concentration and within industry productivity dispersion and, most importantly, are the first to quantify the contribution of each sector to the dispersion of GDP per worker across counties.

Our finding that services such as personal and government services push towards convergence, while tradable services push towards divergence is similar to the observation by Eichengreen and Gupta (2013) on the two waves of service sector growth and Desmet and Rossi-Hansberg (2014) on the importance of the spatial concentration of services. Again, our finer spatial disaggregation at the county level, along with our sectoral price indices, and the much longer time period covered is a distinctive feature of our contribution that allows us to distinguish the role of concentration and productivity as a source of GDP per worker inequality. We show that both tradable services' concentration and productivity dispersion increased, contributing to nominal GDP per worker inequality, but not to real productivity inequality.

2 Construction of nominal and real county GDP

This section describes our construction of county level Gross Domestic Product (GDP) at current prices from 1870 to 2018 and of industry specific GDP deflators.[2] The basic issue in obtaining a measure of sectoral GDP at the county level over a long period of time is the limited information on output and inputs by sectors in the past. The value of both output and and inputs is available only for manufacturing and the value of output only for agriculture. For all the other industries, including services, mining, and construction, one must resort to an indirect method. Our main approach is to build on Fulford, Petkov, and Schiantarelli (2020) and use relative wage earnings or employment by county to allocate value added at the state level for each sector to individual counties. The details of our calculations vary from year to year based on the available data. We describe the broad outlines of our calculations below, but the full details are in Appendix B.

We extend Fulford, Petkov, and Schiantarelli (2020, FPS) in several ways. First, we create consistently measured individual sectors. Second, FPS used county-level personal income to project forward county level GDP after 1950, in this paper we build a direct GDP measure using the same basic methodology over the entire period. Third, FPS used a common national price deflator, we construct sectoral GDP deflators (described in more detail in Section 2.4) to obtain real county level GDP by sector that can then be combined to obtain aggregate real GDP. Finally, we produce county level GDP by industry, while FPS calculated total GDP at the county-group level to match their ancestry data.

We calculate county GDP for the sixteen industries for which we can construct consistent measures over time and across space: 1) Agriculture; 2) Mining; 3) Construction; 4) Manufacturing;[3]

[2]In principle, the data exist to apply our approach in 1850 and 1860. However, the massive structural change of the Civil War, particularly manumission, and the substantial expansion in the number of counties as population shifted west suggest that 1850 and 1860 would not be comparable to later periods.

[3]We can only make the division between durable and non-durable manufacturing after 1963 and have found that even then the division is not possible for smaller counties due to data not being made public to prevent disclosure (there may only be one durable goods manufacturer in a county), and so we do not break down manufacturing between

5) Transportation; 6) Communication; 7) Public utilities; 8) Wholesale trade; 9) Retail trade; 10) Finance and Insurance; 11) Real Estate; 12) Professional services (Professional, Scientific, Technical, and Business); 13) Education and Health services (Education, Health, and Social Services); 14) Recreation services (Recreation, Arts, Entertainment, and Accommodation); 15) Personal services (Personal, Domestic, Repair, and Other);[4] and 16) Government services.

2.1 Estimating GDP when not directly available

In this subsection, we outline the assumptions about production and markets that would justify our indirect approach of allocating GDP to a county according to relative wage earnings. Consider a sector such as transportation services in state s. We omit the sector subscript for ease of notation. The nominal state GDP in this sector is the sum of each county's (c) GDP:

$$Y_s = \sum_{c=1}^{C} Y_c. \tag{1}$$

Suppose that within each county c, the production by a representative perfectly competitive firm is characterized by a Cobb-Douglas production function and that the sectoral prices are common across all counties. Then:

$$Y_c = PA_c K_c^{\alpha} L_c^{1-\alpha}.$$

Then if labor is paid its marginal revenue product, wages in a county must be:

$$w_c = MRPL_c = P(1-\alpha)A_c K_c^{\alpha} L_c^{-\alpha} = (1-\alpha)Y_c/L_c. \tag{2}$$

Combining equations (1) and (2), gives that the county level production is just the fraction of

durables and non durables, or by other categories, such as "high-tech" manufacturing industries, even if such a division is possible in some periods.

[4]The breakdown of Services into the four components of Professional, Education and Health, Recreation, and Personal is driven by the ability to allocate employment or earnings into these broader groupings consistently from 1870. Narrower categories are possible in some years, but not consistently across the period.

the state wage bill in that county:

$$Y_c = \frac{w_c L_c}{\sum_{c \in S} w_c L_c} Y_s. \tag{3}$$

This approach allocates state GDP to counties based on where the labor earnings in that sector occur. While this approach assumes the labor share is the same for all counties within a state for a given sector, it does not assume a common labor share across industries or states. For exposition, we develop Equation 3 assuming firms are perfectly competitive, but we can easily generalize to the case of imperfect competition in the output market. Provided there is a common markup for all firms within a sector in a given state, Equation 3 would still hold.

2.2 Sources and methods by period

We will use Equation 3, or variations of it with stronger assumptions depending on the available data, to construct county GDP. Based on available data, we calculate county GDP at a decadal frequency up to 1950, in 1958 and 1963, and at an annual frequency from 1969. Our calculations require two steps, with some variation by period: (1) We allocate national value added by industry to states; and (2) we allocate state value added to counties.

State GDP by industry

Our first step is to calculate state GDP for the entire period. More details are contained in Appendix B.1. Starting in 1963, the BEA produced yearly estimates of state GDP by industry (U.S. Bureau of Economic Analysis, 2016), but no estimates of industry-state GDP exist before then. We project state GDP by industry backwards from 1963 to 1958 using the national industry growth rate to get estimates of state GDP for 1958. Before 1958, we rely on Equation 3 at the state level to allocate national value added in most sectors, except manufacturing, for which we have direct estimates of output and inputs, and agriculture, for which we have information on output and construct an estimate of inputs using the national input-to-output ratio.

To construct the state wage bill before 1958, we first collect estimates of state wages by industry then combine them with state employment. The 1940 census asked respondents about wages and income. We use the full-count individual records from the 1940 census to construct the average wage within each state and industry and assume that the same relative wage applies in 1930 and 1950. Before 1930, we estimate the wage distribution across states from a variety of historical sources. For example, we create a government services wage by taking an average of postal worker, municipal laborers in sanitation and sewage, and police detectives. Similarly, we use an average of two horse teamster and locomotive engineer wages to create a transportation wage distribution by state. Appendix B.1 details our construction and sources for each industry. The necessary assumption is that the wages we collect reflect the cross-state wage distribution in that industry, not that they are the average wage in the industry.

We combine our state wage by industry estimates with state employment from the decadal census individual records by allocating a census occupation to each industry to create state wage bill estimates. We use the wage bill to allocate national value added by industry to states. The National Income and Product Accounts (United States Department of Commerce, 1993) breaks down national value added by industry starting in 1929. Before that we use Gallman and Weiss (1969) for services and Wright (2006) for mining.

County GDP by industry

Our second step is to allocate state industry GDP to counties using Equation 3. The county-level information varies by period, so we summarize the difference by period below.[5]

County GDP in 1969 and after. In 1969, the BLS started publishing yearly county employment compensation by industry, so from 1969 we have all of the information required to construct the wage bill and to allocate state industry GDP (available since 1963) to each county using Equation

[5] In the census data, employment and earnings are based on place of residency and not on place of work, so commuting across county lines will overestimate GDP in some areas and underestimate it for industries other than manufacturing, where we have direct measures of output and inputs, and agriculture, for which we have data on output and can build a proxy for inputs based on state level information . Starting in 1969, we use BEA county earnings which are allocated by place of work, so commuting does not affect our estimates during the period when cross-county commutes would have been the largest problem. .

3.

County GDP in 1930 and 1940. The 1940 census asked respondents about wages and income. We use the full-count individual records from the 1940 census to construct the wage bill and the average wage within each county and industry and then apply Equation 3. We assume the same geographic distribution of relative wages within each industry holds in 1930 but use the 1930 census to calculate industry employment to create the county wage bill.

County GDP in 1950, 1958 and 1963. Our approach for 1950, 1958, and 1963 is a hybrid of our approach before 1930 and after 1969 depending on whether employment or earnings is available for each industry. We rely on the City and County Databooks (United States Department of Commerce Bureau of the Census, 2012) for these years which provide measures of employment, earnings and the value of manufacturing and agricultural products sold.

County GDP from 1870 to 1920. To allocate state GDP before 1930, we use the relative wages in urban and rural areas in the 1940 census to create an estimate of the industry by state urban-rural wage distribution before 1930. We assume the relative urban-rural wages in 1940 holds before that. We then use available wages to calculate the wage bill for urban and rural areas.[6] Given employment in education in the state for urban and rural areas from the census, we can obtain the respective wage bill. We then allocate state GDP by industry to these urban and rural groupings in proportion to their wage bill. Finally, we assume that within each state-industry-urban/rural grouping, wages are the same so we can use employment to allocate each industry GDP to counties in the state. If wages are equalized across counties in a state within an urban (rural) location, then wages cancel out in Equation 3 and county-industry GDP for urban counties

[6]The exact procedure depends on what kind of wage we observe, since sometimes we observe a state average and sometimes only an urban wage. For example, we use the state average teacher salary for wages in the education sector. To find the urban and rural wage bill in the years before 1930, we use education employment in urban and rural areas, and solve for for the relative urban and rural wage that delivers the urban-rural wage bill ratio observed in 1940 that is consistent with the state average teacher wages for that year.

is:

$$Y_c = \left(\frac{L_c}{\sum_{c \in S, Urban} L_c)} \right) Y_{S,Urban}. \tag{4}$$

This final step improves on Fulford, Petkov, and Schiantarelli (2020) who allocated national value added in a sector using employment, assuming that wages are equalized nationally in each sector. By constructing a state and industry wage distribution and a relative urban-rural wage distribution by state and industry, we are able to relax this assumption and only assume that in each sector wages are equalized within urban or rural areas within a state.

Finance and real estate

Finance, insurance, and real estate pose special challenges. For finance and insurance we use state banking capital, rather than employment and wages, to allocate national finance value added to states before 1929 because the state distribution for finance wages is unreliable before 1930, while banking capital is better measured at the state level. Using the marginal revenue product of capital instead of labor produces equations similar to Equations 2 and 3. If the risk adjusted returns are equalized, which as has some justification as shown by James (1976), we can then use financial sector capital to allocate national GDP in finance to each state. The allocation of state value added to the each county is then based on the relative wage bill or employment within each state.

Real estate poses a special problem which we largely sidestep. Existing buildings produce a flow of services which National Income and Product accounting considers part of real estate in GDP. These flows are typically measured as rent and owner imputed rent. These service flows are important because they allow the NIPA expenditure, income, and production concepts to match. We capture the construction of new buildings, but measuring the continuing service value of existing structures is harder. Moreover, while rental and leasing employment is part of real estate, employment in real estate is not a good way to allocate these existing structure service flows, which make up most of real estate GDP. Instead of using the wage bill to allocate real estate value added to counties, we instead allocate it proportionally based on county GDP without real estate. This approach means that although our measure includes real estate for consistency with existing NIPA practices, real estate is not a direct contributor to county inequality either positively or negatively.

Consistent counties and constructing industry employment

Several other data construction elements support our analysis. Appendix B.2 explains how we construct industry employment from the individual census records. Appendix B.3 discusses how we construct consistent counties over the entire period. There are relatively few changes, but counties do occasionally split and combine and keeping track of them over a long period requires care. Finally, Appendix B.4 describes the construction of county income per person during the sub-period 1950-2018 when it is available for comparison.

2.3 Comparison of our county GDP measure to other approaches

Because ours are the first estimates of county GDP, our estimates at the county level have no direct comparison for earlier periods. However, combing our county GDP into states or nationally produces GDP estimates that are comparable to other estimates. We show these comparisons in detail in Appendix C. Our national GDP estimate constructed by combining industry value added compares closely to other estimates of national GDP. Before 1969, no state GDP estimates exist, so the sum of our counties is the first estimates of state GDP for much of the period, but we compare our state estimates to early estimates of state personal income per person which have been used to study state convergence. Although the concepts are slightly different, our measure closely approximates personal income per person.

Figure A-12 in the Appendix shows that our approach matches sectoral shares of the economy provided by the statistical agencies as well, when these become available after 1929, and provide an independent measure of the industrial composition before that. Indeed, given the difficulty in calculating shares starting in 1929 and during the subsequent Depression, there is some reason to prefer our more stable estimates in the early years.

Finally, the BEA started calculating county GDP using non-public information in 2019 for the period since 2001 and we compare our county estimates to the BEA's estimates. Appendix C shows that excluding counties where mining is more than 40 percent of the economy or utilities are more than 25 percent, our measure lines up nearly exactly with the BEA measure. Excluding these counties, over the period when our measure and the one provided by the BEA overlap, the slope coefficient regressing our log GDP per person on log BEA GDP per person is statistically equal to one, the constant is statistically zero, and the R^2 is 0.92. Because our measure closely corresponds to a county GDP estimates after 2001 calculated by the BEA, these results suggest it is likely to be accurate before 2001 as well.

Main sample. For our main sample, we exclude these heavily mining or utilities counties. Our employment or wage based allocation of GDP to counties may not be as accurate for mining, so we do not want our measurement of inequality to be affected by including these high-mining counties. In excluding some counties, we divide our total period into long sub-periods to maintain as constant a sample as possible while allowing for counties to shift mining and utility concentration. From 1980 on, we exclude counties whose average mining share in the BEA estimates from 2001–2019 was greater than 40 percent and whose utility share was greater than 25 percent. From 1940 to 1979, we exclude counties whose average share mining during the same period was greater than 40 percent and utilities greater than 25 percent. We do the same exclusion for the period 1870 to 1930. In all years, we exclude counties with a population less than 2500. Together, these restrictions exclude from our main sample 6.5 percent of county-years for which we can calculate GDP. Appendix Figure A-1 shows the inequality measures we discuss in the next section with and without the sample restriction. The inequality measures are nearly the same and our exclusions tend to limit county inequality's rise.

2.4 Construction of industry specific deflators and real GDP

For some applications, our measure of nominal county GDP by industry is appropriate. For others, we would like to have real value added by industry to consider the behavior of productivity. No consistent measure of prices by industry exist over the entire time period. We construct a continuous long-term industry-specific national value added deflators, albeit an imperfect one, by splicing together the deflators available for each sub-period, each constructed with various methodologies. Unlike our allocation of industry GDP, which is based on substantial micro-data, the industry price indices are highly dependent on the quality of the sources. We provide a summary of our approach and of the available data here but give more details in Appendix B.5 and sources by industry in Table A-1.

We rely on a number of sources to construct our industry deflators at the national level. To be consistent with the data available at the county level, our industries are often broader than other measures, particularly after 1947. We rely on Kendrick (1961, chapter 6) for most industries for the period 1900-1940. He provides a measure of "unit value added" defined as the value of output divided by the quantity of output. Under the assumption that input and output are used in a fixed proportion one can derive the value added deflator that would obtain when real value added is calculated using the double deflator method (see the calculation in Appendix B.5). For the period before 1900, we use the value added deflator provided by Gallman (1960) for commodities. We rely on Gallman and Weiss (1969) and Barger (1955) to construct a value added deflator for the service sectors, basely mostly on the cost of labor inputs. From 1947 onward, we use the BEA chain-weighted value added deflators for sub-industries combined into an overall Fisher index for the industry.[7] We splice the two indices using the fact that Kendrick's data are available until 1953. We use a national GDP deflator for industries between time periods when we have no available source.

Splicing indices constructed from different data sources and with different methods is obviously imperfect, but the overall measure does well compared to other measures constructed in different ways and with different assumptions. Appendix Figure A-14 shows the aggregate GDP deflator implied by dividing nominal GDP by an estimate of real GDP created by adding our real sectoral GDP estimates. The resulting implied GDP deflator is nearly identical to the aggregate GDP deflator from Sutch (2006) over the entire time period.

[7]We rely on the chain-weighted GDP deflators because the traditional not chain-weighted based price indices are not available for the most recent years.

3 The distribution of economic activity over space and time

This section examines how the distribution of GDP per worker and per person has evolved over space and time. In the next section, we will discuss how these changes are related to the changes in industrial composition at the local level, so we focus on GDP per worker to measure productivity.

At a county level, the U.S. encompasses all levels of development, so studying U.S. counties gives insight into both unequal distributions and growth over time. Figure 1 shows the distribution across counties of the log GDP per worker in 1880, 1920, 1970, and 2018. Panel (A) shows GDP per worker deflated using a common deflator, Panel (B) shows real GDP per worker measured using our industry deflators, and Panel (C) shows GDP per person. The U.S. has grown rapidly since 1870 and this growth is evident as the county distributions shifts right, although the growth slows from 1970 to 2018. In 2010 dollars, our measures suggest many 1880 counties were as poor as the poorest countries have ever been with GDP per worker at or below \$600 while the highest GDP per worker counties in 2018 are as or more productive than any high income country.

Figure 1 also shows that county inequality was large in 1880 and 1920 and decreased until 1970. Less obviously, the spread of the distribution appears to have increased from 1970 to 2018. To measure the change in inequality more precisely, we next examine single inequality indices.

3.1 Inequality over time

We use the Theil inequality index to describe the evolution of GDP per worker:

$$T = \frac{1}{n} \sum_{c} \left(\frac{y_c}{\bar{y}} \ln \frac{y_c}{\bar{y}} \right)$$

where y_c is GDP per worker and $\bar{y} = \frac{1}{n} \sum_c y_c$ is the mean of y_c. Unlike many other measures, the Theil index is additively separable, so that we can decompose overall inequality into an across-state and a within-state component.

Figure 2 shows GDP per worker inequality over time. The shaded areas divide inequality into within state inequality and between state inequality. The Theil index is scale indifferent so it does not matter whether GDP per worker is deflated by a common deflator or not. Figure 3, on the other hand, uses our industry specific deflators to measure industry level labor productivity. While each industry deflator is common across counties, the county industrial mix is not, so these deflators affect county inequality. We use the term "common deflator" to indicate a single national GDP deflator (from Sutch (2006) historically and BEA more recently) and "real" or "industry deflator" to indicate we are using our industry deflators.

The Theil index in Figures 2 and 3 makes more precise what we had already observed in Figure 1:

> **Result 1**: U.S. counties tended to converge from 1870 until 1970, but subsequently grew apart.

Appendix Figure A-2 shows the Gini coefficient and the standard deviation of log GDP per worker and that our overall conclusions are not affected by the choice of a specific measure. Industry deflated GDP per worker inequality (Panel (B)) increases much more than GDP per worker deflated by a common deflator (Panel (A)) since 1970, suggesting that industrial composition is important for understanding productivity inequality. We discuss the sectoral explanations for these increases later in Section 4.

Figures 2 and 3 also reveal that most of the inequality decline until 1970 is between states, although within-state inequality also declines. The increase since 1970 has been mostly within states. There is almost no increase in across state nominal GDP per worker inequality., but we observe a small increase across states in real GDP per capita inequality. We summarize this contrasting pattern as:

> **Result 2**: Falling inequality between states explains most of the fall in county inequality from 1870 to 1970. After 1970, increasing inequality within states explains most of the overall inequality increase.

Our Results 1 and 2 contributes to and extends a large literature (Barro and Sala-i-Martin, 1991, 1992, 2004) that has found that U.S. states converged both relatively (β convergence) and absolutely (σ convergence) from from 1880 until 1960 using state level data on per capita personal income and that state convergence has slowed or stopped since then. While state-level convergence was the primary contributory factor early on, our county measures show that state convergence has mostly stopped and inequality is now explained mostly by within state inequality. The spatial granularity of our county-level data distinguishes our contribution and allows us to decompose the evolution of GDP per worker inequality in the U.S. into an across-state and a within-state component.

Figure 4 Panel (A) shows GDP per person inequality which is higher than GDP per worker inequality, shows a more rapid inequality increase since 1970 but a similar decline before then. The difference between GDP per person and GDP per worker is the employment to population ratio. The gap between per person and per worker inequality has grown since 1970, suggesting that employment inequality has increased.

Panel (B) shows two ways to measure demographic labor force shares. Employment to population is the total employed in a county compared to the total population.[8] The prime-age share is the share of the population aged 25-54. The prime-age share captures a version of the dependency ratio—the share of working age adults to non-working population—while the employment share captures the share actually working. While prime-age share inequality has been relatively flat since 1970, employment-to-population inequality has been increasing. Panel (B) suggests the growth of new retirement communities in places like Florida and Arizona and the "hollowing out" of rural areas, as young people leave, are not major contributors to county inequality. Demographic change's overall contribution to inequality changes since 1970 appear minimal; instead the difference between GDP per person and per worker appears to come from employment. We summarize these results as:

> **Result 3**: Since 1970, GDP per person inequality increases more than GDP per worker inequality. The difference is due to a growing inequality in the employment-to-population ratio not due to changes in the dependency ratio.

[8]A word of caution is necessary, however. The sharp increase in employment inequality from between 1950 and 1960 may be driven by a change in definition. In the census micro-data before 1950, labor force participation is defined as having a market occupation, whereas after that we measure employment by the number of jobs. Starting in 1969, the definition is consistent from the BLS, so the increase in employment rate inequality is meaningful after 1969.

3.2 The geography of GDP per worker

The rise in within state GDP per worker inequality changed the geography of production in the U.S. Figures 5 and 6 map the county difference from U.S. GDP per worker in 1880, 1920, 1970, and 2018 using a common deflator. Counties that are richer than the average appear in blue, counties that are much poorer in red, and counties about average are in yellow. Production tends to be concentrated in highly populated, but geographically small, metropolitan areas so below average (red) counties take up more surface area then the above average (blue) counties. Put a different way, more than half of counties are below U.S. GDP per capita and these counties tend to be large in area.

In 1880 and 1920 there are clear regional differences. The Northeast and Midwest are blue and yellow, as are California, Washington and Oregon. While there are pockets of blue or yellow in the South, most Southern counties were much poorer than than average. By 1970 this pattern had shifted and regional difference were much less clear, and by 2018 it had completely shifted. By 2018, there were no longer fairly uniformly richer regions and poorer regions. The entire country had become a patchwork of small dots of blue and yellow, surrounded by a sea of red. Just as state inequality has fallen, while within state inequality has risen, now the U.S. is composed of mostly red areas with small dots of green in city areas. The maps show the geographic effect of the declining across-state inequality in Figures 2, 3, and 4.

There has been a corresponding shift in the production center of the U.S. that helps show that regional convergence is largely finished. The square in each map is the geographic center of production in the U.S. (using county centroids weighted by county GDP) and the circle is the geographic center of population. In 1880, following the Civil War and incomplete Reconstruction, the square is far north, in a line with Philadelphia and just south of Detroit. Over the next 130 years the square grows and slowly shifts south and west. In 1880, the circle is much further south than the square, showing that while production is mostly in the Northeast and Midwest, the population is more evenly spread. While the circle shifts south and west as well, by 1970 they nearly coincide as the square moves west and south as the relative GDP of these regions grows. By 2018, the center of the U.S. economically was also its population center.

The differing stories of Atlanta and the rest of Georgia and New York City and upstate New York illustrate the new geography of inequality. Atlanta has been growing quickly, and while not as productive as New York City, it has converged substantially. It has brought its closely surrounding counties along, but it has diverged from the rural areas of Georgia and secondary cities. Appendix Figure A-3 shows this process for New York City and Rochester, NY, and Atlanta and Savannah, GA. The importance and size of the economy of Atlanta means that the state of Georgia has converged to New York state, but the large gains are mostly for Atlanta and adjacent areas. Secondary Georgia cities, such as Savannah, and rural areas have been left (relatively) behind. From 1870 to 1970, New York City has continued to grow, although not as fast as Atlanta, while upstate New York has been getting relatively poorer. There used to be significant manufacturing hubs in Rochester (anchored by Kodak) and other mill towns, and upstate New York was an important agricultural producer. Rochester's GDP per worker was equal to New York City's from 1910 to 1970. With the relative decline of these upstate counties, New York City has increasingly diverged from the rest of the state, just as Atlanta has diverged from Georgia. The GDP per worker of Rochester and Savannah are now nearly the same.

These same patterns exist in many states, including Massachusetts where manufacturing cities in the western part of the state have diverged from the Boston metropolitan area. Figure 7 shows the GDP per worker (common deflator and industry deflator) of the top 20 MSAs by total GDP in 2018, all other MSAs, and all other counties.[9] Examining metro areas over long periods can be treacherous because metro areas today are not the same as the past. Las Vegas had a population of nearly zero in 1900, for example. Nonetheless, among these groups there was substantial convergence until approximately 1960. Since 1960, when the comparison is more reasonable, the top 20 MSAs have grown more quickly than other MSAs, while other MSAs and non-MSAs have grown

[9] We define these MSAs using the BEA 2016 definition, including all counties that are part of the MSA. The top 20 MSAs are the largest nominal GDP MSAs according to our GDP measure in 2018. They produce slightly less than 50 percent of all output in 2018. They include, in ascending order of GDP: Charlotte, Miami, Baltimore, Denver, San Diego, Detroit, Phoenix, Minneapolis, San Jose, Washington D.C., Seattle, Atlanta, Philadelphia, Boston, Houston, Dallas, San Francisco-Oakland, Chicago, Los Angeles, and New York.

at nearly the same pace. The top cities pulled away from the rest of the country.

An extensive literature examines the convergence or divergence of metropolitan statistical areas in recent decades (Moretti, 2012). Our data go much further back that this literature which focuses on wages rather than GDP. Keeping in mind that comparing current MSAs before 1950 is problematic, Figure 8 shows how inequality among MSAs (defined an MSA as all counties in a given MSA in 2016), among non-MSA counties, and the ratio of MSA to non-MSA GDP per worker. The inequality decline from 1870 to 1970 occurred both among MSAs and among non-MSAs. The ratio of MSA to non-MSA GDP per worker also declined during that time. Since approximately 1970, MSA inequality increased, while non-MSA inquality moved up and down as commodity prices moved, but generally increased. The ratio between MSAs and non-MSAs GDP per worker decreased from 1900 to 1960 and has increased since 1970, contributing to the rise in inequality across all counties. Our results using GDP are thus consistent with increasing wage dispersion documented in the MSA literature, but we show that a similar dispersion also occurred among non-MSAs. Divergence is not a phenomenon confined to cities.

3.3 Relationship between state GDP per worker and inequality

A different way to understand how across-state convergence and within-state divergence shaped the geography of production is to look at which states are the most unequal. Figure 9 shows how state GDP per worker relates to inequality within states. Before 1970, high GDP per worker states were the most equal. The relationship became mildly positive in the 1970s and strongly positive more recently so that the highest GDP per worker states are also the most unequal. Appendix Figure A-4 shows the relationship is negative before 1958 and becomes positive in the 1970s. Many large urban centers were established largely for their role in trade. In cities such as Chicago, New York, St. Louis, San Francisco, New Orleans, Galveston (and later Houston), and Charleston, the primary industry was moving, trans-shipping, packing goods, and financing the moving of goods. New York and Chicago, through the Erie Canal and then railroads, were the primary U.S. destinations of a vast agriculture industry. This type of urban area focused on trade industry required a highly productive catchment area. New York City had high GDP because upstate New York had high GDP. After 1950, this relationship no longer holds as urban areas become decoupled from their hinterlands. We summarize this relationship as:

> **Result 4**: Before 1970 there is a negative relationship between state GDP per worker and inequality; more productive states were more unequal. In the 1970s the relationship becomes positive; more productive states were more unequal, particularly in more recent years.

4 Structural transformation in the U.S. and its contribution to inequality

We have documented how the county-level GDP per worker distribution evolves from 1870 to 2018 and described its main features. This long period encompassed a series of structural transformations as well, such as the decline in the role of agriculture, the rise of manufacturing and the increasing importance of services. Our data, with their sectoral dimension, allows us to document this transformation and provide new evidence on how it has affected inequality. We start by summarizing the overall industrial composition. We then show how GDP per worker and industrial composition have evolved in Section 4.1. In Section 4.2, we formally decompose inequality by sector.

Panel (A) in Figure 6 show the evolving aggregate share of nominal GDP by sector and Panel (B) shows employment shares by sector. Figure 6 captures the shrinking share of agriculture over the entire period, the increasing importance of manufacturing until the early 1960s, followed by a decline in importance, and the rising services' share that accelerated from 1960 onward. Manufacturing's declining share in Figure 6 does not imply a decline in manufacturing production. The U.S. produces more manufactured value added now than in the 1950s, and is much more productive, so it employs fewer people.

While it has received somewhat less attention, the structural transformation within services is substantial and because, services make up more than half the economy since at least 1870, just as important. Figure 6 shows the shrinking share of personal services particularly after 1960, of retail trade over the entire period, as well as the rising importance of professional and technical services after 1930, the rise in importance in finance, insurance and real estate during the whole period, with the significant exception of the two decades following the Great Depression. Finally, the share of services in education and health services expands rapidly after 1950 and government expands after 1930.

4.1 Industry shares

Figures 11, 12, and 13 show how the importance of each industry varies from low GDP to high GDP counties. They contain the county share of GDP per worker (common deflator), real GDP (using the industry deflators), and employment plotted against log GDP per worker for several major grouped industries at different points in time. To reduce the complexity and for ease of presentation, we group industries which have a similar role in production or consumption into: Tradable services, which includes financial, insurance, and business and professional services; Non-tradable services, which includes recreation, personal, and retail services; Trade services including wholesale trade and transportation; and government, education, and health services. We deflate log GDP per worker using a common deflator to keep it on a comparable scale, but it could equally well be expressed as the rank from lowest nominal GDP to highest nominal GDP in a given year.

Low GDP per worker counties used to be primarily agriculture counties. This relationship became less and less important over time until in 2018 there is no strong relationship. Indeed, as a share of nominal GDP, agriculture is now a slightly increasing share of higher GDP per worker counties.

From 1870 to 1930, manufacturing became increasingly the activity of high GDP per worker counties. From 1980, manufacturing as a share was higher in middle GDP per worker counties than either low or high GDP per worker counties. High manufacturing concentration is no longer the sign of being a high GDP per worker county, but is still a valuable contribution to GDP. Trade services (transportation and wholesale trade) were much more common in high GDP per worker counties in 1870. As discussed earlier, many urban areas were defined by their role in trade. This concentration declined until, in 2018, trade services were fairly evenly spread.

Tradable services, on the other hand, have become increasingly the activity among high GDP per worker counties. These services have become increasingly concentrated in a few highly successful urban areas. Non-tradable services, on the other hand used to be either an approximately equal share of low and high GDP counties, or an increasing share of employment in high-GDP counties. They have become more common in low-GDP counties where relatively little other productive activity occurs, but capital transfers, whether from government or holding of financial securities, still support consumption of locally produced and consumed services.

Government, education and health services used to be an approximately equal share of high and low GDP per worker counties, but have come to be a large share of the lowest GDP counties. We show in the next section they are actually equalizing.

We summarize these results as:

> **Result 5:** Agriculture used to be the primary activity of the poorest counties. Now, the poorer the county, the larger the share in government, education, and health.

> **Result 6:** The path to riches has changed from manufacturing to tradable services. From 1870 to 1950 manufacturing became increasingly concentrated in the richest counties. The manufacturing share is now the highest in middle income counties, while the richest counties increasingly produce tradable services.

4.2 Industry contributions to inequality

We next turn to understanding how changes in industrial composition explain the overall changes in inequality across countries. To do this, we develop a sectoral decomposition of the Theil index. Shorrocks (1982) provides an axiomatic approach to breaking down income inequality into the components coming from different income sources. Because we consider GDP per worker, not total GDP, and we are interested in the contribution of various sectors to aggregate productivity inequality, the Shorrocks (1982) approach is not directly applicable. However, we develop a variant of it that provides a measure of each industry contribution to inequality.

Denote the GDP share of each industry $s_c^k = Y_c^k/Y_c$, where $\sum_k s_c^k = 1$, summing over k constituent industries. Then the Theil index can be broken into k "pseudo-Theil" components giving the contribution of industry k to inequality:

$$T = \frac{1}{n}\sum_c \left((\sum_k s_c^k) \frac{y_c}{\bar{y}} \ln \frac{y_c}{\bar{y}} \right) = \sum_k \left(\frac{1}{n} \sum_c s_c^k \frac{y_c}{\bar{y}} \ln \frac{y_c}{\bar{y}} \right) = \sum_k \tilde{T}^k.$$

The industry contribution can alternatively be written also as:

$$\tilde{T}^k = \frac{1}{n}\sum_c s_c^k \frac{y_c}{\bar{y}} \ln \frac{y_c}{\bar{y}} = \frac{1}{n}\sum_c \hat{s}_c^k \frac{y_c^k}{\bar{y}} \ln \frac{y_c}{\bar{y}}$$

where $\hat{s}_c^k = N_c^k/N_c$is the share of workers in sector k in county c (because $s_c^k = \hat{s}_c^k \frac{y_c^k}{y_c}$). Unlike a standard inequality index, it is possible for the pseudo-Theils to be less than zero.

We can rewrite the industry pseudo-Theils in a more intuitive way. There are two components that determine when the contribution of industry k to inequality will be positive or negative. One is the mean share because small industries necessarily contribute relatively little on average to inequality. The other contribution is the covariance of the share with the Theil component $\frac{y_c}{\bar{y}} \ln \frac{y_c}{\bar{y}}$. Formally, the psuedo-Theil can also be rewritten as:[10]

$$\tilde{T}^k = Cov[s_c^k, \frac{y_c}{\bar{y}} \ln \frac{y_c}{\bar{y}}] + \bar{s}^k T \tag{5}$$

where $\bar{s}^k = \sum_c s_c^k$ is the mean share of GDP in industry k.

Equation 5 helps provide intuition for the psuedo-Theils. If all counties have the same share, so the covariance is 0, then the contribution of industry k is simply its average share of the Theil.

[10]Define $x_c = \frac{y_c}{\bar{y}} \ln \frac{y_c}{\bar{y}}$ and note that $T = \bar{x} = \frac{1}{n}\sum x_c$. Then

$$\begin{aligned} Cov[s_c^k, x_c] &= \frac{1}{n}\sum (s_c^k - \bar{s}^k)(x_c - \bar{x}) \\ &= \frac{1}{n}\sum (s_c^k x_c) - (s_c^k \bar{x}_c) - (\bar{s}^k x_c) + (\bar{s}^k \bar{x}_c) \\ &= \tilde{T}^k - \bar{s}^k T - \bar{s}^k T + \bar{s}^k T = \tilde{T}^k - \bar{s}^k T. \end{aligned}$$

Mechanically, larger industries contribute more to inequality in the second term.

Industries with a larger positive covariance between the share and the Theil component also have a larger contribution to inequality in Equation 5's first term. The relationship between y_c and $\bar{s}^k$ is not entirely intuitive because the Theil component $\frac{y_c}{\bar{y}} \ln \frac{y_c}{\bar{y}}$ is not a monotonic transformation of y_c. However, if $y_c/\bar{y} > e^{-1} \approx 0.37$, then the Theil component is increasing in y_c. The implication is that, for all but the poorest counties, a positive relationship between y_c and s^k indicates a positive covariance between the share and the Theil component. Figures 11, 12, and 13 provide intuition by showing the relationship between y_c and s^k relationship directly, measuring s^k in several ways.

Figure 14 shows the share each industry contributes to GDP per worker inequality ($\tilde{T}^k/T$) using a common deflator and Figure 15 shows contribution to using industry specific deflators. Appendix Figures A-5 and A-6 show the corresponding direct industry contribution $\tilde{T}^k$. We show all industries except real estate. Several important points stand out.

First, the rapid decline in inequality from 1870 to 1970, whether nominal or real is explained by a broad inequality decline across several industries including manufacturing, transportation, communication, utilities, wholesale trade, and government. But the sharp decline from the 1930 to the 1970 is almost entirely explained by the diminishing contribution of manufacturing. While manufacturing's contribution to inequality increases from 1870 to 1930, that is because manufacturing inequality is relatively constant while other industries declined (see Appendix Figures A-5 and A-6). Manufacturing went from accounting for approximately 40 percent of inequality before 1940 to a much smaller contribution after 1970, although its contribution rises somewhat around 2000. Manufacturing's declining importance for inequality occurs for both nominal and real inequality. After 1970, manufacturing has contributed to the increase in nominal and real inequality as well, but not on the scale of its previous contribution.

Wholesale trade and transportation, although relatively minor in their overall contributions to inequality because of their relatively small share, also declined significantly from 1870 and helped explain the fall in inequality to 1970. Tradable services' contribution to the nominal inequality.

increase is noticeable in recent decades, but they do not contribute to the increase in productivity inequality

Second, agriculture and mining inequality have spikes in their contribution to nominal inequality largely explained by price swings. These spikes come from rapid changes in prices which rapidly change the nominal GDP of agricultural or resource extraction counties, but not their real output. Industry deflated inequality removes these price changes and does not show the same spikes. Because counties where agriculture or mining are important also typically have relatively small populations, commodity price swings can have a big impact on their GDP per worker and thus inequality. The spike in agriculture's nominal contribution in the early 1970s comes from the rapid increase in grain and oil seed prices from 1971 to 1974.[11] Oil price fluctuations in the 1970s and 1980s, as well as the more recent fracking boom, explain the changing contribution of mining to nominal inequality.

Third, agriculture becomes more and more important for real inequality after 1970. Figure 6 helps explain why. Nominal agriculture production increased rapidly during the Green Revolution in the 1960s as new high-yield crops spread. Meanwhile, increased mechanization meant that agriculture employment decreased. Prices fell dramatically after 1950 which means that agriculture becomes a smaller share of nominal GDP in Figure 6. Holding relative industrial prices fixed at 1950 using our industry deflator means that agriculture is much more important for real production than it is for nominal production, so has a much larger impact on real inequality. When we fix relative industrial prices to 2018 instead of 1950, agriculture contributes less to inequality because the share in Equation 5 is small, so real inequality increases less dramatically. As we show next, moreover, agricultural technological progress is unevenly distributed, so agriculture productivity inequality is increasing. While many counties engage in some agriculture, the Green Revolution has been more concentrated in some areas than in others.

Fourth, competing trends explain the rise in nominal inequality since 1970. The tradable services' contribution to inequality has been increasing. Together, they now explain more than 40

[11] See the excellent summary here: ers.usda.gov/amber-waves/2009/march/agricultural-commodity-price-spikes-in-the-1970s-and-1990s-valuable-lessons-for-today/

percent of all nominal inequality. Manufacturing's contribution to inequality increased since 1970. Meanwhile, government services which had increased inequality before 1950, instead decrease inequality after 1970.

Different industrial trends explain the increase in real inequality since 1970. The increase in real inequality seems to be caused by agriculture's growing concentration and productivity increase in agriculture and, to a lesser extent, manufacturing. Unlike for nominal inequality, neither finance nor professional and business services contribute much to real inequality. As we discuss in Section 4.1, these services are increasingly concentrated in the highest GDP counties, but they are not necessarily more productive, just more concentrated.

We can go deeper into the sectoral mechanism that generates inequality in GDP per worker by focusing on the concentration of each industry and the degree of productivity dispersion within each industry. One way to measure concentration across counties is the isolation index shown in Figure 16., Isolation measures the average industry share of nominal GDP where the average dollar of production in that industry takes place.[12] High values indicate that most production in that industry occurs in counties where that industry represents a large fraction of local production, so the industry is highly concentrated; low values indicate production occurs relatively evenly across counties.

Three trends are evident that help explain the change in production: (1) Agriculture used to be primarily produced in counties that mostly produced agriculture. Today the average dollar of agriculture is produced in counties where it is around 10 percent of county GDP. It is worth remembering that, even in most agriculture-intensive counties, agriculture is no longer the largest industry. (2) Manufacturing concentration first increases and then decreases. At the peak, manufacturing was highly concentrated in counties where it represented 30 percent or more of production. The subsequent decline in concentration partly explains the decline in manufacturing's contribution to

[12] The isolation index, with N denoting national production, is:

$$\text{Isolation}_t^k = \sum_c \left(\frac{Y_{ct}^k}{Y_{Nt}^k}\right)\left(\frac{Y_{ct}^k}{Y_{ct}}\right)$$

inequality. (3) Tradable services used to be fairly evenly spread out and a small share overall. They have become increasingly concentrated, so the average dollar of tradable services is now produced in a county where they represent 25 percent of GDP.

Figure 17 shows how productivity inequality has changed for major industries. We calculate the Theil index of industry deflated GDP per worker. Because industries with very low production may have unrealistically high (or low) productivity, we trim the top and bottom one percent of counties from the measure of inequality.

Three facts stand out: First, manufacturing productivity inequality increases until 1940, significantly more equal from 1940 to 1970, and slightly increases since then. Both a decrease in manufacturing concentration and a decrease in the manufacturing productivity dispersion account for the reduction in manufacturing's contribution to inequality from 1930 to 1970. Second, Agriculture productivity inequality increased up to 1940, decreased from 1940 until 1970, and then substantially increased since 1970. Third, there has been a small increase in the tradable services' productivity inequality since 1990.

While there are many overlapping changes, we summarize the most important ones as:

> **Result 7:** Manufacturing's contribution to inequality is the largest before 1960 and its decline is the main explanation for the fall in inequality from 1930 to 1970. Manufacturing's declining contribution to inequality is explained by both greater geographical diffusion and falling cross-county productivity inequality. As for other sectors, agriculture explains most of the increase in real GDP per worker inequality since 1970 and its rise is mostly due to increasing productivity inequality. Both agriculture and mining's contribution to inequality in nominal GDP per worker has large spikes associated with material prices fluctuations. Finance and professional services contribute to the rise in nominal GDP per worker inequality, mostly because they have become more concentrated.

Figure 13 and Result 5 show that government services have become a larger share of the poorest counties' economies since 1930. Using the psuedo-Theil, Figures 14 and 15 show explicitly that government services directly reduce inequality whether using a common deflator or our industry specific deflators. We summarize this as:

> **Result 8:** After 1950, government services reduce inequality. Before 1950, government services increased inequality.

5 Factors in convergence and divergence

We have documented a massive convergence across U.S. counties from 1870 to 1970 and a subsequent divergence. What changed and what role did the process of industrial transformation play? We offer some partial answers that connect with a growing literature.

We first show a large decline in people moving to highly productive areas. Standard convergence theory suggests that factor mobility should drive convergence as people and capital move to where they will have their highest marginal return. Figure 18 shows the relationship between GDP per worker (common deflator) and population growth over the next decade. During the period of rapid GDP per worker convergence up to 1970, the higher GDP per worker counties' population grew much more quickly, partly because they were a destination for immigrants. However, starting in the 1960s, the population of high GDP per worker counties grew only slightly faster than other counties, and grew *slower* during the 1980s and early 1990s as people moved out of the highest GDP per worker places (Appendix Figure A-7 shows year by year linear regression coefficients). While the relationship turned modestly positive again starting in the mid-1990s, it was no longer strongly favoring convergence.

Recent research (Hsieh and Moretti, 2015; Glaeser and Gottlieb, 2009; Ganong and Shoag, 2017) has emphasized the importance of housing costs in preventing moving to high productivity areas. An individual worker, even if her wage and marginal product is higher in a more productive area, may not find moving to that area improves her welfare because of the high cost of housing. While our results do not provide a reason for the shift, they show that pro-convergence population growth was large during the period of convergence and has since diminished or has favored divergence.

Human capital also converged through the 1970s but its role has become more complicated in recent decades. Appendix Figure A-8 shows county inequality in education using three measures: the share literate before 1930, years of education from 1940 to 2010, and the share with a college degree (or more) from 1970 to 2020. Appendix Figure A-9 shows the same measures across the top MSAs, other MSAs, and all other counties. There was rapid education convergence from 1870 until 1970 which may explain the rapid GDP per worker convergence until 1970. Indeed, the education convergence may have been a precondition to manufacturing's geographical diffusion. By 1990, average years of education inequality had diminished substantially and was approaching zero. Since 1970, inequality in the share of the population with a college degree has diminished slightly and remains mostly within state inequality.

While Figure A-8 suggests education inequality continued to decline after 1970, the top MSAs have been pulling away from other MSAs and non-MSAs in college share. In 1970, the college share in top MSAs was 2 percentage points higher than in other MSAS; by 2020 it was 9 percentage points higher. Thus, while Figure A-8 shows an overall convergence across all counties in education when treating counties as the unit, Figure A-9 shows that the top MSAs have increasingly pulled in the most educated workers as they have come to dominate tradable services.

Other research points to the increasing importance of agglomeration economies (Glaeser and Gottlieb, 2009; Moretti, 2012). Figure 19 shows the productivity (industry deflated GDP per worker) of manufacturing and tradable services across the top 20 MSAs, all other MSAs, and all other non-MSA counties. Top MSAs and other MSAs had the same manufacturing labor productivity for most of the period, but have since diverged suggesting that agglomeration economies in manufacturing are growing. Even more pronounced, the top MSAs have become much more productive in producing tradable services than other areas. Tradable services are also becoming more concentrated in high GDP per worker areas (Result 6). These results, taken together, suggest that the interaction between agglomeration effects and industrial shifts is contributing to the recent divergence.

We summarize these results as:

> **Result 9:** Population growth and education used to be strongly pro-convergence, but after 1970 became neutral or anti-convergence. At the same time, agglomeration effects in manufacturing and tradable services appear to have increased.

6 Conclusion

Our novel data set containing nominal GDP by counties and industries and value added price deflators by industry from 1870 to 2018 allows us to compute both nominal and real GDP by county and industry. We document a fall in GDP per worker inequality from 1870 to about 1970 and then a subsequent rise. This rise is mostly due to increasing within state inequality as leading metropolitan areas have converged while diverging both from other cities and rural areas. Inequality is no longer primarily regional. Indeed, the highest GDP per worker states are now the most unequal. Atlanta looks more like New York City, but upstate New York looks more like the rest of Georgia.

Our data let us analyze how sectoral transformations contribute to this convergence and then divergence. Manufacturing's geographic diffusion underlies much of the decline in productivity inequality until the 1970s, while tradable services' growth and its increasing concentration contribute to the rise of nominal GDP per worker inequality after that. Meanwhile, there are equalizing forces as government, education, and health have come to be a larger share of the least productive counties and government services reduce inequality directly.

Are we still growing together? No, but why and how are complicated. The conditions that led to the rapid convergence until 1970 no longer apply. Population mobility slowed, and it is no longer directed towards the highest GDP per worker counties. Education converged across all counties, but the top MSAs have aquired a large advantage in the percentage of college educated workers. Manufacturing's geographic diffusion slowed and then partially reversed. And new agglomeration economies appear to be driving greater concentration in tradable services. Our results add novel evidence to the rich literature on regional and subregional development and they emphasize the importance of further research on the impediments to growing together.

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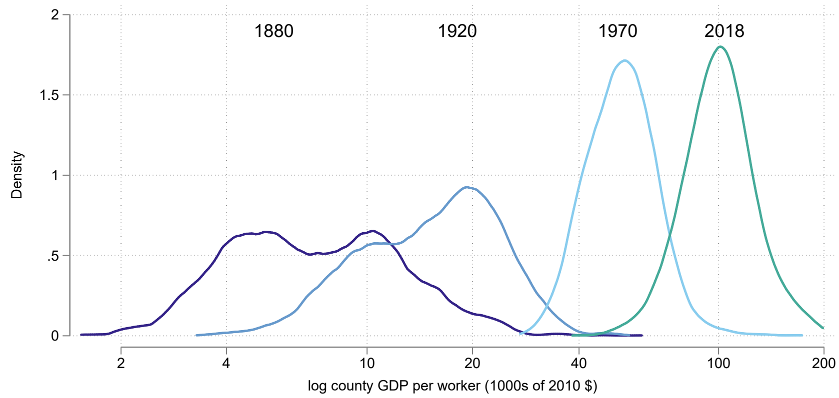
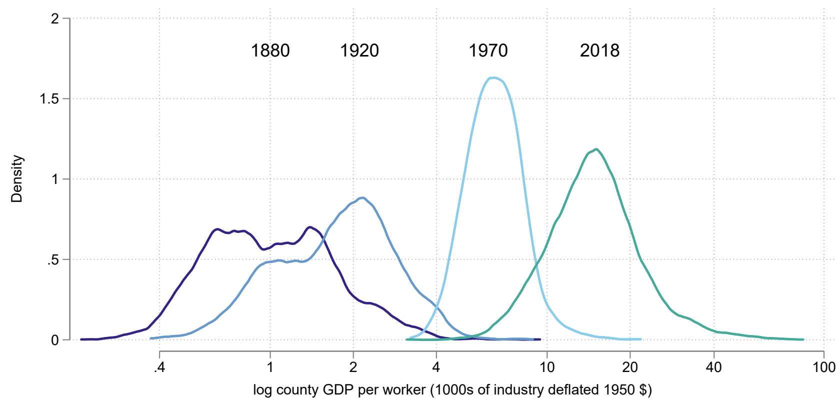
Figure 1: The distribution of county GDP per worker and per person: 1880 to 2018

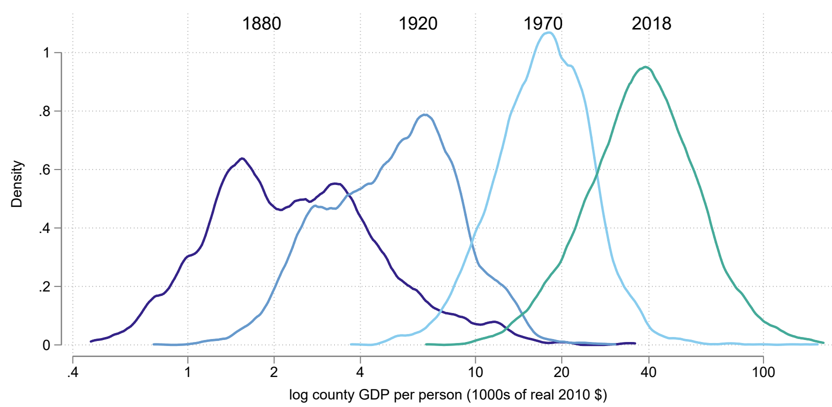
Panel (A): GDP per worker (common deflator 2010$)



Panel (B): Real GDP per worker (industry deflator 1950$)

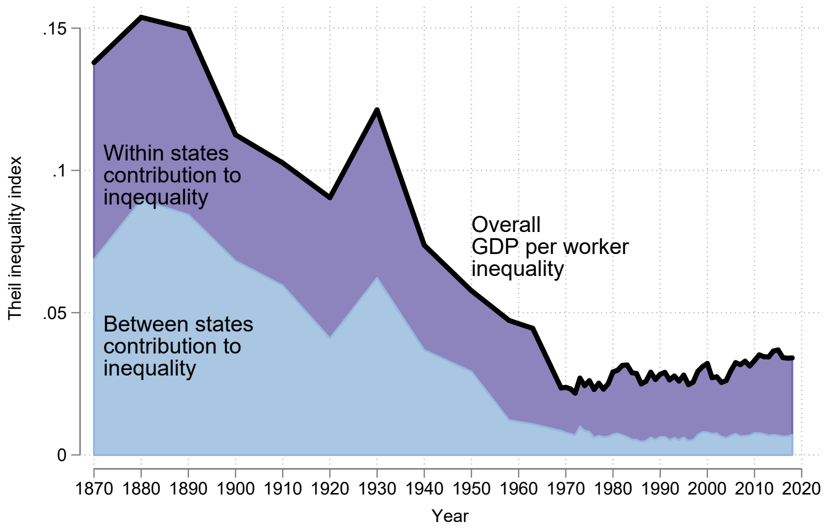


Panel (C): GDP per person (common deflator 2010$)



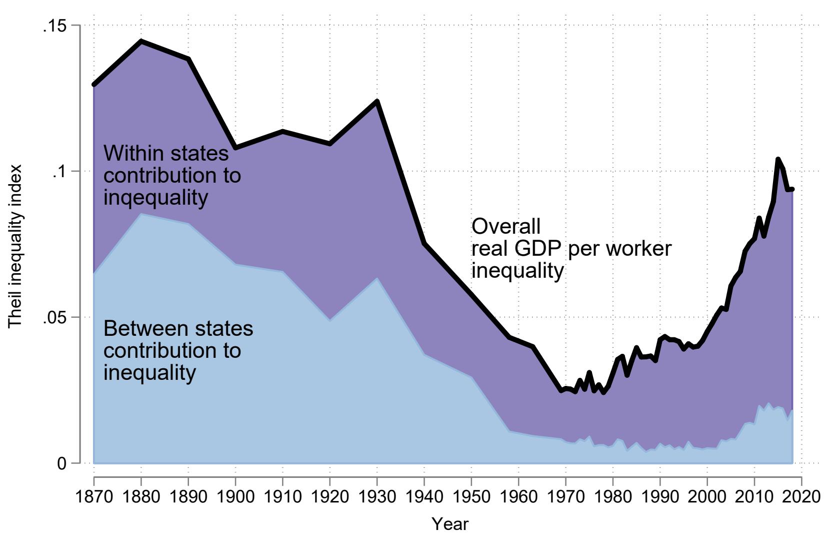
Notes: The common deflator in Panel (A) and (C) is from Sutch (2006) and the BEA. In Panel (B), real county GDP is obtained by deflating each industry nominal GDP by industry level GDP deflators and then all industries are added together.

Figure 2: GDP per worker inequality (common deflator)



Notes: Main sample excludes counties with mining share of GDP greater than 40 percent, utilities share greater than 25 percent, or have a populations smaller than 2500 (see Section 2.3).

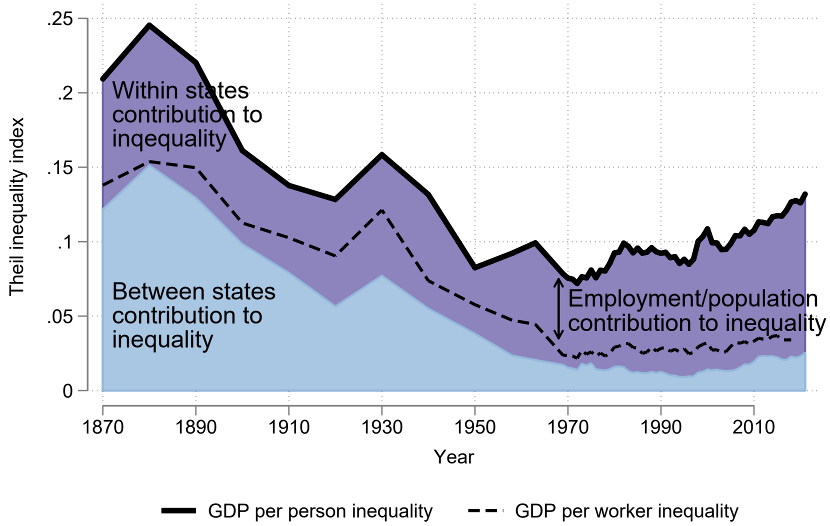
Figure 3: Real GDP per worker inequality (industry deflator)



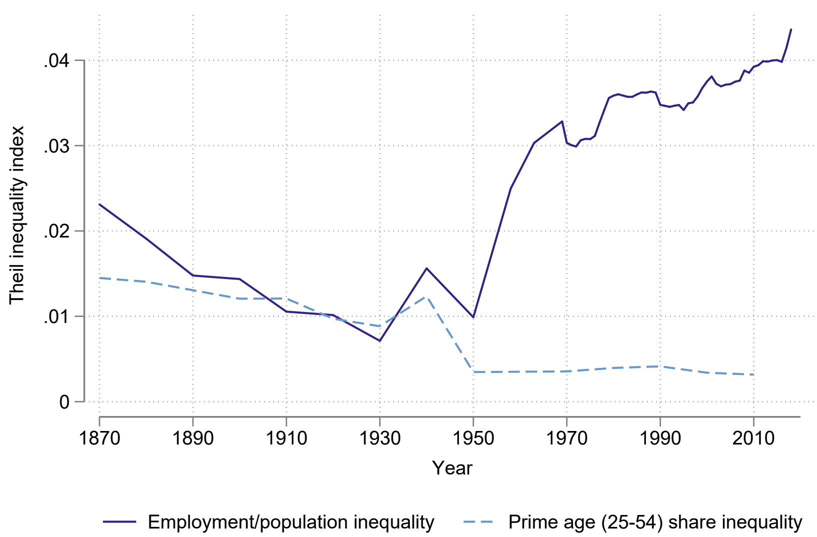
Notes: Real county GDP is the sum of county industry GDP each deflated using industry specific deflators. Main sample (excluding high mining and utility counties and very small counties; see Section 2.3).

Figure 4: GDP per person inequality and dependency inequality

Panel (A): GDP per person inequality



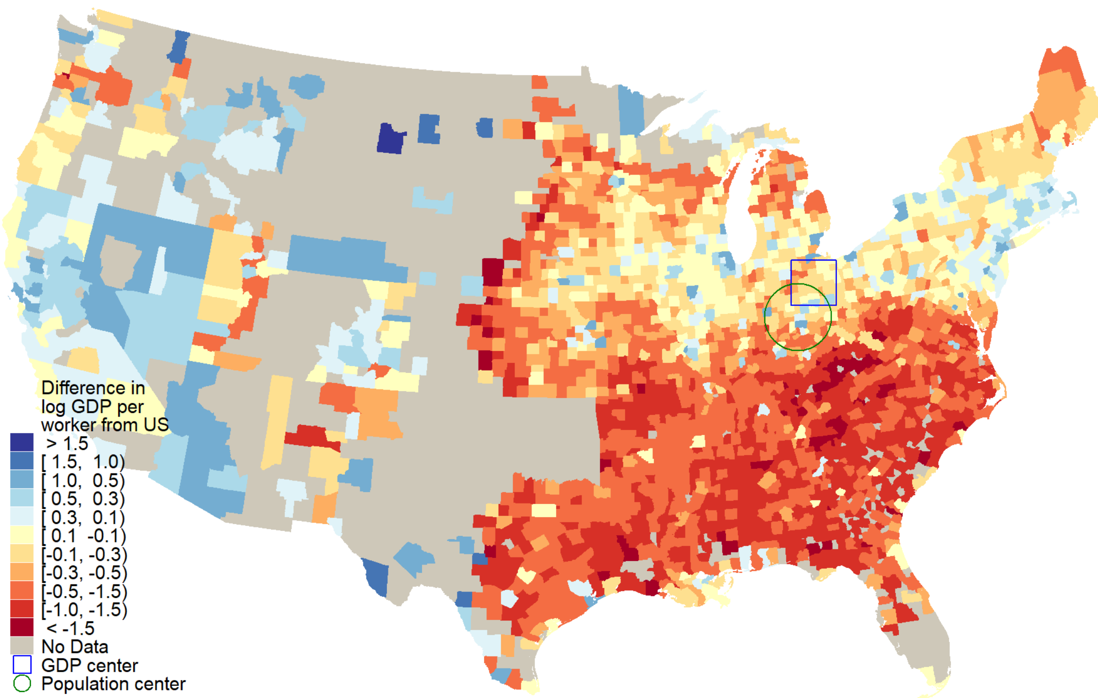
Panel (B): Employment and dependency inequality



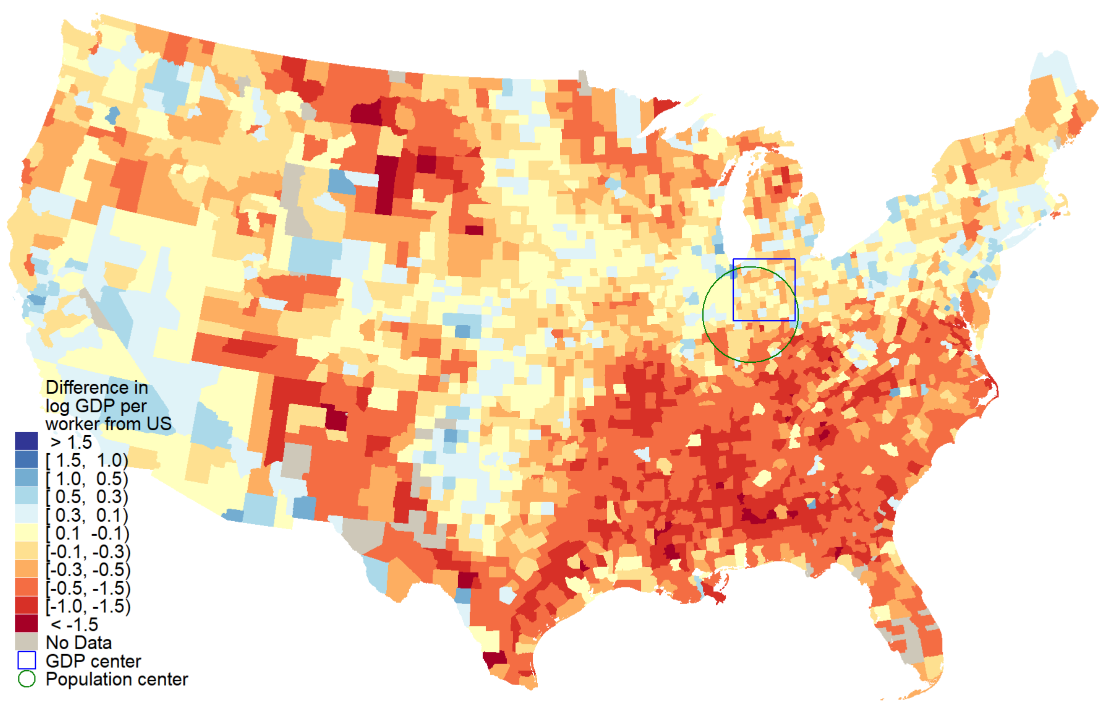
Notes: Common deflator. Employment in 1950 or before is based on Census occupation that includes market based activities. Starting in 1969 it is the BLS jobs definition. Employment to population is for all ages. Prime age is the share age 25-54 of the population. Main sample (excluding high mining and utility counties, and very small counties; see Section 2.3).

Figure 5: The geographic distribution of GDP per worker: 1880 and 1920

1880



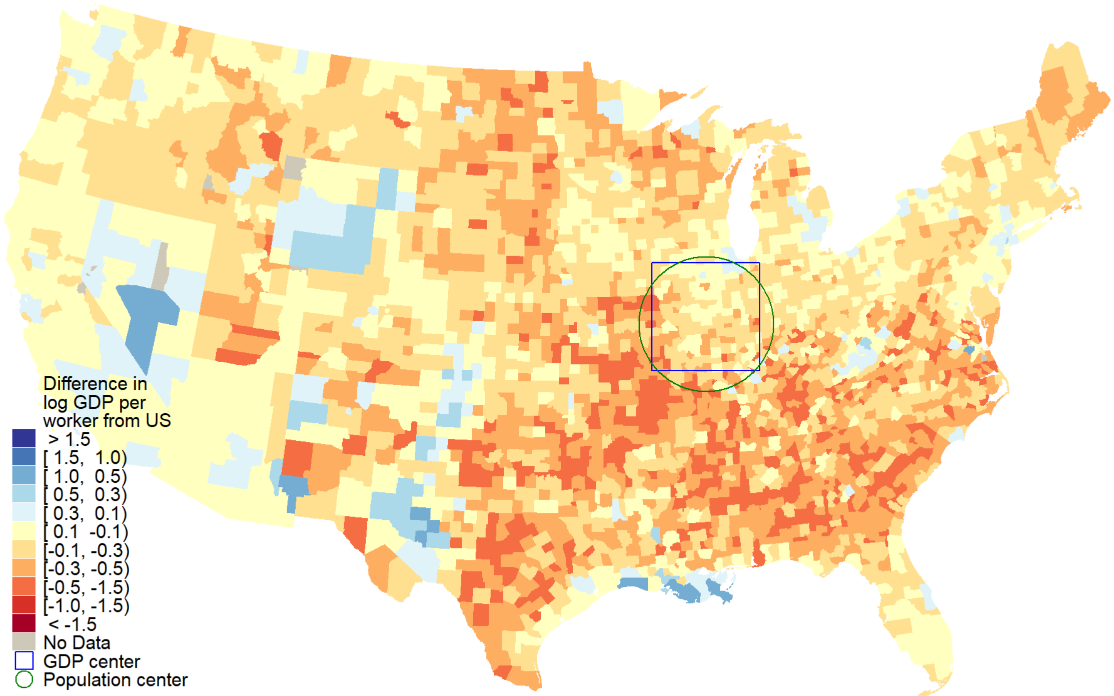
1920



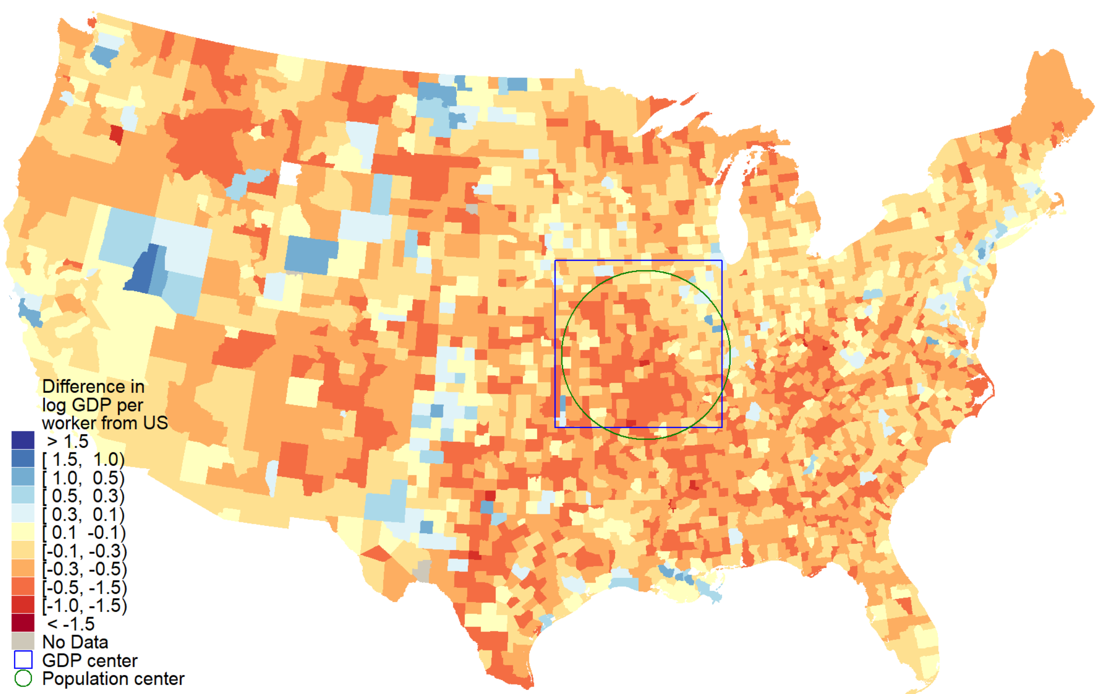
Notes: Shading in each county is by the difference in log county GDP per worker and log U.S. GDP per worker. The circle is the population center of the U.S. and is proportional to population in 2010. The square shows the GDP center of the U.S. and is proportional to 2010 real GDP per person. Uses county definitions from Minnesota Population Center (2011) and mapping software from Pisati (2007). The sample excludes counties with population less than 2500.

Figure 6: The geographic distribution of GDP per worker: 1970 and 2018

1970

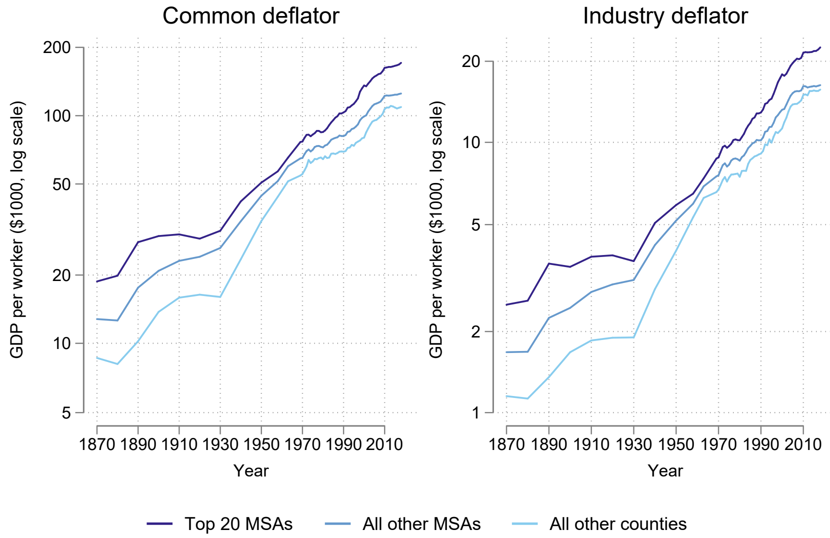


2018



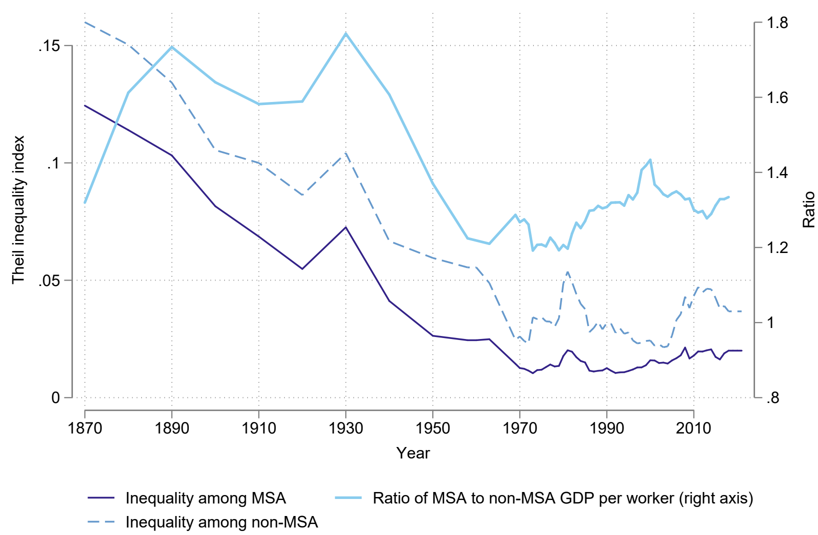
Notes: Shading in each county is by the difference in log county GDP per worker and log U.S. GDP per worker. The circle is the population center of the U.S. and is proportional to population in 2010. The square shows the GDP center of the U.S. and is proportional to 2010 real GDP per person. Uses county definitions from Minnesota Population Center (2011) and mapping software from Pisati (2007). The sample excludes counties with population less than 2500.

Figure 7: GDP per worker across metropolitan and non-metropolitan areas



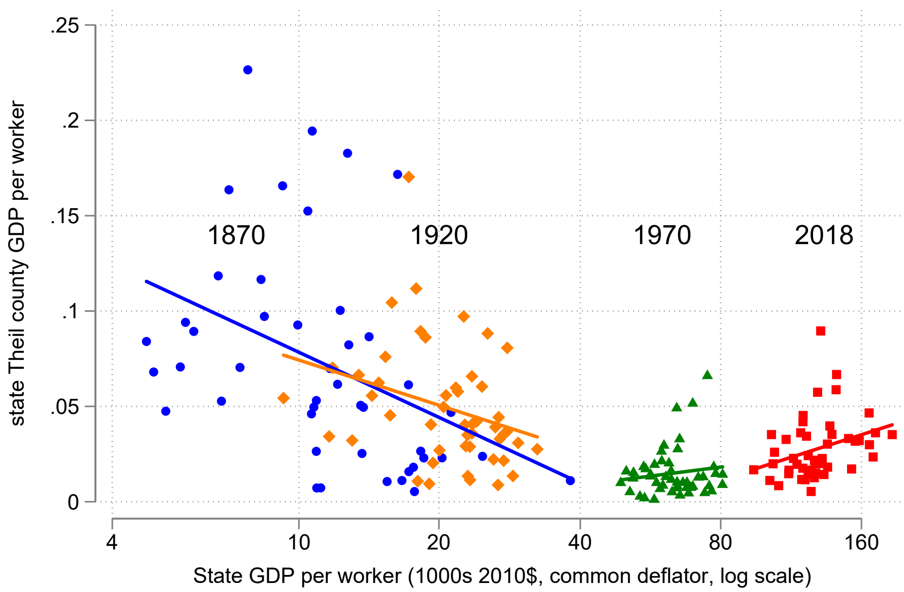
Notes: We use the counties in MSAs as defined by BEA in 2016. GDP per worker is the total GDP in the grouping divided by total employment. The top 20 MSA are the largest nominal GDP MSAs according to our GDP measure in 2018.

Figure 8: Inequality among metropolitan areas and non-metropolitan areas



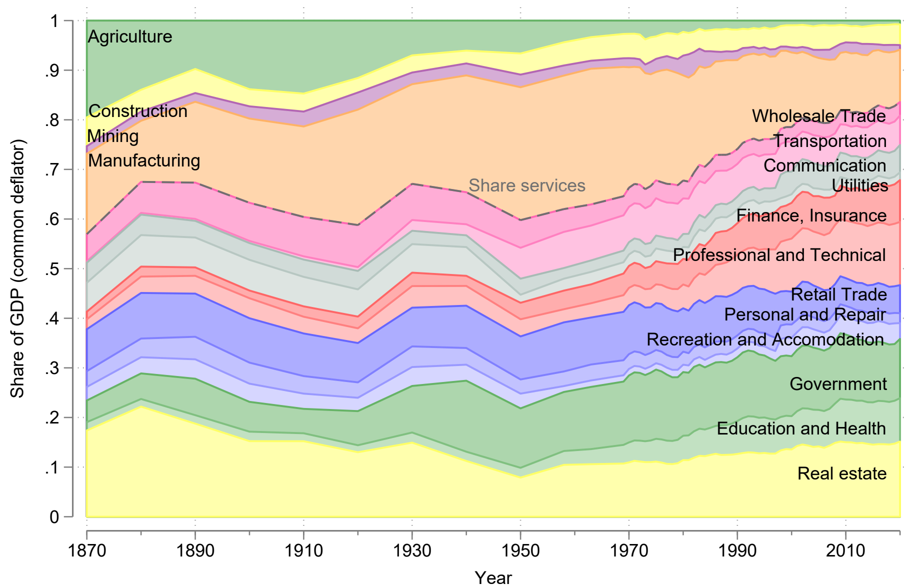
Notes: We use the counties in MSAs as defined by BEA in 2016. We combine all counties in an MSA as a single unit. Non-MSAs are counties that are not in an MSA, treating each county as a distinct unit. The ratio is the GDP per worker of all MSAs (total GDP of all MSA divided by total employment) divided by the GDP per worker of all non-MSA counties.

Figure 9: Inequality within states and state GDP

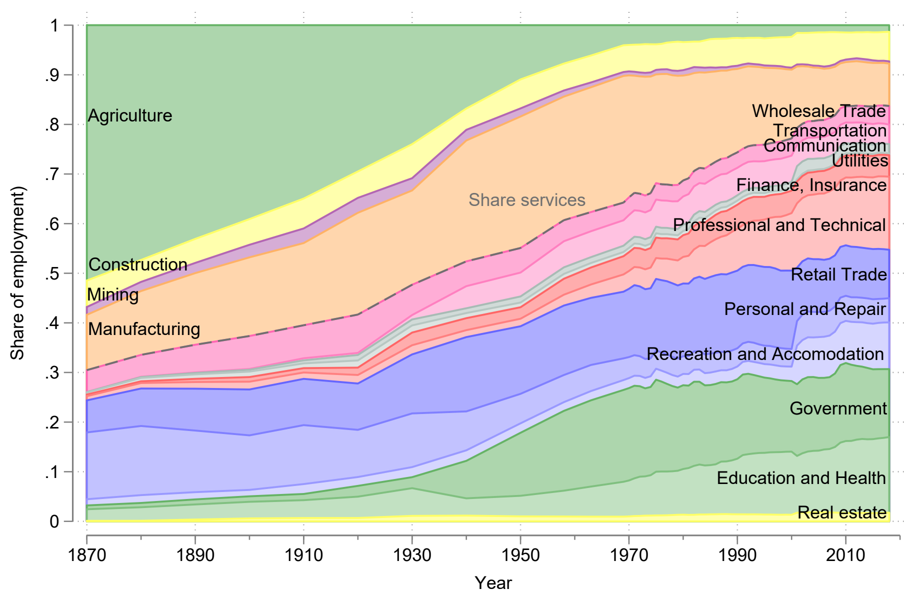


Notes: Each point is a state in a given year showing its (log) GDP per worker calculated by adding counties, and the Theil index of GDP per worker across counties in that state. Lines are the best fit for that year among the states. Main sample (excluding high mining and utility counties, and very small counties; see Section 2.3).

Figure 10: Industry shares of GDP and employment
Panel (A): Industry share of GDP



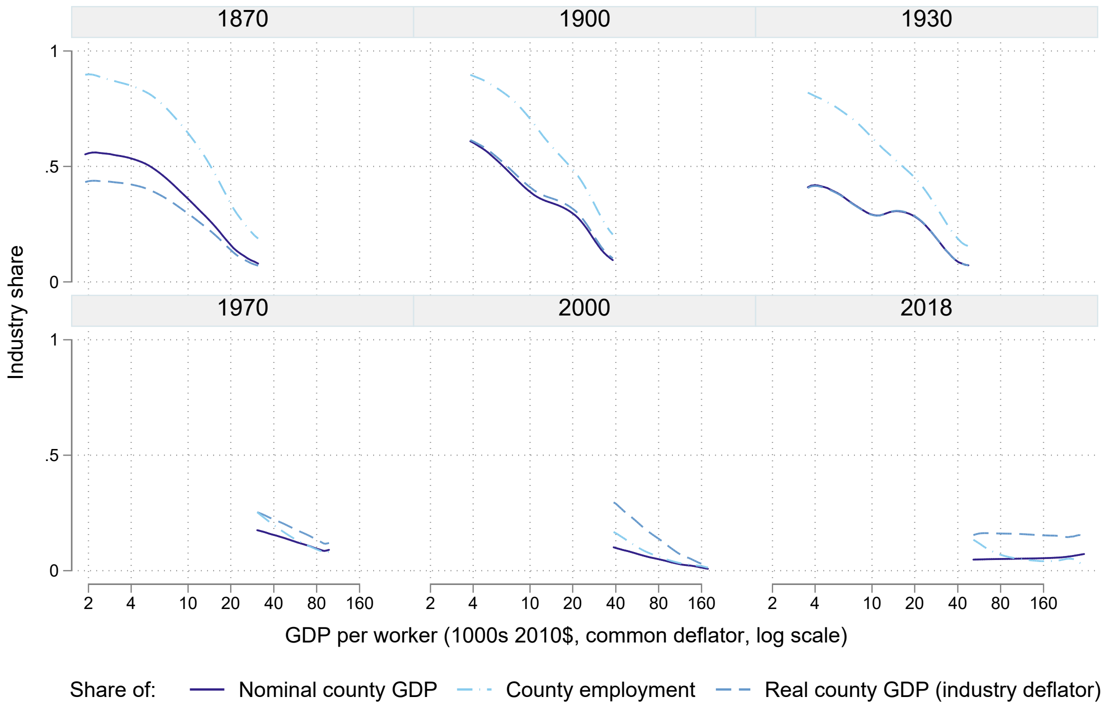
Panel (B): Industry share of employment



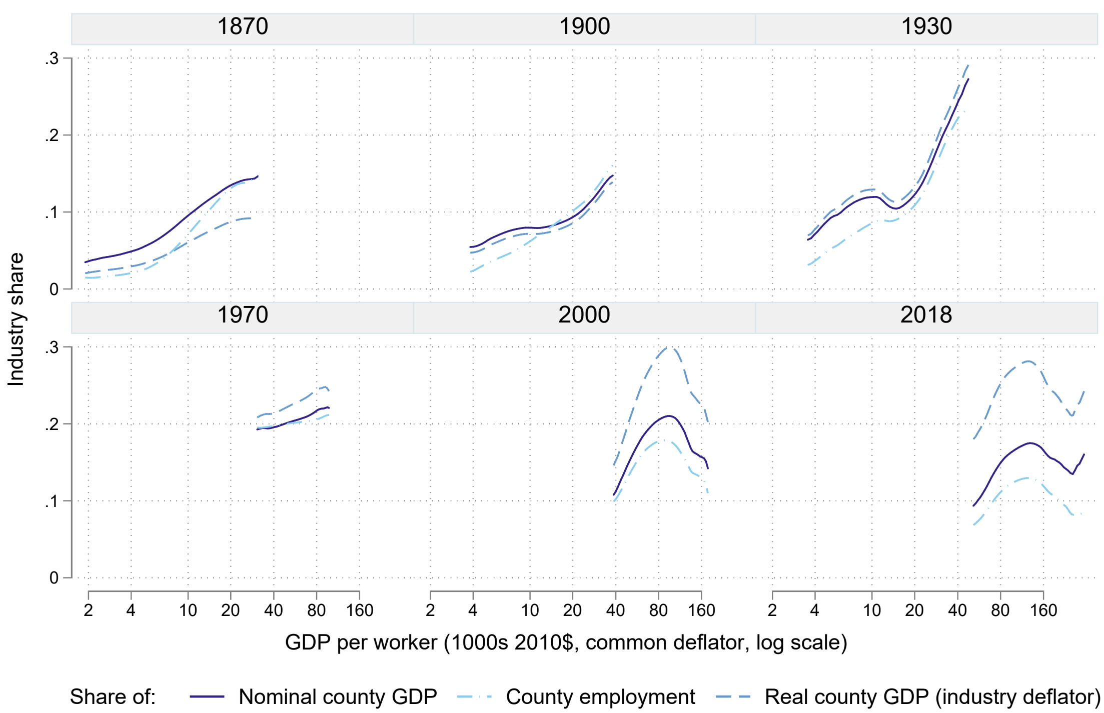
Notes: The solid lines are the implied national share of U.S. GDP by sector from aggregating counties.

Figure 11: Share of agriculture and manufacturing by county GDP per worker

Share agriculture



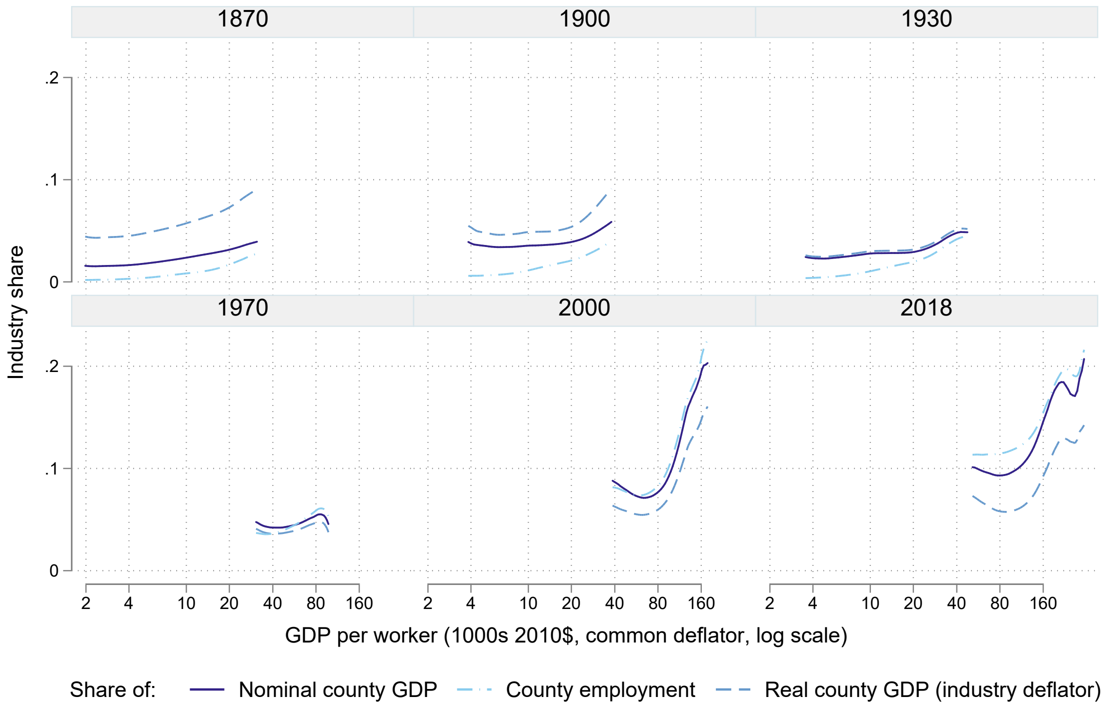
Share manufacturing



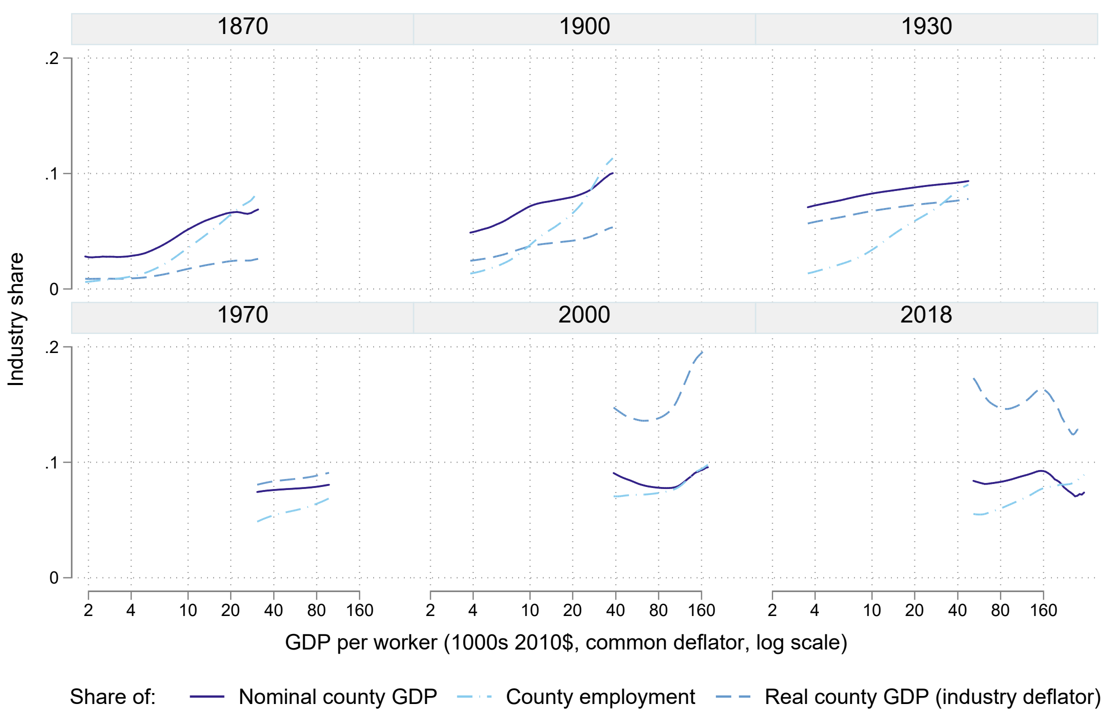
Notes: X-axis GDP per worker is measured with a common deflator. In each year the top and bottom 0.25 percent of counties are trimmed. Main sample (excluding high mining and utility counties, and very small counties; see Section 2.3). To obtain real county GDP we have deflated nominal GDP in each sector by the sector specific GDP deflator.

Figure 12: Share of tradable and trade services by county GDP per worker

Share all tradable services



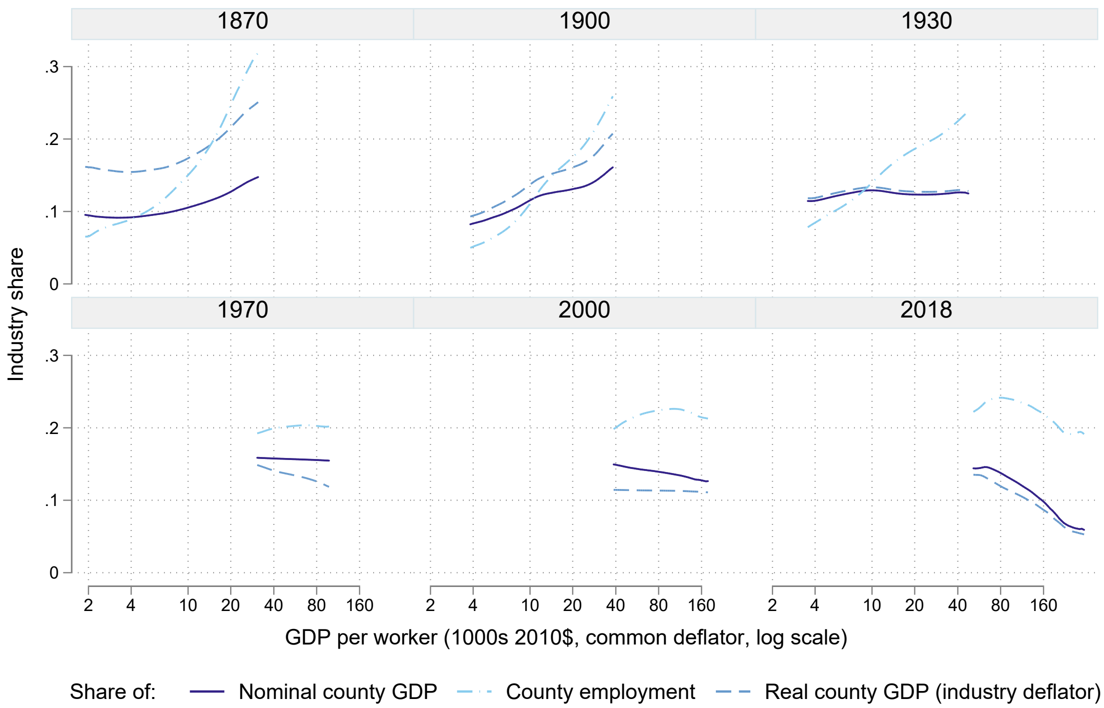
Share trade services



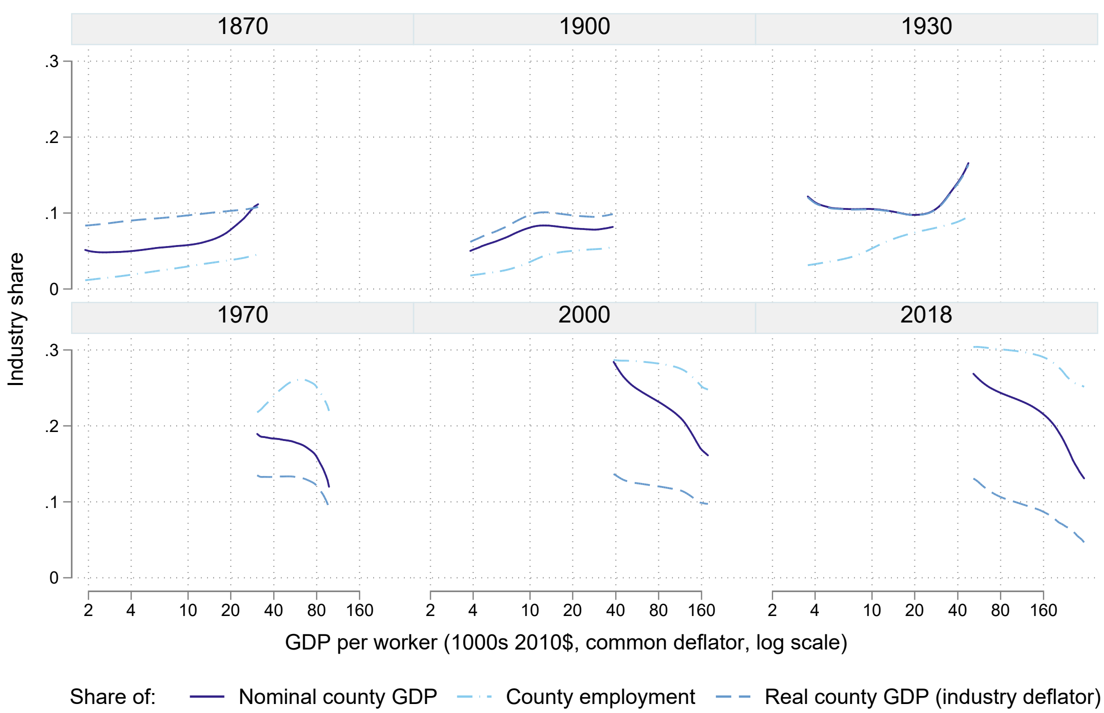
Notes: X-axis GDP per worker is measured with a common deflator. In each year the top and bottom 0.25 percent of counties are trimmed. Main sample (excluding high mining and utility counties, and very small counties; see Section 2.3).

Figure 13: Share of non-tradable services and government, education, and health services by county GDP per worker

Share non-tradable services

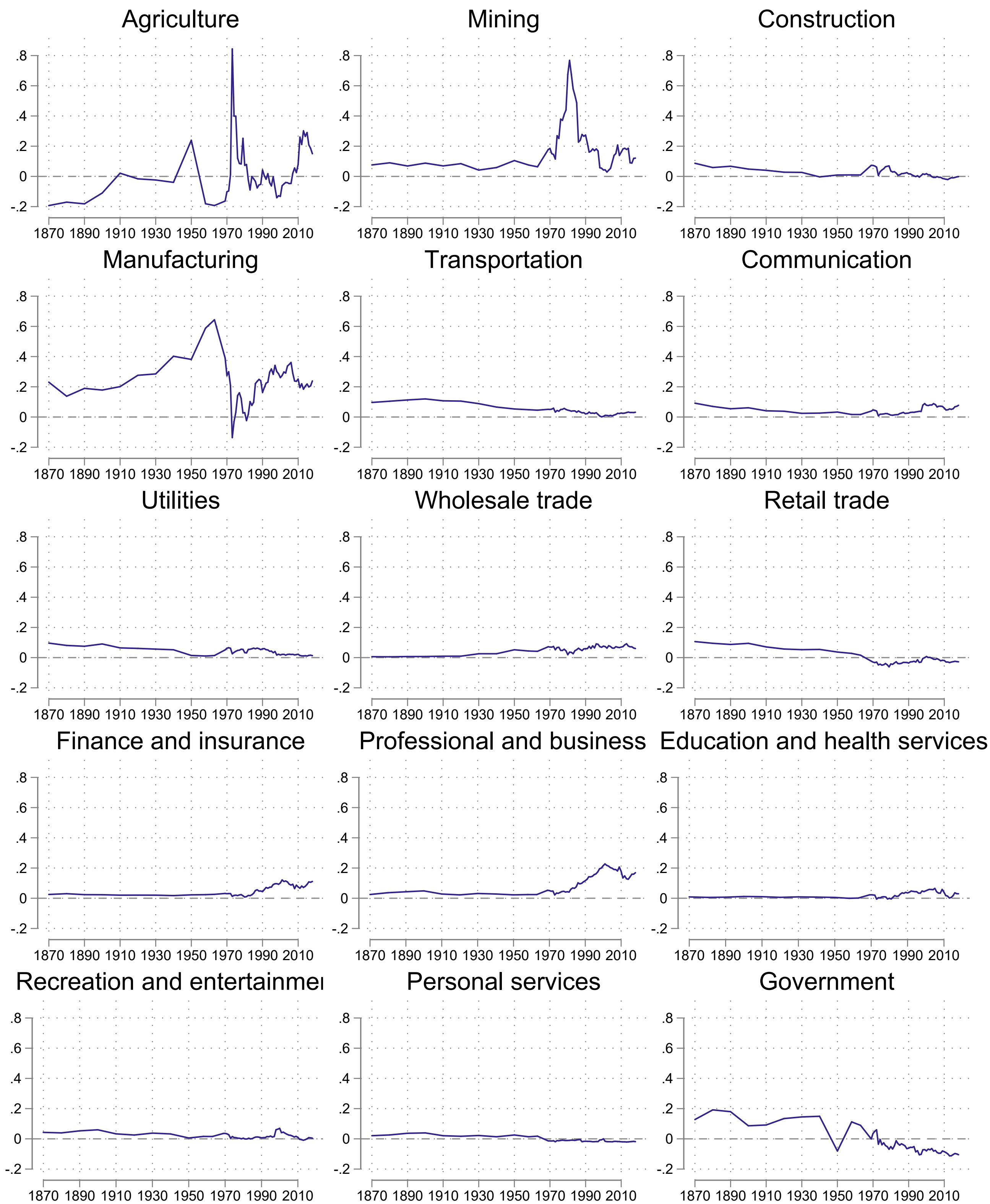


Share government, education, and health services



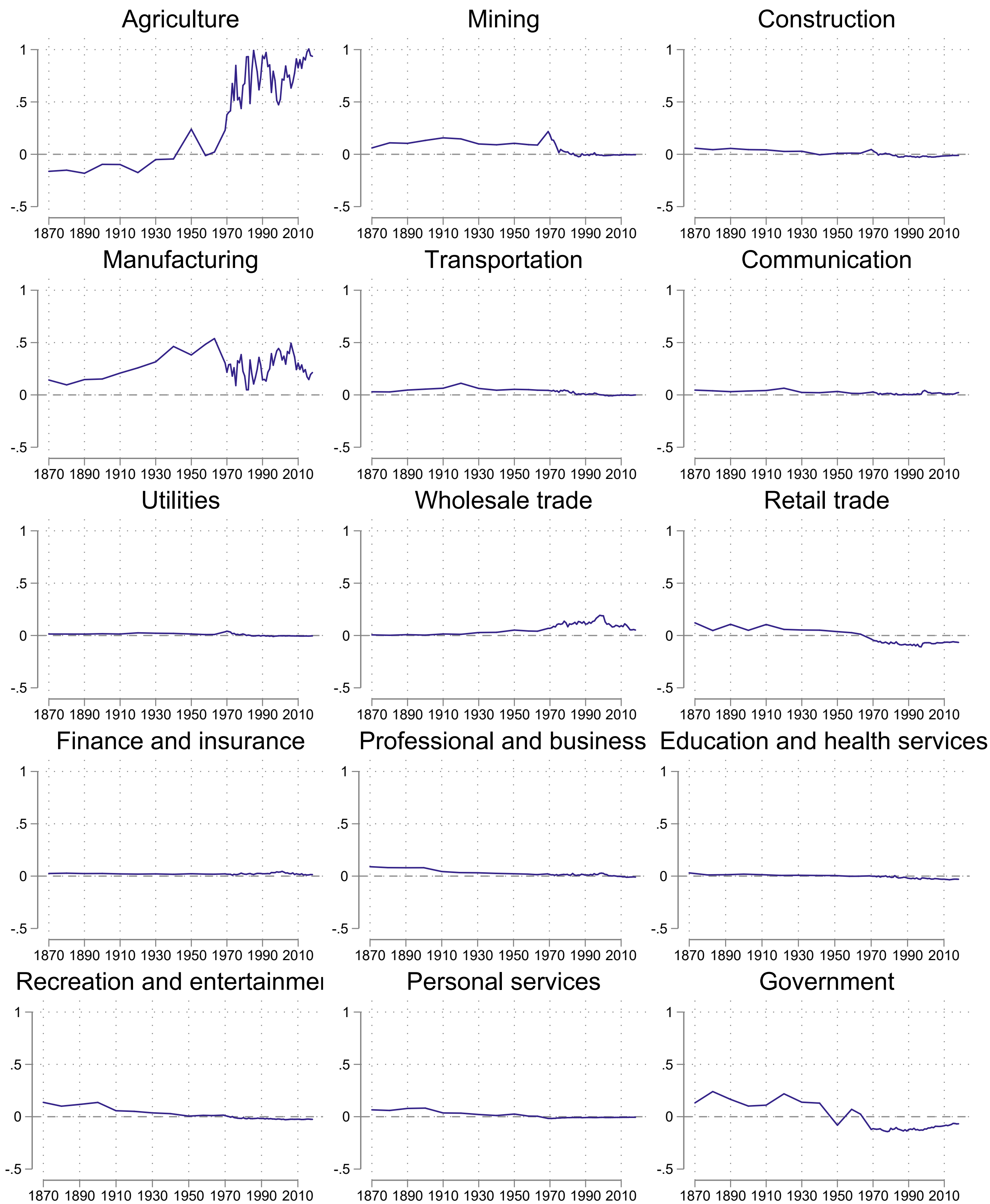
Notes: X-axis GDP per worker is measured with a common deflator. In each year the top and bottom 0.25 percent of counties are trimmed. Main sample (excluding high mining and utility counties, and very small counties; see Section 2.3).

Figure 14: Sectoral share of GDP per worker inequality as a fraction of the Theil index, common deflator



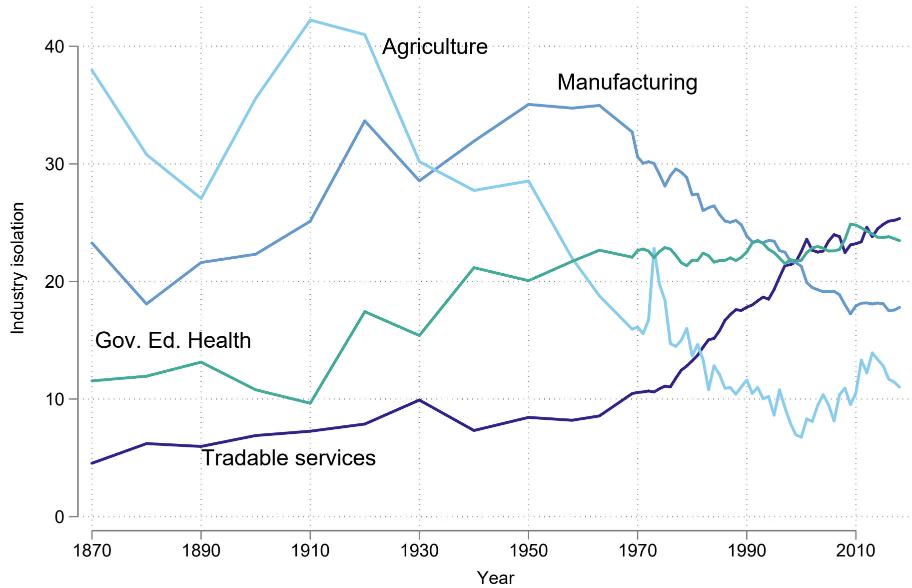
Notes: Real estate not shown. Main sample (excluding high mining and utility counties, and very small counties; see Section 2.3).

Figure 15: Sectoral share of GDP per worker inequality as a fraction of the Theil index, industry deflator



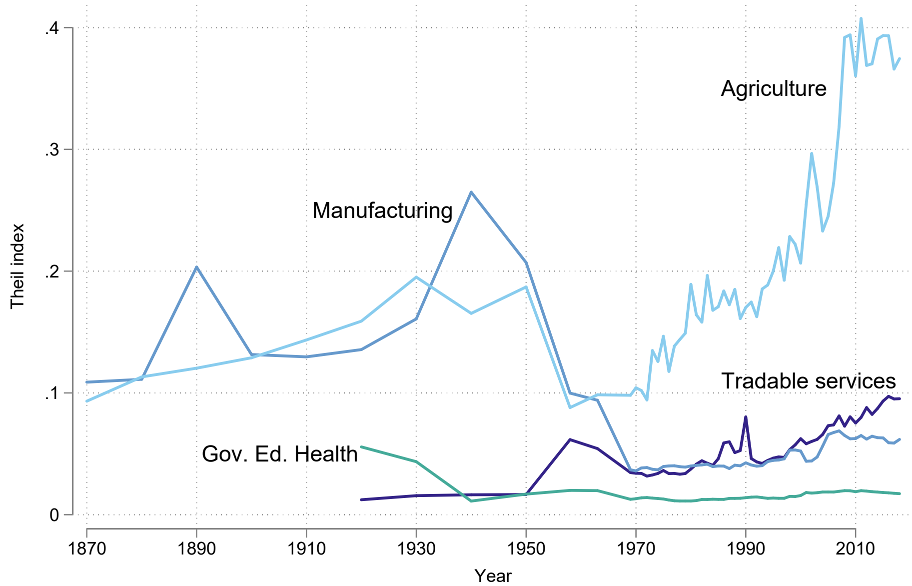
Notes: Real estate not shown. Main sample (excluding high mining and utility counties, and very small counties; see Section 2.3).

Figure 16: Industry concentration, isolation index



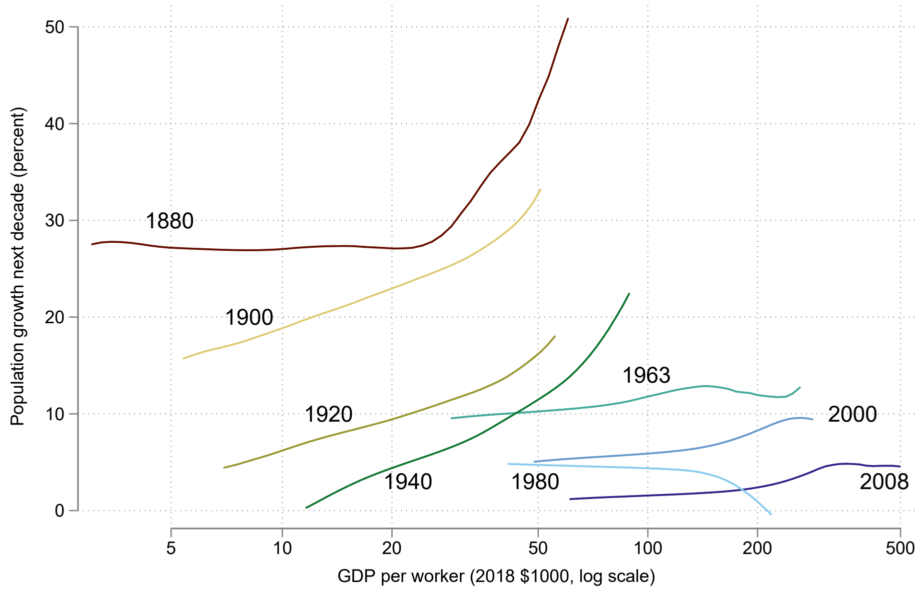
Notes: Main sample (excluding high mining and utility counties, and very small counties; see Section 2.3).

Figure 17: Productivity inequality by industry (using the Theil index)



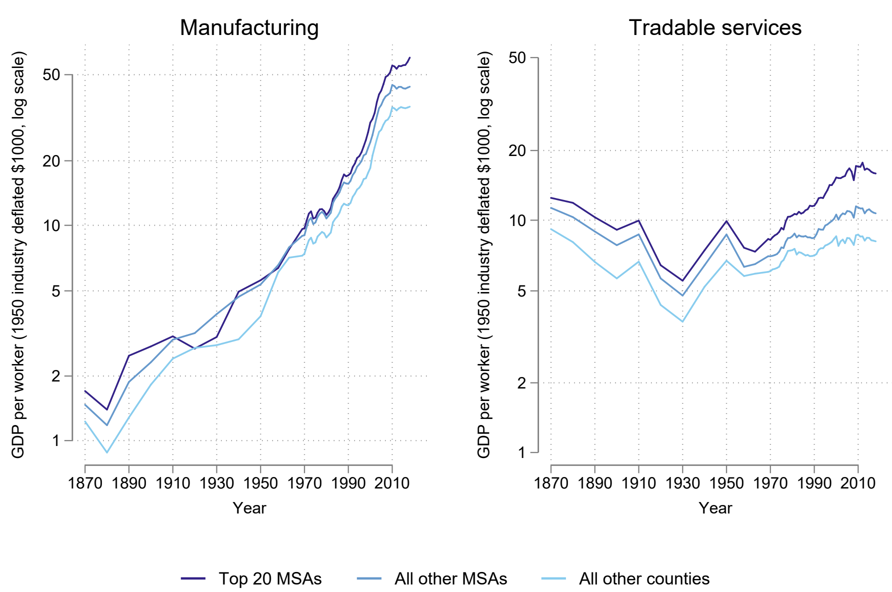
Notes: Productivity is industry deflated county industry GDP per worker. We cannon meaningfully calculate service productivity inequality before 1920, so it is not shown in the figure. We trim the top and bottom 1 percent of the distribution in each year. We note there is a change in data sources in 1969 when the BEA wages series becomes available, so one should be cautious in interpreting changes around that date. Main sample (excluding high mining and utility counties, and very small counties; see Section 2.3).

Figure 18: Population growth and GDP per worker



Notes: The lines are local polynomials smoothed. We exclude counties whose absolute value population change was greater than 300 percent and the bottom 5 percent of counties by GDP per worker in a given year. Population growth is over the next decade. Main sample (excluding high mining and utility counties, and very small counties; see Section 2.3).

Figure 19: Manufacturing and Tradable services productivity across metropolitan and non-metropolitan areas

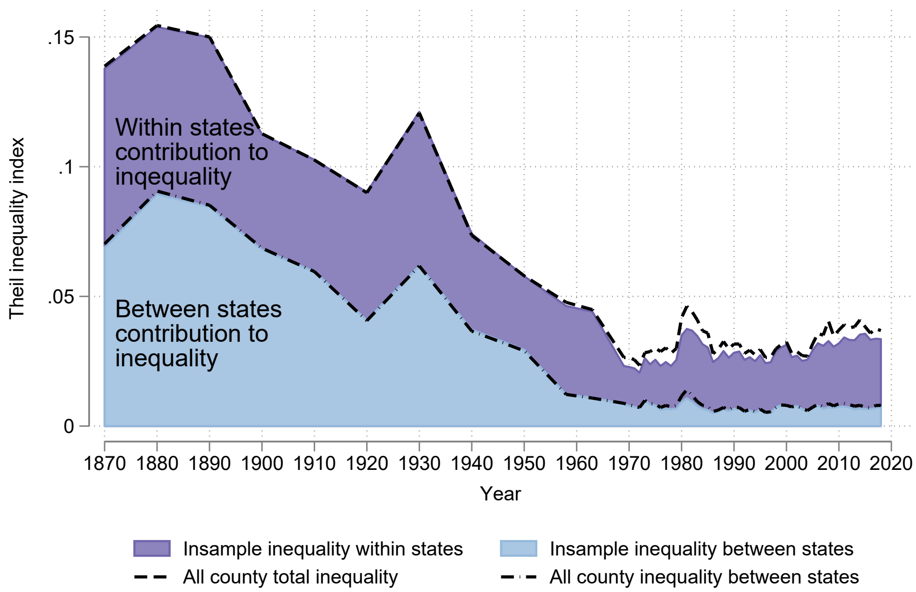


Notes: Notes: We use the counties in MSAs as defined by BEA in 2016. GDP per worker is the total industry deflated GDP in the grouping divided by total employment. The top 20 MSA are the largest nominal GDP MSAs according to our GDP measure in 2018. They produce slightly less than 50 percent of all output. Main sample (excluding high mining and utility counties, and very small counties; see Section 2.3).

Appendix

A Additional tables and figures

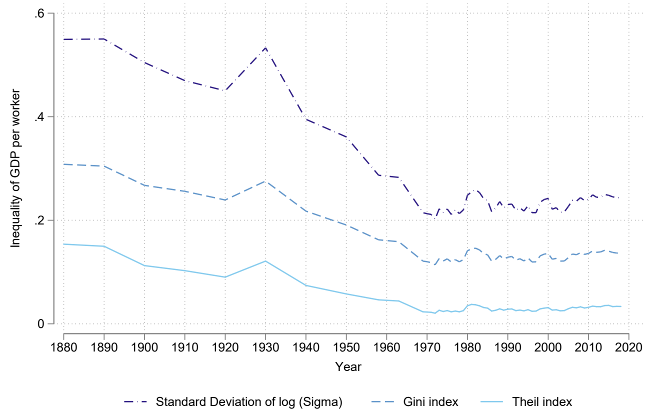
Figure A-1: Inequality for main sample and all counties



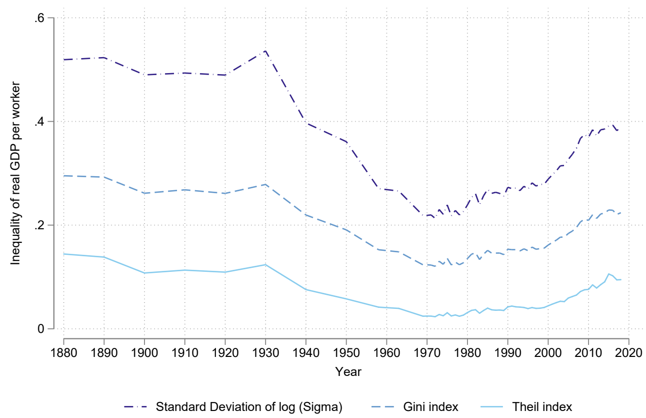
Notes: Compares the Theil index for our main sample (that excludes high mining and utility counties, and very small counties; see Section 2.3) and for all counties, not excluding the high mining and utility counties.

Figure A-2: Comparison of inequality measures

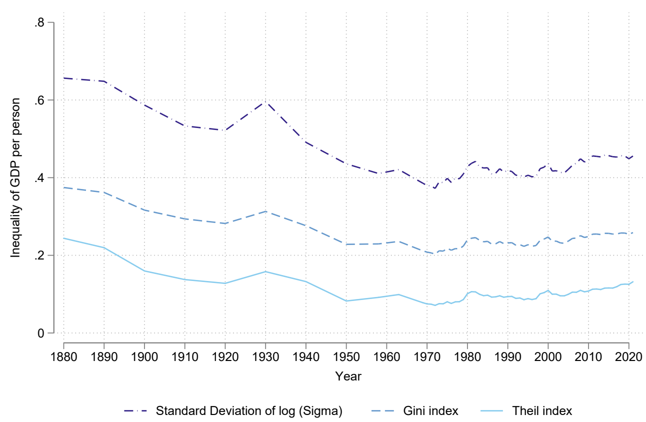
Panel (A) GDP per worker



Panel (B) Real GDP per worker

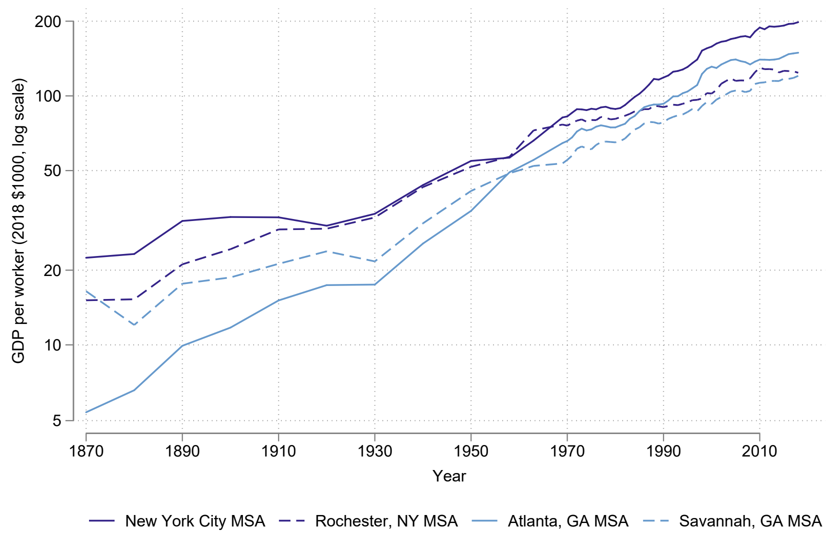


Panel (C) GDP per person



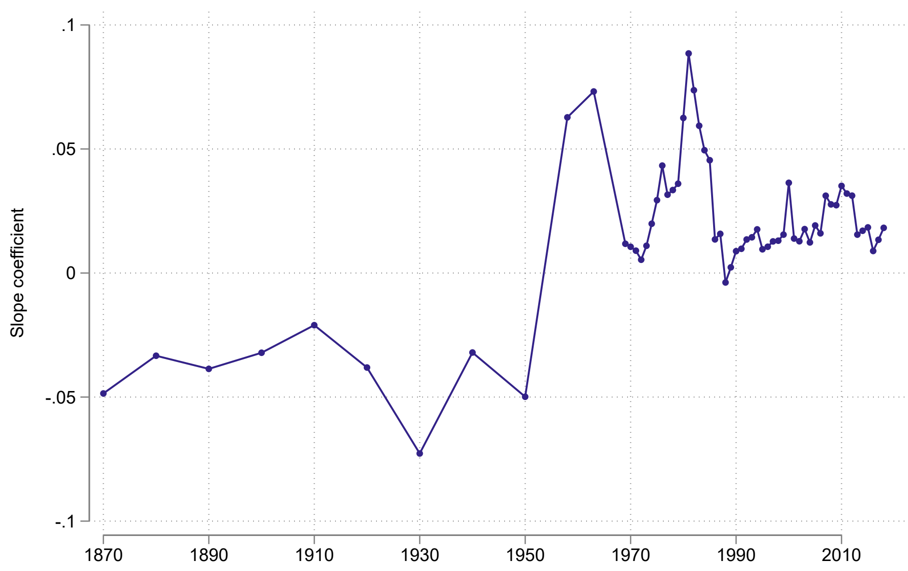
Notes: Shows different measures of inequality of real GDP per person over time. Main sample (excluding high mining and utility counties, see Section 2.3).

Figure A-3: GDP per worker of select metro areas



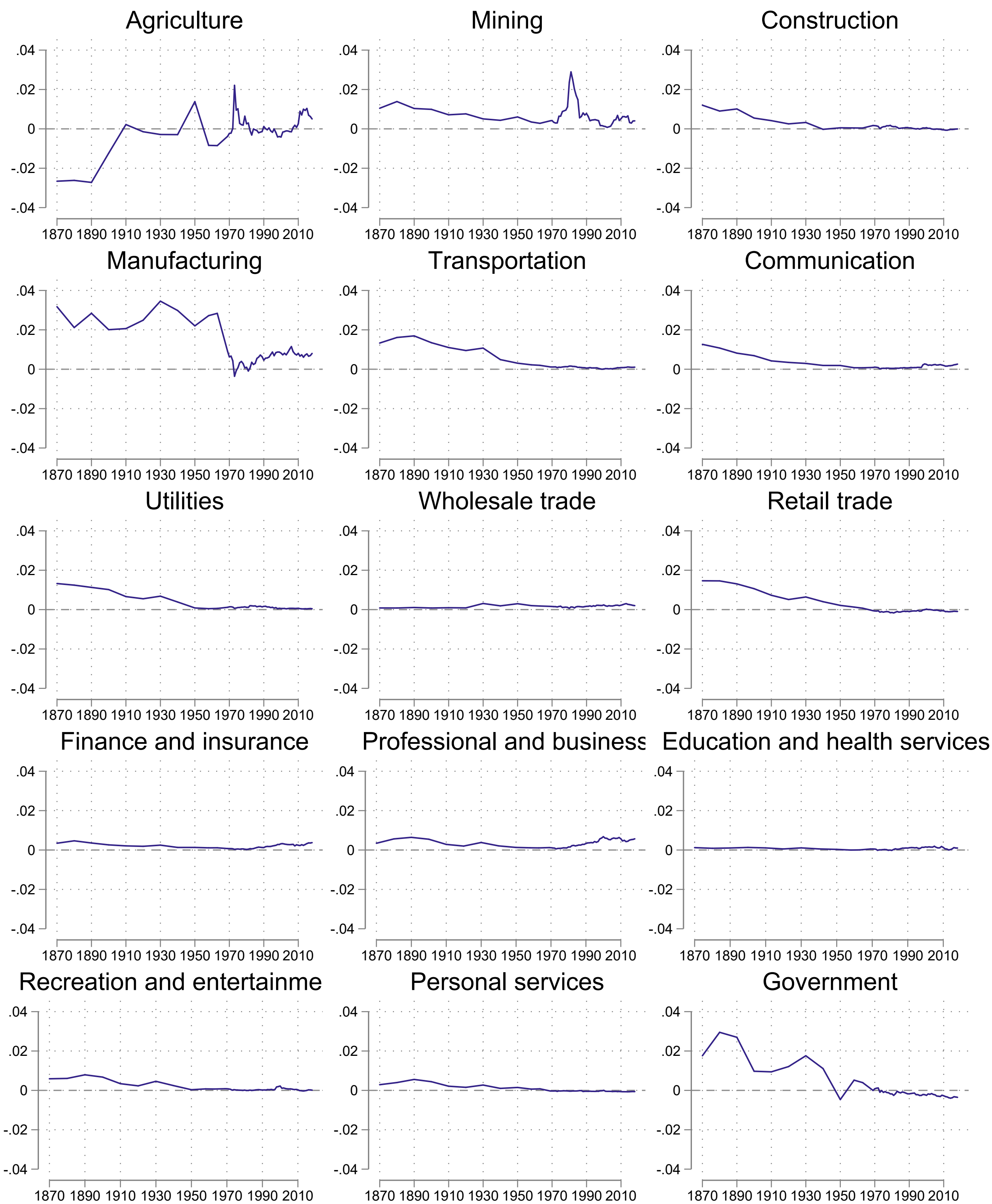
Notes: We use the counties in MSAs as defined by BEA in 2016. GDP per worker (common deflator) is the total GDP in the MSA divided by total employment.

Figure A-4: Inequality within states and state GDP per worker across all years



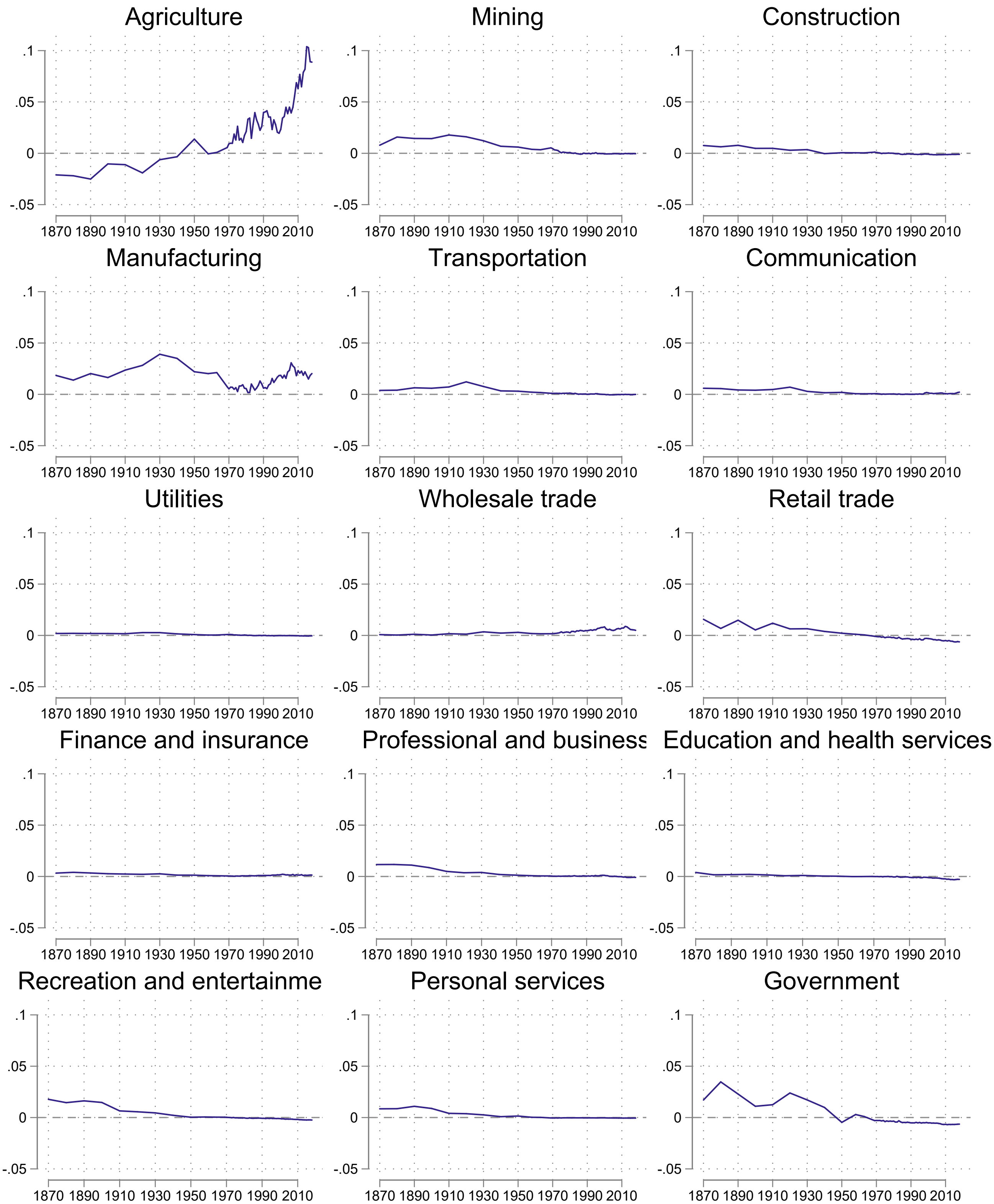
Notes: Each point is the slope of a regression across states in a given year with the dependent variable the Theil index of GDP per worker across counties in each state and the independent variable log state GDP per worker. Main sample (excluding high mining and utility counties, and very small counties; see Section 2.3).

Figure A-5: Sectoral contribution to Theil index GDP per worker inequality, common deflator



Notes: Real estate not shown. Main sample (excluding high mining and utility counties, and very small counties; see Section 2.3).

Figure A-6: Sectoral contribution to Theil index GDP per worker inequality, industry deflator

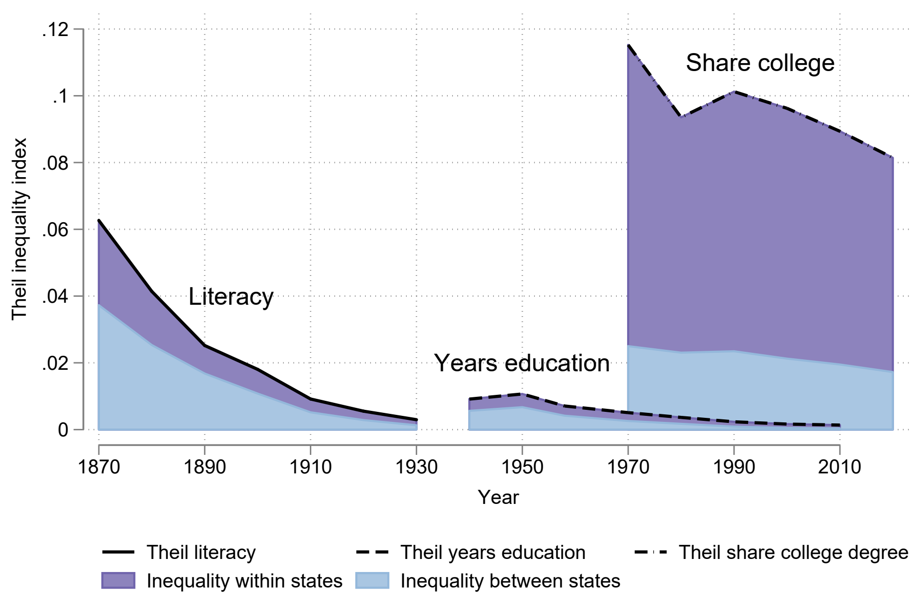


Notes: Real estate not shown.Main sample (excluding high mining and utility counties, see Section 2.3).

Figure A-7: Population growth and GDP per worker regression by year

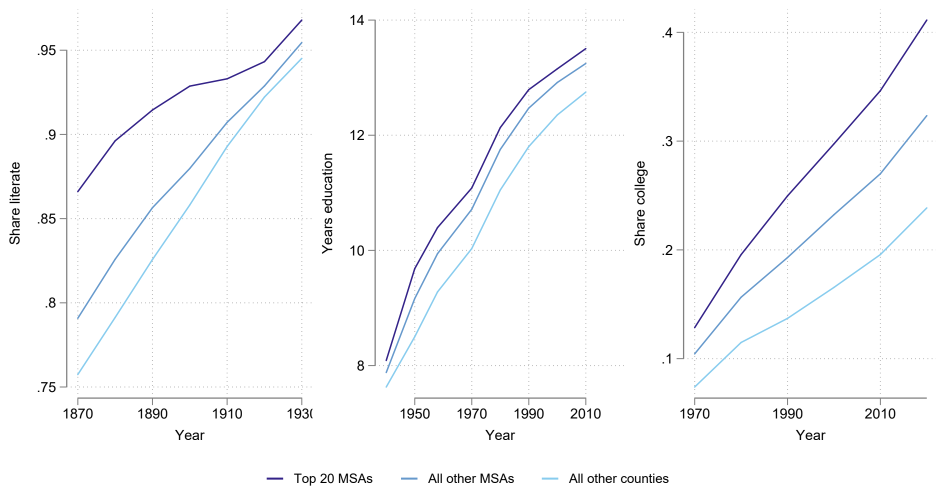
Notes: Each point is the regression coefficient for the linear relationship between Population growth in the next decade and log GDP per worker (common deflator). We exclude counties whose absolute value population change greater was greater than 300 percent and the bottom 5 percent of counties by GDP per worker in a given year. Main sample (excluding high mining and utility counties, and very small counties; see Section 2.3).

Figure A-8: Education inequality



Notes: Main sample (excluding high mining and utility counties, and very small counties; see Section 2.3).

Figure A-9: Education in metropolitan and non-metropolitan areas



Notes: Averages are calculated using population weight within each group. We use the counties in MSAs as defined by BEA in 2016. GDP per worker is the total GDP in the grouping divided by total employment. The top 20 MSA are the largest nominal GDP MSAs according to our GDP measure in 2018. Main sample (excluding high mining and utility counties, and very small counties; see Section 2.3).

B Data appendix

B.1 Constructing GDP by industry

In this Section we describe in detail how we construct GDP estimates for our 16 sectors for different periods. The sectors are 1) Agriculture: Agriculture, forestry, and fishing and agriculture services; 2) Mining; 3) Construction; 4) Manufacturing; 5) Transportation; 6) Communication; 7) Public utilities; 8) Wholesale trade; 9) Retail trade; 10) Finance: Finance and Insurance; 11) Real Estate; 12) Professional: Professional, Scientific, Technical, and Business services; 13) Education and Health: Education, Health, and Social Services; 14) Recreation: Recreation, Arts, Entertainment, and Accommodation; 15) Personal: Personal, Domestic, Repair, and Other; 16) Government.

B.1.1 County GDP 1969-2018

We next describe our procedure for each period, starting with the most recent since it requires the fewest assumptions and adjustments and so illustrates the approach. Bureau of Economic Analysis measures of earnings by industry are available at the county level starting in 1969 and state GDP by industry starting in 1963 (U.S. Bureau of Economic Analysis, 2016). We use the earnings by industry to allocate state GDP by industry to the counties within the state using equation (4).

The change from SIC to NAICS classification system in 1997 left these broad industry groupings mostly consistent. The only large inconsistency at this level is the new NAICS Information industry which took some components from the several other industries including Arts and Entertainment services and Communications. We included Information in Communications for consistency, although we are unable to fully adjust for the change.

For each year we allocate state GDP by industry to the counties in the state based on the ratio of county earnings by industry to total state earnings by industry. We use the sum of county earnings by industry rather than the total given by the BEA because BEA totals sometimes include allocations not to individual counties. Doing this means all of state GDP will be allocated and so the total per county will add up to state GDP. Very rarely, industry earnings are negative, for example, during a drought in an agricultural county. To deal with this problem in any industry-state-year in which a county had negative earnings we adjust all counties by adding the absolute value of the earnings of the most negative county to all counties. The total industry earnings is then the sum of all of these adjusted earnings. The most negative county has zero adjusted earnings, and so gets allocated zero of state GDP within that industry, while other counties are allocated their proportion of adjusted earnings. For Real Estate in 2008 and 2009 several states have negative earnings in total. We set the state earnings to zero, and so do not allocate any earnings for missing values to counties. The broader FIRE industry still has positive earnings, and so this procedure allocates GDP entirely based on the other components of FIRE.

Some industries in some counties are not reported to "avoid disclosure of confidential information, but the estimates for this item are included in the [state] totals" according to the county earnings data notes. When a sub-industry is not reported but is part of a larger industry whose total is reported, we allocate the difference between the reported sub-industries and the total based on the state ratios. For example, in the SIC classifications, the total of Transportation, Communication, and Utilities is reported, although the sub-industries Water Transportation and Pipelines may not be. The difference between the reported for the industry and the sum of each sub-industry gives how much should be in Water Transportation and Pipelines. We divide the non-reported amount based on the state share in the not-reported industries. We follow the same procedure for our fifteen industry groups: we calculate the total not-reported for that county, and allocate this amount based on the state share in the not-reported industries. Not-reported industries at the county level are typically small, but matter for small counties since there may often be only one firm in that industry.

B.1.2 County GDP 1850-1940

In this section we describe our construction of county GDP from 1850-1940. The construction is similar to Fulford, Petkov, and Schiantarelli (2016) of county group level GDP, but breaks down GDP into its component parts and makes several improvements. For instance, the calculations use a finer disaggregation of the service sector into eleven sectors rather than six. We use direct calculations of value added for manufacturing and agriculture and construct estimates of value added in the remaining industries using county employment constructed from the full census counts in Ruggles et al. (2019).

County manufacturing and agricultural value added 1850-1940 The census recorded for each county the total value of agricultural output and the value of manufacturing output and costs of inputs. We construct nominal value added of manufacturing by subtracting the cost of inputs from the total output. In 1850, the census did not collect manufacturing inputs. We use the average of the 1860 and 1870 county level ratio of outputs to inputs in manufacturing to calculate manufacturing inputs in 1850. For agriculture during this period the only local measures that exist are of output, not value added. To account for agricultural inputs, we construct a national measure of the ratio of value added to total output by subtracting intermediate inputs from total agricultural output using series K 220 -250 from U.S. Census Bureau (1975). While intermediate inputs were small early on at about 6% in 1850, increasing to nearly 12% by 1900, by 1940 they were nearly 40%. Adjusting for intermediate inputs hastens the relative decline of agriculture after 1900. We apply the ratio between nominal value added and output at the national level to the value of county level agricultural output to obtain an estimate of agricultural value added at the county level.

The census did not collect manufacturing data in 1910, although estimates of it exist at a national level. To create county level manufacturing, we interpolate between 1900 and 1920 using the national growth in manufacturing value added and allocating growth to each decade so that manufacturing value added grows in each decade in each county at the same rate it does at the national level.

Services, Construction, and Mining employment 1850-1940 We construct county level industry employment using the full individual level census data from the 1850, 1880, 1920, 1930, and 1940; the 5% sample in 1900, and the 1% sample in the remaining years. Ruggles et al. (2019) has created occupation and industry divisions for each individual based on their responses. We allocate the occupations to correspond to the 16 broad industrial categories described in the previous section, roughly following the divisions established by Carson (1949). Doing so creates a measure of the total workers employed in a given industry in each decade. We combine this employment measure with estimates of national value added in each industry allocated to each state and urban or rural area based on the relative wages and employment. We describe the full construction of each of these pieces below, as well as how we combine them using the production theory outlined above.

There are several important difficulties with creating county employment: occupations change over time and some occupations such as legal services that may be classified as a service for an individual are part of manufacturing value added when performed for a manufacturing firm. Since the physical census records from 1890 were largely destroyed by fire, there is no micro-sample from 1890. We linearly interpolate for each county the employment by industry category in 1890 using 1880 and 1900.

Allocating employment by industry We largely follow the mapping of individual occupations and titles into industries used in the census micro data Ruggles et al. (2019) and described in great detail in Bureau of the Census (1950). Although we do not use the employment in farming or manufacturing to construct GDP in these industries, we calculate employment in these industries using the same classification. Military occupations are classified as Federal public administration and so are included in government services.

Value added in the service, construction, and mining industries The construction of value added for services, mining and construction varies by sub-period depending on the information available.

Value added by services category 1840-1900. Gallman and Weiss (1969) construct measures of services value added and employment for eight categories at a national level from 1840 to 1900: trade; transportation and public utilities; finance professional services, personal services, government, education, and “hand trades.” Hand trades are composed of smithing, shoe repair, and tailoring. While these occupations may be included in manufacturing output, we include them in the Personal and Repair services for consistency with later periods.

Value added by services category 1930-1960. The National Income and Product Accounts (United States Department of Commerce, 1993) break down the value added by industry from 1929-1958 We use the equivalent tables in United States Department of Commerce (2001) to construct nominal value added in production for the post-war period. The NIPA tables provide only an overall value for Professional, Education, Recreation, and Personal services industries, but provides a compensation of employees in more detailed industries. We divide up the overall value into the four components using the share of compensation in each industry.

Constructing value added for services in 1910 and 1920. No estimates that we have found connect the Gallman and Weiss (1969) and United States Department of Commerce (1993) estimates of services value added by category. To combine these two sets of estimates we assume that the share of each industry in national value added grows linearly between 1900 and 1930. For some services, such as Retail Trade, the shares are almost identical in the two estimates, and so Retail Trade value added grows with nominal GDP. For other services there are larger changes in shares, particularly for Professional Services which Gallman and Weiss (1969) estimates to be a much larger portion of the economy than NIPA, and Finance which is much smaller. Since these two categories have similar value added per worker in 1900, the change has little impact in overall GDP or its county allocation. Finally, since Gallman and Weiss (1969) provides only estimates of the combined Wholesale and Retail Trade, Personal Services (including both Arts and Recreation, and Personal), and Transportation and public utilities (including Transportation, Public Utilities, and Communication), we assume that each component industry grows at the same rate as the combined industry so that their relative contributions to value added in the combined industry are not changing.

Value added for construction and mining. We use the values of mining and contract construction from the National Income and Product Accounts in 1930 and 1940 to construct national value added per worker. From 1880 to 1920 we also use the estimates of Wright (2006) for mining. From

1850 to 1870 we use the ratio of the value added per worker in mining to the value added in transportation in 1880 times the value added per worker in transportation in 1850, 1860, and 1870. This approach assumes that the value added in transportation and mining grow at the same rate from 1850 to 1870. An important part of the value of mineral and fuel extraction comes from transporting it to populated areas. Transportation value added per worker grew at close to the same rate as overall national product per person during the period. Our approach for construction is similar but involves even stronger assumptions. Construction value added per worker before 1930 is simply its ratio to national income per person in 1930 and 1940. This approach assumes that construction value added grows at the same rate as the national economy, and that employment in construction is a good measure of the distribution of construction activity. Construction is a relatively small component of GDP—it composed only 5% of national product in 1950 and our estimates suggest it was smaller before that—and this approach puts a reasonable value on construction.

Distribution of wages by period and industry For most of the period we only observe wages at the state level, but we use the distribution of wage across counties in 1940 to allow counties within a state to differ. The 1940 census was the first to ask about income or wages and has a complete sample. The sources we use typically do not have coverage for all states in all years. We use the average wage in the census division the state belongs to fill in the wage for missing states in each year. There are nine census divisions which correspond to the broad economic and climatic zones of the United States. Moreover, the state wage for particular occupation can be either a weighted average across urban and non urban areas or represent an urban or rural wage. We use the state level information and the ratio between urban and rural wages in 1940 to construct estimates of the state-urban/rural specific wages in an industry in the decades up to 1920. We define urban and rural using the 1950 allocation to metropolitan and non-metropolitan areas, the first year such an allocation is available.

1930 and 1940. The 1940 census asks for wages or income and we use the same classification system for employment to find the average wage within each county and industry. We assume the same geographic distribution of relative wages within each industry applies in 1930.

Wages by state for Trade 1850-1920. We use the wage in each state for bakers (1880-1898 across states, 1907-1928 for select cities) and dress makers (1875–1898 across states) from the United States Department of Labor (1934), page 148 and 219. Since the coverage is fragmentary for different states we take the average wage over several years to form the decade distribution across states. For bakers: 1880 is the average from 1880 to 1887; 1890 the average from 1886 to 1895; 1900 the average from 1891-1898; 1910 the average from 1907-1916; 1920 the average from 1917-1926 we assume the distribution for 1850, 1860, and 1870 follows 1880. For dressmakers: 1880 is the average from 1875 to 1886; 1890 the average from 1886 to 1895; 1900 the average from 1891-1898; we assume the distribution for 1850, 1860, and 1870 follows 1880; and the distribution in 1910 and 1920 follows 1900. Both wages are from urban areas. To form the wage for Trade we take the average of bakers and dress makers.

Wages by state for Transportation. We use the wage in each state for teamsters (male one horse teamsters from 1875-1900 across states, male two horse teamsters from 1913-1928 for select cities) and engineers (male in locomotive railroad from 1875-1898) from the United States Department of Labor (1934), starting on pages 449, 438 and 453. We convert both series into dollars per day, and we exclude the engineers in states which report only in per mile terms. Since the coverage is fragmentary for different states we take the average wage over several years to form the decade distribution across states. For both occupations we take averages over several years. For teamsters: 1870 is the average of 1875-1880; 1880 the average of 1876-1885; 1890 the average of 1886-1895; 1900 the average of 1891-1900; 1910 the average of 1913-1917; 1920 the average of 1916-1925; we assume the distribution for 1850 and 1860 follows 1870. For engineers: 1870 is the average of 1875-1880; 1880 the average of 1876-1885; 1890 the average of 1886-1895; 1900 the average of 1891-1900; we assume the distribution for 1850 and 1860 follows 1870; and the distribution in 1910 and 1920 follows 1900. We take both wages to be an average from urban and rural areas. To form the wage for Transportation we take the average of teamsters and engineers.

Wages by state for Education. We use the average monthly salaries of teachers in public schools as recorded in the Report of the Commissioner of Education for 1880 (Table 1, Part1, page 408), 1900 (volume 1, Tables 9-10, page 72), and 1915-16 (volume 2, Table 11, page 77). We use the average wage across all male and female teachers, and where the average is not reported for a state compute it as the weighted average of male and female teacher's salaries using the share of male and female teachers in the total. We assume 1850 through 1870 follow the 1880 distribution; 1890 follows the 1900 distribution; and 1910 and 1920 come from the salaries in 1915-1916. These are the average wages for the state.

Wages by state for Mining. We use the wage in each state for coal miners (male coal miners from 1875-1898) and iron miners (male, 1875-1899) from the United States Department of Labor (1934), page 330 and 333. In 1919 we use male hand miners of bituminous coal across states from the United States Bureau of Labor Statistics (1919), Table 3, page 9. Few wages exist early on, and so we use the average of 1880-1889 for the wage distribution in 1880, the average of 1880 to 1889 for 1890, and the average of 1890-1899 for 1900. We assume 1850 through 1870 follow the 1880 distribution; and 1910 and 1920 follows the 1919 distribution. The mining wage is the average of coal and iron mining wages in each year. Both mining wages are for rural areas.

Wages by state for Construction. We use the wages of bricklayers, carpenters, and masons from 1875 to 1928 first for states until 1900 and then select cities from the United States Department of Labor (1934), pages 155, 161, and 190. We assign the city wages to the state, and assume that all wages are urban wages. For each occupation we form 1870 using the average of 1875-1880; 1880 average of 1876-1885, 1890 average of 1886-1896; 1900 average from 1891-1900 since the series change in 1901; 1910 average from 1906-1915; and 1920 average 1916-1925. We take the average of the three occupations in each year to form a construction wage.

Wages by state for Government. The Annual Reports of the Postmaster General (1900) recorded the average compensation of fourth class postmasters by state. It is unclear from the text what frequency the salary is paid, but based on the maximum salary ($4000 to the postmaster general himself), the reported salaries appear to be quarterly. We were unable to find another report that gives a similar breakdown by state. We assume the distribution is the same as 1900 from 1850-

1900. We also use the wages of male municipal laborers in sanitation and sewage from 1890-1903 from the Nineteenth Annual Report of the Commisisioner of Labor (1905), page 470. We form 1890 using the average of 1890-1895, and 1900 using the average of 1896-1903. We assume that 1850-1880 follows 1890. We form 1850 through 1890 by combining the wages of municipal laborers and postmasters Municipal wages are per hour, and so we combine them with postmasters assuming a 50 hour week and 52 week year. Finally, we form the 1910 and 1920 distribution of wages using the wages paid to police detectives as collected by the Bureau of Municipal Research of Philadelphia (1916). We treat all of these wages as urban wages.

Wages by state for Communication and Miscellaneous Transportation, Professional Services, and Personal Services. We use Transportation for Communication, Education wages for Professional Services, and Trade for Personal Services. These services have a reasonably close approximation to the skill mix in the services for which good wages are difficult to find.

Value added by state for Finance and Insurancee For finance and insurance, we instead use the banking capital by state to allocate national value added. Before 1930, we do not have good observations of wages in finance, and insurance, so rather than follow an earnings allocation approach, it is useful to make some additional assumptions to allocate national value added per worker in finance services based on state banking capital. Suppose capital in financial services is mobile and paid its risk adjusted marginal revenue product across states:

$$MRPK_s = P\alpha A_S K_S^{\alpha-1} L_S^{1-\alpha} = \alpha Y_S / K_S = r_S.$$

Note that here Y_S, denotes nominal value added and K_S real capital. Then, because $Y_{US} = \sum_S Y_S$ and in each state $Y_S = r_S K_S / \alpha$, we can obtain :

$$Y_S = \frac{r_S K_S}{\sum_S r_S K_S} Y_{US} \tag{6}$$

which allocates national value added per worker in finance and insurance to states based on their relative capital returns. If we assume risk adjusted returns are equalized $r_S = r$, which as has some justification, as shown by James (1976), then national valued added can just be allocated by state capital. For 1880--1910 we use the total assets in national banks in each state collected from the annual report of the Comptroller of the Currency by Weber (2000). For 1870, we use the capital of individual banks aggregated to the state level collected by Fulford (2015). We assume that the distribution of capital in 1850 and 1860 is the same as in 1870 and 1920 is the same as 1910. The 1870 assumption is problematic since the banking capital of the south was largely destroyed by the Civil War, and there were few national banks in the south by 1870. Within states, we allocated state value added to counties using the wage bill or employment, following our standard method.

Combining employment, national value added, and wages We combine the employment, national value added, and wages to create a measure of value added at the county level. In 1940, this procedure is straightforward since we can observe the wage bill and and so apply equation (3) directly using the national value added rather than the state. We similarly use the 1940 wages to apply equation (3) to allocate 1930 value added using 1930 employment but 1940 wages. This approach assumes that the geographic distribution of relative wages within industry is similar in 1930 and 1940.

We use the relative wages in urban and rural areas in 1940 to create a state by urban-rural distribution of wages before 1930. The exact procedure depends on what kind of wage we observe, but we illustrate with teacher salaries. The teacher salaries we observe are the average for the state. To find the urban and rural wages we take urban and rural education employment in that year and solve for the relative wages that give the average wage so that urban-rural ratio is the same as in 1940.[13]

With a distribution of wages and employment by state and urban, we allocate national industry value added to these larger groupings using equation (3). Within each state urban/rural area we then allocate the value added using the relative employment of counties using equation (6).

For Finance, Insurance, and Real Estate, we instead allocate value added to state urban/rural

[13] In equations: we observe the average wage and employment but not the urban and rural wages: $\bar{w}_{s,t} = w^u_{s,t} emp^u_{s,t} + w^r_{s,t} emp^r_{s,t}$. By assuming that $w^u_{s,t}/w^r_{s,t} = w^u_{s,1940}/w^r_{s,1940}$ we have two equation and two unknowns and so can solve for the urban and rural wages.

areas using national banking capital in each state and the relative wages in FIRE in 1940. We then use equation (6) to allocate national value added to state urban and rural areas, and relative employment across counties within each of these areas to allocate value added to counties.

B.1.3 County GDP 1950, 1958, and 1963

Our approach for 1950, 1958, and 1963 is a hybrid of our approach before 1940 and after 1969 based on available data. While it is useful to have information connection 1940 to 1969, there are many assumptions that vary by year based on what is available. Starting in 1950, the census micro-samples no longer report the current county of residence so it is no longer possible to construct county employment shares by industry. The City and County Databooks (United States Department of Commerce Bureau of the Census, 2012) provide measures of employment, earnings, as well as manufacturing and agricultural products sold. The kind of information they provide changes from year to year, and they do not always perfectly align with what we can construct from the micro-data, so we provide details for each year separately.

Manufacturing. The manufacturing values in the the Databooks are reported as value added in 1947, 1954, 1958, and 1963. We use the values of 1958 and 1963 directly since other data match these years, and calculate a value for 1950 using the average growth rate in each county 1947 and 1954. Taking the linear average misses the rapid growth during the period, and so we take the average growth rate in each county from 1947 to 1954, and use the county specific growth rate for three years starting in 1947 to find county manufacturing in 1950.

Agriculture. The agriculture values in the Databooks give the total value of farm products sold in 1950, 1959, and 1964. We form 1958 and 1963 values by multiplying the county value by the nominal national increase in the total output in agriculture between 1958 and 1959 and 1963 and 1964 using series K 220-239 in U.S. Census Bureau (1975). We adjust for intermediate inputs and own consumption on the farm using the same series K 220-239. Own consumption was slightly more than 6% of total farm output in 1950. Of much larger importance is the value of intermediate inputs which were close to 40% of total output in 1950.

Mining. The Databooks report a value added measure of mining in 1963, output value in 1954, 1958, and 1963, and employment in 1940 and 1950. However, in 1958 and 1963, the employment, output, and value added of a large portion of counties appear to have been suppressed. These counties had mining reported in 1969 and 1940, but are reported as “Not available” in 1963. Counties with zero are reported as such, so treating “Not available” as zero creates more inequality from mining. We form value added in mining in 1950 by using the 1950 employment and the 1940 distribution of wages. Because of the data suppression, we then interpolate the values in 1958 and 1963 using the the national growth rate in mining and the county mining value added in 1950 and 1969.

Construction. The Databooks report county construction employment in 1950 and 1960. We form construction employment in 1958 and 1963 by adjusting for the national growth in the civilian non-agricultural labor force using U.S. Census Bureau (1975) series D11-25. We form value added in construction in 1950 by using the 1950 employment and the 1940 distribution of wages.

Services employment in 1950. In 1950, the Databooks report the employment in transportation and public utilities; wholesale and retail trade; finance, insurance, and real estate; personal services; professional services and overall employment. We use overall employment to construct a residual government employment in 1950 by subtracting out the other categories and setting the residual to zero if it would be negative.

Constructing county GDP in 1950. We combine our value added measures of agriculture and manufacturing at the county level, with valued added in mining, construction, and each of the services based on the employment in each of these industries and the 1940 distribution of wages. Our measure of value added comes from Tables 6.1B in United States Department of Commerce (2001) and we allocate the four sub-industries of Services (Professional, Personal, Education/Health, Recreation) based on the total compensation of employees. The 1950 census has only a 1% sample, and asked questions about income and wages to only one in five respondents (not all of whom had any income). We therefore use the 1940 wage distribution at the county level for 1950 in equation 4 to form the relative wage, but use the 1950 employment from the Databooks which was originally calculated from the full census. This approach is very similar to our approach before 1940, except that we use actual employment by industry as reported in the Databooks, rather than an estimate based on occupation in the census micro-samples. Since the Databooks do not break down some industries by employment within a county, we use the 1940 county employment ratios in each industry to break Trade employment into Retail and Wholesale; the combined Transportation and Public Utilities employment into Transportation, Communications, and Utilities; and Select Services employment into Education/Health and Professional. Finally, we form the residual of employment not in an industry by subtracting the employment in each industry from the reported total employment. The residual contains Government and Recreation which we allocate based on their 1940 county employment shares.

Constructing county GDP in 1963. In 1963, we allocate state GDP by industry from the BEA to the counties within a state using several measures of local production since we observe employment in some industries, earnings in others, and value added in others. We allocate state GDP for agriculture based on the share of agriculture output in each county. We allocate state GDP for mining and manufacturing based on the share of county value added.

For several industries we observe only employment in 1963. We create a measure of earning in these industries by calculating the 1969-1970 average earnings per worker in each county-industry and use this earnings distribution to calculate county earnings in 1963. We allocate state GDP for Transportation, Communication, Public Utilities, FIRE, Government, and Construction based on the share of state earnings in each of these industries. We construct government employment as the sum of 1963 local government employment and an estimate of federal government employment based on the ratio of federal to local government in 1967.[14] We form 1963 transportation employment using the 1960 county transportation employment, which includes communication and public utilities in 1963 increased by the national rate of growth in employment. We allocate state GDP in each of these industries based on the overall transportation employment so that counties within a

[14]We construct our estimate of federal employment assuming that local employment and federal employment grow at the same rate in a county from 1963 to 1967: Federal emp. in 1963 = (local government emp. in 1963) * (Federal emp. in 1967)/(local government emp. in 1967).

state receive the share of each sub-industry in proportion to their employment in the overall category. We construct county employment in Education, FIRE, and Construction using employment in 1960 times the national rate of employment growth. We form professional employment using the share of "white collar occupations" in 1960 and use it to allocate state Professional value added.

Finally, we allocate state GDP for wholesale trade, retail trade, personal, and recreational, based on the earnings in these services reported in the Databooks. We construct Personal and Recreational services using "select services" which include: hotels, personal services, miscellaneous business services, auto repair, repair, motion picture, and recreation. We allocate state GDP in both Personal and Recreational services based on the county earnings in select services and so implicitly assume that the geographic distribution of these services is the same.

Constructing county GDP in 1958. We follow a hybrid approach in 1958, combining the measures of manufacturing, agriculture, and mining value added that we construct for each county from the Databooks with county services constructed by allocating a measure of state GDP based on earnings or employment. We create a measure of state GDP in 1958 by taking the 1963 state GDP in each industry and reducing it at the national rate of growth in that industry based on the NIPA tables in Carter (2006). We construct a measure of county earnings for Construction, FIRE, Government, Transportation, Communication, and Public Utilities using county employment times the 1969-1970 average earnings per worker in these industries. Then we allocate the constructed state GDP for for these industries based on their share of total county earnings for each state. on employment in these industries. We observe only the sum of employment in Transportation, Communication, and Public Utilities, so allocate constructed state GDP for each sub-industry assuming that these industries are in constant employment proportion to each other. We allocate wholesale trade and retail trade based on earnings in these industries; and state personal and professional services based on earnings in select services. We construct Mining using the mining output value in 1958 times the value added-to-output-value ratio in 1963. We allocate state agriculture GDP using state agriculture output compared to the state total. We combine these employment or earnings based estimates with the manufacturing value added from the county books, and the agriculture and mining estimates to calculate total GDP in each county.

B.2 Employment by industry

We create estimates of employment by industry from the same sources as our measures of GDP. In many years, constructing employment is an intermediate step to constructing county GDP for many industries and so we describe it in the construction of GDP. Although we use direct value added measures for manufacturing and agriculture, we construct the employment in these industries using the census micro-samples before 1950 since alternative measures are not consistent.

From 1969 on we use the BEA measures of total employment by industry in each county (series CA25 and CA25N). Because of data limitations, the BEA does not divide between full time and part time jobs, and so the figures are the total number of jobs not the number of people with a job.[15] Since the calculations from the census micro-data before 1950 and from the city and county data books are for individuals, not jobs, the aggregate employment is different between these two series.

We adjust for non-reported or non-disclosure in the same way as for earnings. For codes marked (L) which represent 10 or less, we give 5 jobs. For codes marked (D) which are not reported to avoid confidential disclosure, but which are included in the state totals we allocate the non-reported total proportional to the broader industrial category in a county if it is reported We first calculate the fraction of each industry in a state that is not reported. We then calculate the difference between total employment in a county and employment from the sum of the major industrial categories. Within each county, we then allocate this difference between total and reported employment for the major industries in each county so that it has the same proportion as the not-reported for the state total. This procedure ensures that within each county the allocated total employment or earnings adds up to the reported total.

For the SIC industrial codes (series CA25 from 1969 to 2000), the BEA does not report the employment breakdown within services, or for the combined transportation and public utilities at

[15] See `https://www.bea.gov/regional/pdf/spi2015.pdf` for a discussion.

the county level, but does report the breakdown at the state level. We allocate employment within the broader sector using the state earnings per worker within each industry. We observe county earnings in each sub-industry. Variations in sub-industry earnings across counties could come from variations in the amount of employment in a county or from variations in earnings per worker across counties. Since it is implausible that the employment share is constant across counties, we make a more plausible assumption that the relative earnings per worker in each sub-industry is the same across counties, although overall earnings per worker may be higher and lower. We observe the sub-industry earnings $E^j_{c,t}$, and the state earnings $E^j_{s,t}$ and employment $L^j_{s,t}$ in each sub-industry, but not county employment in the sub-industries of services $L^j_{c,t}$. We assume that:

$$\frac{E^j_{c,t}}{L^j_{c,t}} = \phi_{c,t}\frac{E^j_{s,t}}{L^j_{s,t}}$$

for each of the j industries giving j equations for some earnings multiple $\phi_{c,t}$. This assumption implies that the ratio of earnings by janitors and lawyers is the same in New York City as in upstate New York, although both janitors and lawyers may earn more in New York City. Sub-industry labor, which we do not observe, must add up with each county:

$$\sum_j L^j_{c,t} = L_{c,t}.$$

The j earnings per worker equations and sum of labor equation give $j+1$ equations for $j+1$ unknowns (the $L^j_{c,t}$ and $\phi_{c,t}$). And so it is possible to find the labor breakdown within each sub-industry using the earnings:

$$L^j_{c,t} = E^j_{c,t}\left(\phi_{c,t}\frac{E^j_{s,t}}{L^j_{s,t}}\right)^{-1}$$

and substituting this equation into the total labor equation gives that:

$$\phi_{c,t} = \frac{1}{L_{c,t}}\sum_j E^j_{c,t}\frac{L^j_{s,t}}{E^j_{s,t}}.$$

Place of residence, jobs, and workers When considering production at a fine geographic level, the difference between residence and place of work becomes important. Our measures of employment by industry from the census micro-data before 1950 are by place of residence not place of work. Since commuting across county lines would have been relatively uncommon, the difference between where people lived and where they worked should be relatively unimportant before 1950. In 1950, 1958, and 1963 our measures of earnings and employment come from the City and County Data books. While it is sometimes difficult to tell the definition of the measure of employment in the Data books, the primary source of data is the census and so the earnings or employment location is by residence not place of work. Since we observe agriculture and manufacturing value added in a county directly, these industries are the output of the county. To the extent that commuting is large in these industries, we will tend to overstate the production per worker in some counties and understate it in nearby ones. After 1963, the BEA defines earnings by place of work rather than place of residence.

At the county level, the BEA definition of local employment is by jobs. [16] One person can have multiple part time jobs. The big difference is in self-employment where proprietors can have multiple jobs if they own multiple businesses or are employed but also own a business. This difference creates a large discrepancy between our earlier measures of employment which are based on individuals, not jobs, since the number of business owned by self-employed is much larger than the number of people with jobs. It makes no difference for the allocation of state GDP by county earnings, however, since earnings correctly adjusts for the earnings share of the business. The BEA reports in NIPA Tables 6.8B-D the "Persons engaged in production" by industry which is the number of full time equivalent employees and self-employed. To create a consistent series of employment, we adjust the county jobs in each industry so that the sum of the jobs in all counties within each industry is the same as the national "persons engaged in production from the NIPA tables. This adjustment has no effect on the allocation of GDP geographically, instead it shifts the production per worker up by reducing the number of jobs to the number of workers. Adjusting for

[16] See p. 76 `https://www.bea.gov/regional/pdf/lapi2015.pdf` for discussion (accessed 10 April 2017).

full-time equivalent by industry has a small effect on relative productivity across counties to the extent that some industries have more self-employed with multiple businesses and industries are concentrated in some some areas more than others.

B.3 Creating consistent counties

There are some adjustments that are necessary to calculate consistent geographic measures over more than 160 years. We standardize on 1950 counties using the county boundary definitions from the National Historical Geographic Information System (Minnesota Population Center, 2011). We follow the BEA and early censuses by including Virginia independent cities in their surrounding counties. See `https://www.bea.gov/regional/pdf/FIPSModifications.pdf` for a source of BEA code modifications and the cities that are included in each county.

For historical consistency we also combine counties that have split more recently. We combine the following counties with a single origin county: Menominee, Wisconsin with Shawano; Broomfield, Colorado with Boulder; Ogolala Lakota, South Dakota is Shannon before 2015; Cibola, New Mexico with Valencia; La Paz, Arizona with Yuma.

In addition, since our calculations for services before 1950 rely on samples from the census which are unreliable for small counties, we exclude all counties with a population less than 1000 in all time periods. To mitigate the effect of this exclusion, we combine counties which have a population in 2010 below 1000 with other nearby counties. We combine the next door counties of Grant Hooker, Thomas, Logan, McPherson, and Arthur, Nebraska with each other. We assign the following counties to next door counties, noting the county that was absorbed in capitals: Nebraska BANNER to Kimball; Nebraska HAYES to Frontier; Nebraska BLAIN and LOUP to Custer; Nebraska GARFIELD to Wheeler; Nebraska KEYA PAHA to Brown; Nevada ESMERALDA to Mineral; New Mexico HARDING to Union; North Dakota BILLINGS to Golden Valley; North Dakota SLOPE to Golden Valley; Texas KENEDY to Brooks; Texas BORDEN to Dawson; Texas KENT to Stonewall; Texas KING to Dickens; Texas LOVING to Winkler; Texas MC MULLEN to La Salle; Texas ROBERTS to Hemphill; South Dakota WASHABAUGH has 1020 people and does not show up in BEA to Jackson; South Dakota ARMSTRONG to Stanley; Colorado combine SAN JUAN and MINERAL to Hindsdale; Idaho CLARK to Butte; Montana GOLDEN VALLEY to Wheatland; Montana PETROLEUM to Fergus; Montana TREASURE to Rosebud.

B.4 County income per person 1950-2014

Starting in 1950 official statistics report measures of personal income per capita at the county level. We combine the county level income data from the County Data Books (United States Department of Commerce Bureau of the Census, 2012) with the county income from the census in 1980, 1990, 2000, and the combined 2008-2012 American Community Survey collected by Minnesota Population Center (2011). In 1950, the census only reported median household income at the county level, while in other years we have mean income per person. To account for this discrepancy we multiply the 1950 median household income by the mean income to median income ratio in 1960 for each county. Starting in 1969, we also use BEA measures of personal income.

B.5 GDP industry deflators

Appendix Table A-1 shows the sources for the industry deflators we use for various periods. The particular form of the industry deflator index—output deflator, double deflator or chain weighted index—varies by the source. The information to turn one kind of index into another is not available. We rely on Bureau of Economic Analysis chained industry deflators by industry after 1947 following the same convention of treating Information as the same as the Communication industry after 1997 that we use for the construction of nominal GDP. We splice industry indices before 1947 with the BEA industry indices after 1947 by projecting back the BEA indices using the percent change in the pre-1947 indices.

For 1900 to 1947, we rely on Kendrick (1961, chapter 6) for most industries. Kendrick (1961) is often opaque, even compared to contemporary sources, so understanding what he reports is non-trivial. A double deflation index for value added, with base year b, compared to the year t, and denoting the price of inputs p_t^I, the real quantity of inputs q_t^I and outputs analogously, is:

$$I_t^{VA} = \frac{p_t^O q_t^O - p_t^I q_t^I}{p_b^O q_t^O - p_b^I q_t^I} = \frac{(p_t^O - p_t^I q_t^I / q_t^O)}{(p_b^O - p_b^I q_t^I / q_t^O)}$$

where the denominator values real production at t at prices in base year b. Kendrick reports the "unit value added" as an index by industry which is the value added divided by the real quantity of output. In modern notation, for each industry,

$$I_t^{VA} = \frac{(p_t^O q_t^O - p_t^I q_t^I)/q_t^O}{(p_b^O q_b^O - p_b^I q_b^I)/q_b^O} = \frac{(p_t^O - p_t^I q_t^I / q_t^O)}{(p_b^O - p_b^I q_b^I / q_b^O)}$$

If the relative real quantity of output and input are in fixed proportion:

$$\frac{q_b^I}{q_b^O} = \frac{q_t^I}{q_t^O},$$

then $I_t^{VP} = I_t^{VA}$. This assumption is likely only reasonable as long as the industrial process does not change radically over time, so we use it only for the period during which we rely on Kendrick. We combined manufacturing industries using a Fisher index with weights based on nominal value added as reported in the 1947 Census of Manufactures Volume II (United States Bureau of the Census, 1949) and a base year of 1929. We combine the sub-industries Kendrick reports for Mining, Public Utilities, Transportation, and Communications using a Fisher index with base year 1929 and based on output weights for those sub-industries reported in the appendix to Kendrick (1961).

For retail and wholesale trade from 1870 to 1940, we rely on Barger (1955) who reports the cost of retail and wholesale trade as a percentage of the retail value of commodities in tables 17 and 29. For internal consistency, we create a commodity price Fisher index based on Barger (1955) Table 10, with base year in 1929, and create retail and wholesale deflators measured as the cost of trade times the commodity price index.

Before 1900, we rely mainly on Gallman (1960) for commodities and Gallman and Weiss

(1969) for services. For services, Gallman and Weiss (1969) generally report an index based on wages. We use the change in wages reported for a related service industry when the the particular service industry is not available.

For some service industries noted in Table A-1, we rely on wages reported in the NBER macro history database to construct price changes over different periods.[17] We use Series 08061 "Index of Composite Wages," Series 08060 "Increases in Average Annual Earnings of Teachers," and Series 08058 "Average Annual Salaries of Postal Employees." From 1930 to 1947 we use the increase in the GDP deflator from Sutch (2006) instead. The deflation during the 1930 and price controls during the war make it difficult to provide accurate prices for this period.

[17] Available `https://data.nber.org/databases/macrohistory/contents/`, accessed 25 November 2019.

C Comparison to other measures

This appendix compares our GDP and GDP deflator measures to other measures.

We begin by showing that the sum our counties closely matches U.S. GDP per capita over time. Figure A-10 shows the sum of our county GDPs divided by their population, and U.S. GDP per person from Sutch (2006). While for services in the early period we use national estimates of value added per worker, modified by local wages, we are not otherwise using national estimates and so the close correspondence is not by construction. Instead, it likely reflects that for agriculture, manufacturing, and services the historical sources that we use are very similar for much of the period to the sources used by Sutch (2006): census estimates of production and employment, augmented in intercensal years by output of commodities such as pig iron that is available at a yearly frequency.. We seem to be systematically lower in the very early years. The census in 1850 did not record occupations for women, and was inconsistent for the slave work force before emancipation. We may also be missing output that occurs in counties not yet covered in the census that estimates of early GDP include. In any case, the difference quickly disappears and we match Sutch (2006) nearly exactly after 1890. We take the fact that we match both the level and the growth path well as a strong indication that our overall approach is capturing the broad trends in the economy.

Figure 6 shows that our approach matches sectoral shares of the economy as well when these become available after 1929, and provide an independent measure of the overall economy before that. Indeed, given the difficulty in calculating shares starting in 1929 and during the subsequent Depression, there is some reason to prefer our more stable estimates in the early years.

Figures A-10 and 6 also illustrate the massive change in the level and composition of production that have taken place in the U.S. since 1850. While the U.S. has become much richer, how it produces has shifted, as agriculture declined relative to services as a share of the economy. The share of manufacturing expanded until 1950, but it has since declined. Set against the backdrop of overall growth in Figure A-10, it is important to realize that the decline in manufacturing share in Figure 6 does not imply a decline in manufacturing production. The U.S. produces more manufac-

Table A-1: Industry deflators: Notes and Sources

Industry	Notes and sources
Agriculture	1870-1900 Galman (1960); 1900-1947 Kendrick (1961); 1947-1997 BEA historical GDP by industry; 1997-2019 BEA GDP by industry
Mining	1870-1900 Galman (1960); 1900-1947 Kendrick (1961); 1947-1997 BEA historical GDP by industry; 1997-2019 BEA GDP by industry
Construction	1870-1947, follow manufacturing; 1947-1997 BEA historical GDP by industry, 1997-2019 BEA GDP by industry
Manufacturing	1870-1900 Galman (1960); 1900-1947 Kendrick (1961), weighted with 1947 Census of Manufactures in 1899-1947; 1947-1997 BEA historical GDP by industry; 1997-2019 BEA GDP by industry
Transportation	1870-1900 Galman and Weiss (1969) railroad and shipping freight rates; 1900-1947 Kendrick (1961); 1947-1997 BEA historical GDP by industry; 1997-2019 BEA GDP by industry
Communication	1870-1900 Galman and Weiss (1969) distribution; 1900-1947 Kendrick (1961); 1947-1997 BEA historical GDP by industry; 1997-2019 BEA GDP by industry
Public utilities	1870-1900 Galman and Weiss (1969) distribution; 1900-1947 Kendrick (1961); 1947-1997 BEA historical GDP by industry; 1997-2019 BEA GDP by industry
Wholesale trade	1870-1940 Barger (1955) wholesale cost times commodity price index; 1947-1997 BEA historical GDP by industry; 1997-2019 BEA GDP by industry
Retail trade	1870-1940 Barger (1955) retail cost times commodity price index; 1947-1997 BEA historical GDP by industry; 1997-2019 BEA GDP by industry
Finance, Insurance, and Real Estate	1870-1900 Galman and Weiss (1969) medical; 1900-1930 follow Education; 1930-1947 Sutch (2006) GDP deflator; 1947-1997 BEA historical GDP by industry; 1997-2019 BEA GDP by industry
Professional, Scientific, Technical, and Business services	1870-1900 Galman and Weiss (1969) medical, 1900-1947 follow Education; 1947-1997 BEA historical GDP by industry; 1997-2019 BEA GDP by industry
Education and Health services	1870-1900 Galman and Weiss (1969) medical; 1900-1930 NBER teacher; 1930-1947 Sutch (2006) GDP deflator; 1947-1997 BEA historical GDP by industry; 1997-2019 BEA GDP by industry
Recreation services	1870-1900 Galman and Weiss (1969) domestic; 1900-1930 NBER composite wage; 1930-1947 Sutch (2006) GDP deflator; 1947-1997 BEA historical GDP by industry; 1997-2019 BEA GDP by industry
Personal services	1870-1900 Galman and Weiss (1969) domestic with linear interpolation; 1900-1930 NBER composite wage; 1930-1947 Sutch (2006) GDP deflator; 1947-1997 BEA historical GDP by industry; 1997-2019 BEA GDP by industry
Government	1870-1900 Galman and Weiss (1969) service sectors variant 1; 1900-1930 NBER postal ; 1930-1947 Sutch (2006) GDP deflator; 1947-1997 BEA historical GDP by industry; 1997-2019 BEA GDP by industry

Notes: Kendrick (1961) reports 1919 and 1937, we adjust to 1940 and 1920 using aggregate GDP price deflator from Sutch (2006).

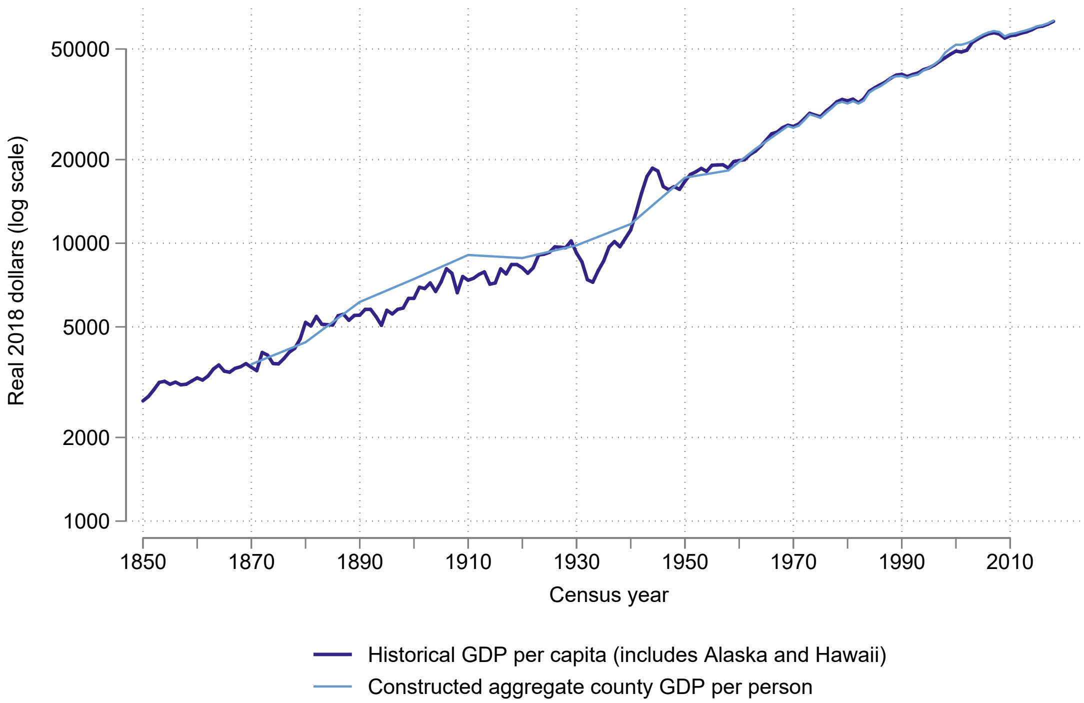
tured value added now than in the 1950s, and is much more productive, so it employs fewer people. These aggregate sectoral shifts seem to be part of a broader pattern of development (Herrendorf, Rogerson, and Ákos Valentinyi, 2014).

Figure A-11 shows how our county GDP measure compares to state measures of Personal Income from Easterlin (1960), Leven (1925), and Schwartz and Robert E. Graham (1956). These measures formed the basis for the Barro and Sala-i-Martin (1991) analysis of the convergence across states. Personal Income is distinct from our value-added concept of county GDP because it includes income earned from production done elsewhere and does not include corporate profits. These distinctions suggest that our measure of aggregate state GDP should not be exactly the same as state personal income although the two should be broadly similar. To remove aggregate differences and instead focus on the geographical distribution, we compare each state's share of U.S. GDP based on the county total to the state share of US Personal Income. Our measures closely match the state personal incomes from 1880 to 1940 and by construction match the BEA state GDPs exactly since 1969. The figure shows how different each state's share of total GDP (defined as the sum of county GDPs) is from that state's share of total income. We order them based on the share of total income from that source. Since the shares add up to one, the differences in shares must sum to zero, and so Figure A-11 is essentially graphing the residuals from a regression of state GDP share on state income share. The differences are small, and at least in the early years seem to be systematically related the difference between income and value-added, since the states where we place more GDP than the estimates of personal income are also states with large capital exporting cities.

Finally, the BEA started publishing county GDP estimates for the years after 2001.[18] These estimates use more information than the wage bill, including non-public information on local production. Figure A-13 shows a scatter plot in 2001 and 2019 of log GDP per person calculated using our earnings approach and the new BEA estimates. While most counties align closely, there are a few outliers. The figures show that in both 2001 and 2019, the counties where our measure

[18] See Aysheshim et al. (2020) for the methodology and `https://www.bea.gov/data/gdp/gdp-county-metro-and-other-areas` for the BEA page.

Figure A-10: Aggregate county GDP and estimates of U.S. GDP

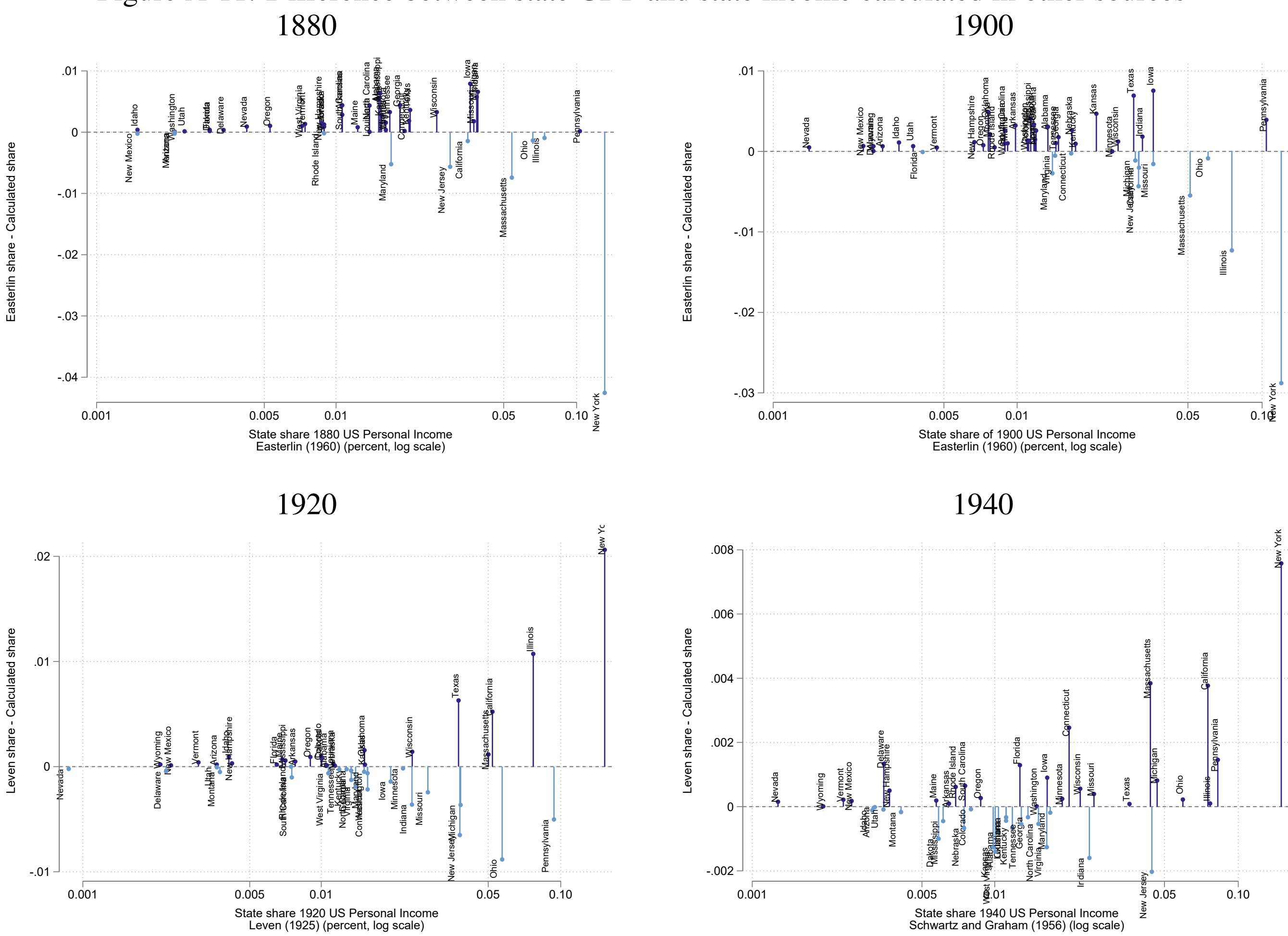


Notes: Compares U.S. GDP created by combining all counties with U.S. GDP from Historical Statistics of the United States, Earliest Times to the Present, GDP series by Sutch (2006).

and the BEA do not closely align are almost all ones where mining or utilities were a large share of the economy. In 2019, the highest GDP per person counties by the BEA estimates are counties where mining is a large share of the economy. Using earnings to allocate mining or utilities may be less accurate because of the high capital involved.

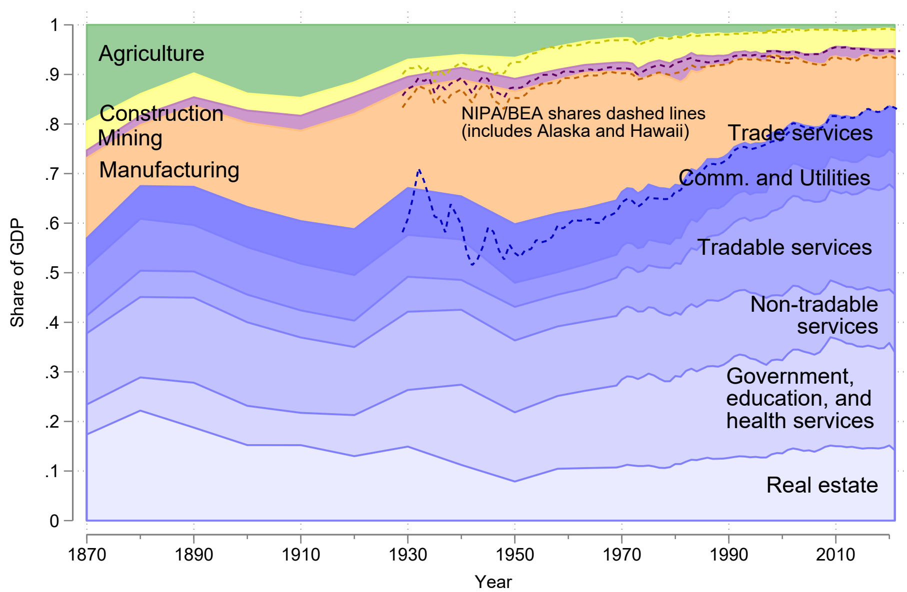
Table A-2 shows simple regressions with our measure of log GDP per person against the BEA measure from 2001–2019. With no exclusions for mining or utilities, our measure is highly correlated with the BEA estimates, with a slope coefficient of 0.829 and and $R^2$of 0.78. Excluding the high mining and utility counties that are the outliers in Figure A-13, however, and the fit improves dramatically. The slope coefficient is statistically indistinguishable from 1, the constant is close to zero and the $R^2$is 0.92.

Figure A-11: Difference between state GDP and state income calculated in other sources



Notes: Each figure shows the difference between the share of total U.S. GDP our county calculations give that state and the share of total U.S. personal income from Easterlin (1960), Schwartz and Robert E. Graham (1956), and Leven (1925).

Figure A-12: Industry shares of GDP and employment



Notes: The solid lines are the implied national share of U.S. GDP by sector from aggregating counties. Industries are grouped by broad sector. The dashed lines show the National Income and Product (NIPA) from 1929–2002 Carter (2006) and 1996–2020 from BEA.

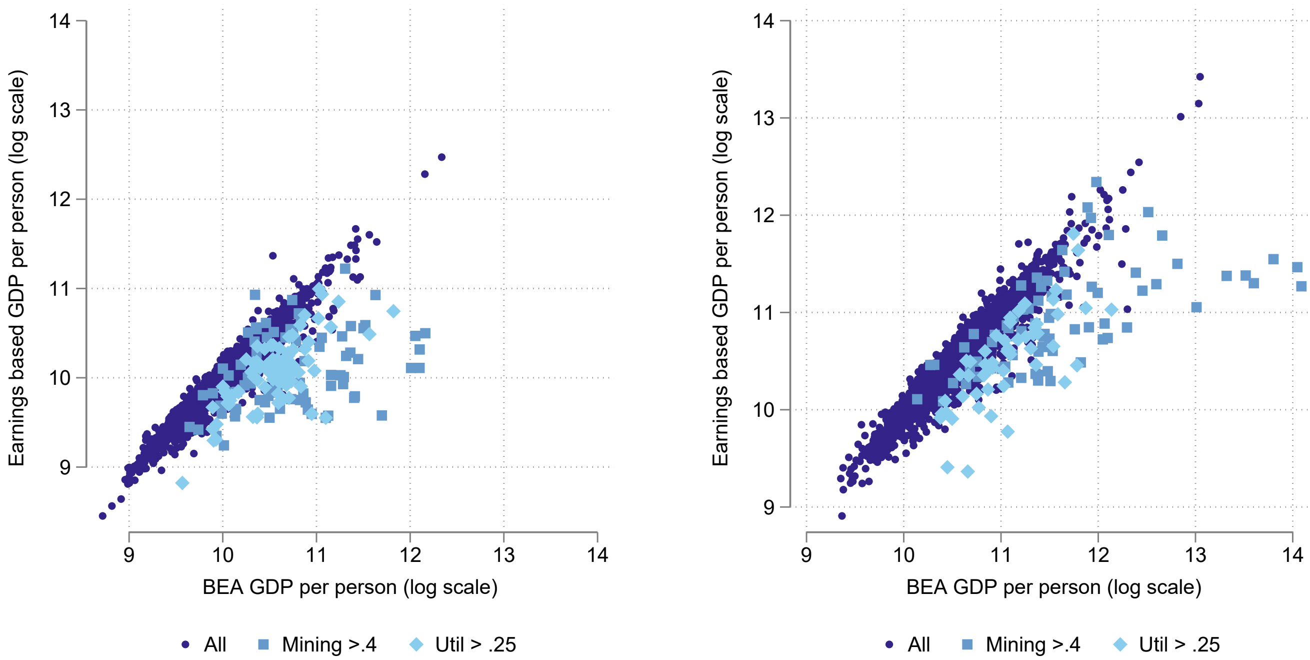
Table A-2: Regression comparison of county GDP per person measures

	All counties	In sample	All counties	In sample
	ln GDP per person			
ln BEA GDP per person	0.829***	0.999***	1.041***	1.053***
	(0.00182)	(0.00128)	(0.00178)	(0.00163)
Constant	1.716***	-0.0221*	-0.434***	-0.563***
	(0.0189)	(0.0132)	(0.0188)	(0.0172)
Observations	57,775	53,060	56,080	53,060
R-squared	0.783	0.920	0.949	0.967
Population weighted			Yes	Yes

Notes: Compares the log GDP per person based on our earnings estimates and from BEA from 2001 to 2019. Both measures are deflated using a common GDP deflator. The first column includes all counties for which both measures calculate GDP. The second includes only our main sample that excludes counties with high mining or utilities share of GDP and populations with fewer than 2500. The third and fourth columns weight each county by population size. *** p<0.01, ** p<0.05, * p<0.1

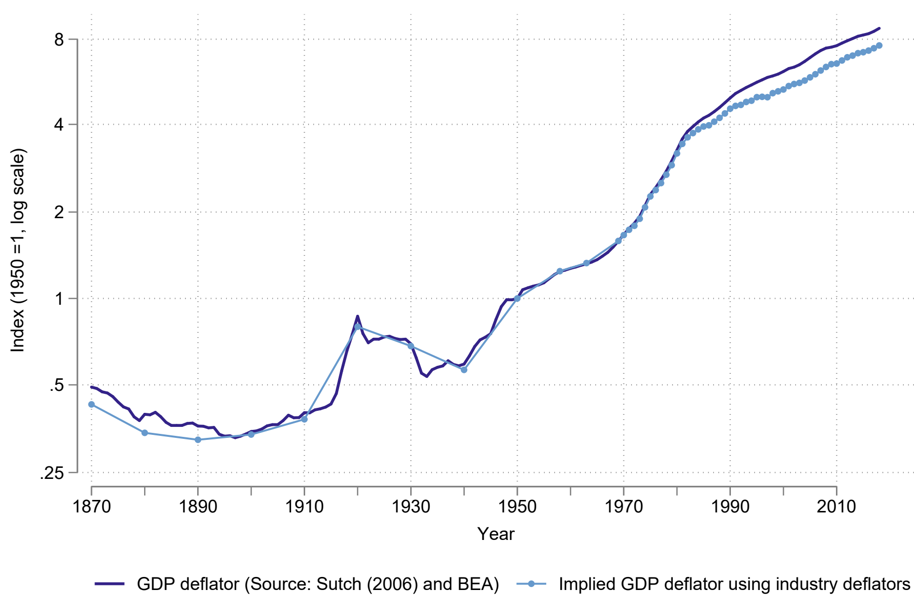
Figure A-13: Comparison of county GDP per person measures

Panel (A): 2001 comparison   Panel (B): 2019 comparison



Notes: The y-axis is the the earnings based county GDP per person developed in this paper, the x-axis the BEA county GDP per person estimates, both in a log scale adjusted for inflation with a common deflator. The mining >.4 are counties whose GDP is more than 40 percent mining using the BEA measure, and similarly for utilities.

Figure A-14: Comparison of aggregate GDP deflators



Notes: Shows the GDP deflator implied by dividing our measure of nominal national GDP from summing counties with our measure of real GDP created by summing real county GDP constructed using industry deflators. The an aggregate GDP deflator is from Sutch (2006) updated using the chained BEA deflator. The BEA switched to a chained deflator in 1996.