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

Scott L. Fulford† Fabio Schiantarelli‡

November 2024

Abstract

We construct the first estimates of U.S. county nominal and real GDP by broadly defined

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 e

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

uniquely capture services' importance and distribution which is crucial for understanding sectoral transformatons 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.
>
> **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.
>
> **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 convergence, using 1880–2000 state level data on personal income per person.[1] There is similar evidence inelop

Second, a more recent literature is mostly concerned with the regional, state and city divergence after 1970 and its reasons. Moretti (2012), Hsieh and Moretti (2015), and Eckert (2019) 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 and 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

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 insures over time and across space: 1) Agriculture; 2) Mining; 3) Construction; 4) Manufacturing;[3] 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.

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

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

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 Sc 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 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 continu-

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:

$$T = \frac{1}{n} \sum_{c} \frac{y_c}{y} \ln \frac{y_c}{y}$$

where y_c is GDP per worker and $y = \frac{1}{n} \sum_c y_c$ is the mean mea59 3.487 Taer0(chanr0(chan3 Td [(is)-259(the)-2f

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 contribute to and extend a large literature (Barro and Sala-i-Martin, 1991, 1992, 2004) that has found that U.S. states converged both relatively (convergence) and absolutely (

convergence) 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 Flor((is)-344(the)-345(emp.7,)-243(in)-243(placualityGrizth

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 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 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 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 shows 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 1960speriocl5(.n76)15ure 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

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:

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

The industry contribution can alternatively be written also as:

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

where $\tilde{s}_c^k = N_c^k / N_c$ is the share of workers in sector k in county c (because $s_c^k = \tilde{s}_c^k \frac{y_c^k}{y_c}$). 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

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

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 inequalpercent 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.

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:

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 8(2)-19s9b(r-535(Thus,)-344(while)-325(Figure)-325(A-8)-326(sho)25(w)1(s)-326(an)-325(o)15(v)15(era

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 in-

References

Annual Reports of the Postmaster General. 1900. *Report of the Postmaster General*. Washington, D.C.: Government Printing Office.

Aysheshim, Kirubel D., Jacob R. Hinson, , and Sharon D. Panek. 2020. "A Primer on Local Area Gross Domestic Product Methodology: First Official Release of Gross Domestic Product by

Carter, Susan B. 2006. *Historical Statistics of the United States, Earliest Times to the Present: Millennial Edition*, chap. National income, by industry group: 1929–2002. Cambridge University Press, Table Ca35–53. URL http://dx.doi.org/10.1017/ISBN-9780511132971.Ca1-26.

Caselli, Francesco and Wilbur John Coleman, II. 2001. "The U.S. Structural Transformation and Regional Convergence: A Reinterpretation." *Journal of Political Economy* 109 (3):pp. 584–616. URL http://www.jstor.org/stable/10.1086/321015.

Chetty, Raj, Nathaniel Hendren, Patrick Kline, and Emmanuel Saez. 2014. "Where is the land of Opportunity? The Geography of Intergenerational Mobility in the United States." *The Quarterly Journal of Economics* URL http://qje.oxfordjournals.org/content/early/2014/10/16/qje.qju022.abstract.

Comin, Diego A., Danial Lashkari, and Martí Mestieri. 2015. "Structural Change with Long-run Income and Price Effects." Working Paper 21595, National Bureau of Economic Research. URL http://www.nber.org/papers/w21595.

Cowell, F.A. 2000. "Chapter 2 Measurement of inequality." Elsevier, 87–166. URL https://www.sciencedirect.com/science/article/pii/S1574005600800056.

Desmet, Klaus and Esteban Rossi-Hansberg. 2009. "Spatial growth and industry age." *Journal of Economic Theory* 144:2477–2502.

———. 2014. "Spatial Development." *American Economic Review* 104 (4):1211–43. URL http://www.aeaweb.org/articles?id=10.1257/aer.104.4.1211.

Easterlin, Richard. 1960. *Trends in the American Economy in the Nineteenth Century*, vol. 24. Princeton University Press. URL http://www.nber.org/chapters/c2475.

Eckert, Fabian. 2019. "Growing Apart: Tradable Services and the Fragmentation of the U.S. Economy."

Eckert, Fabian and Michael Peters. 2022. "Spatial Structural Change." Working Paper 30489, National Bureau of Economic Research. URL http://www.nber.org/papers/w30489.

Eichengreen, Barry and Poonam Gupta. 2013. "The two waves of service-sector growth." *Oxford Economic Papers* 65:96–123.

Fulford, Scott, Ivan Petkov, and Fabio Schiantarelli. 2016. "Does It Matter Where You Came From? Ancestry Composition and Economic Performance of US Counties, 1850 - 2010." URL http://ssrn.com/abstract=2612312.

———. 2020. "Does It Matter Where You Came From? Ancestry Composition and Economic Performance of US Counties, 1850 - 2010." *Journal of Economic Growth* 25 (3). URL https://doi.org/10.1007/s10887-020-09180-9.

Fulford, Scott L. 2015. "How important are banks for development? National banks in the United States 1870–1900." *Review of Economics and Statistics* 97 (5):921–938. URL http://fmwww.bc.edu/ec-p/wp753.pdf.

———. 2001. *National Income and Product Accounts of the United States, 1929-1997*, vol. Volume 2. Washington, D.C.: U.S. Government Printing Office. URL https://fraser.stlouisfed.org/docs/publications/nipab/nipa_1929_97_v2.pdf.

United States Department of Commerce Bureau of the Census. 2012. "County and City Data Book Consolidated File: County Data, 1947-1977 (ICPSR07736-v2)." Inter-university Consortium for Political and Social Research [distributor]. URL http://doi.org/10.3886/ICPSR07736.v2.

United States Department of Labor. 1934. *History of Wages in the US from Colonial Times to 1928*. Washington, D.C.: Goverment Printing Office, republished by gale research company, detroit, 1966. ed.

U.S. Bureau of Economic Analysis. 2016. "Local Area Personal Income Accounts Tables CA5 and CA5N." URL http://www.bea.gov/regional/downloadzip.cfm.

U.S. Census Bureau. 1975. *Historical Statistics of the United States, Colonial Times to 1970, Bicentenial Edition, Part 1*. Washington, D.C.: U.S. Government Printing Office. URL https://www.census.gov/prod/www/statistical_abstract.html.

Weber, Warren E. 2000. "Disaggregated Call Reports for U.S. National Banks, 1880-1910. Research Department, Federal Reserve Bank of Minneapolis." Research Department, Federal Reserve Bank of Minneapolis. Available: http://research.mpls.frb.fed.us/research/economists/wewproj.html, accessed 30 April 2013.

Wright, Gavin. 2006. *Historical Statistics of the United States, Earliest Times to the Present: Millennial Edition*, chap. Mineral operations - establishments, receipts, value added, employment, and expenses: 1880-1997. Cambridge University Press, Table Db1–11. URL http://dx.doi.org/10.1017/ISBN-9780511132971.Db1-154.

Young, Andrew T., Matthew J. Higgins, and Daniel Levy. 2008. "Sigma Convergence versus Beta Convergence: Evidence from U.S. County-Level Data." *Journal of Money, Credit and Banking* 40 (5):1083–1093.

.

.

.

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

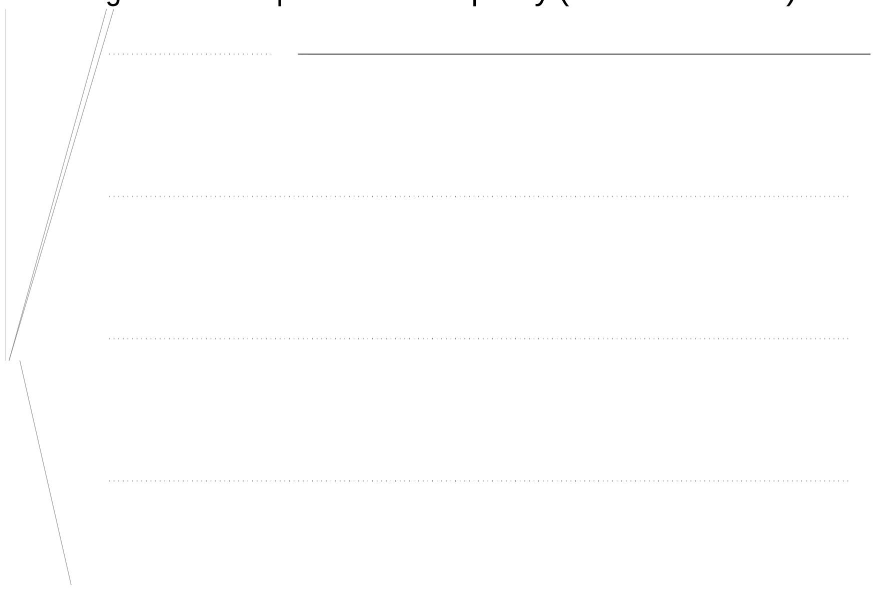
Panel (A): GDP per worker (common deflator 2010$)

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

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

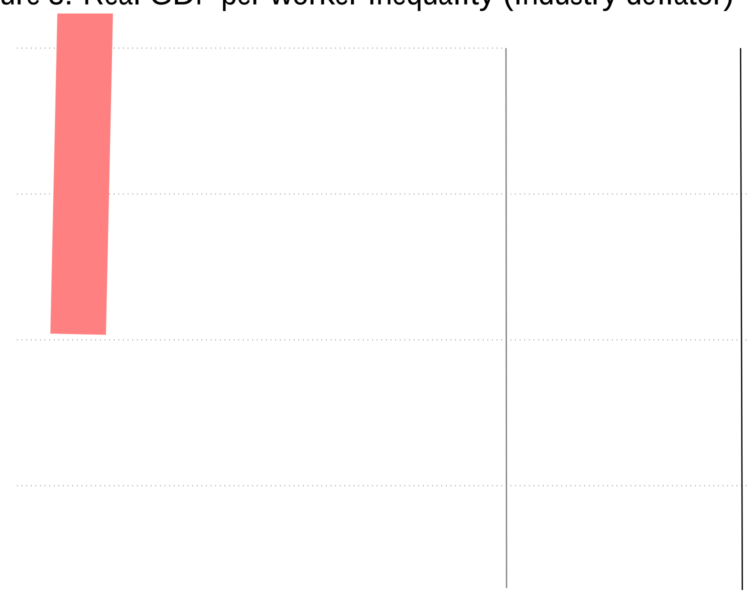
Notes: The common deflator in Panel (A) and (C) is from Sutch (2006) and the BEA. In Panel (B), real county GDP is obtained by deflating each industry nominal GDP by industry level GDP deflators and then all industries are added together.

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).

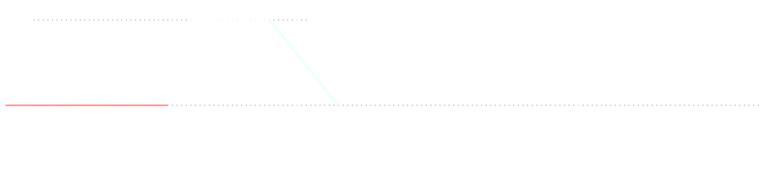
Figure 3: Real GDP per worker inequality (industry deflator)



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 excludif116udif1cludif11withudif11240(populatiif11lessmple)

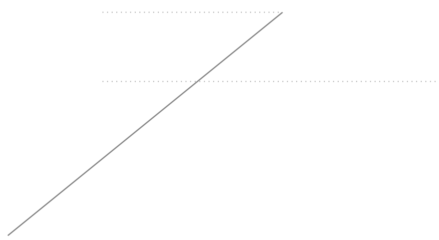
Figure 6: The geographic distribution of GDP per worker: 1970 and 2018

1970

2018

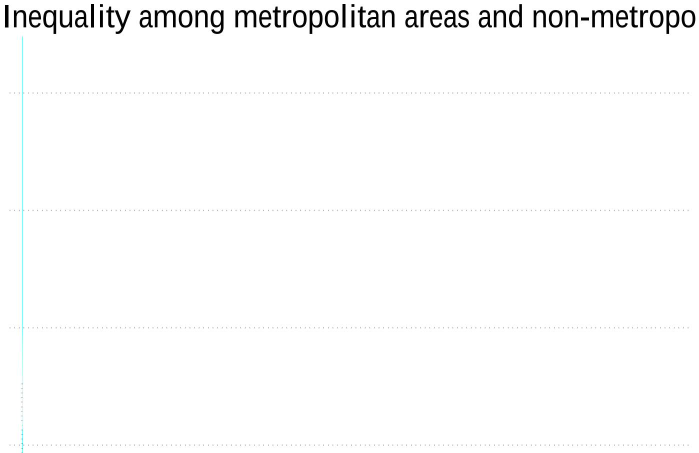
Notes: Shading in each county is by the difference in log county GDP per worker and log U.S. GDP per worker. The circle is the population center of the U.S. and is proportional to population in 2010. The square shows the GDP center of the U.S. and is proportional to 2010 real GDP per person. Uses county 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

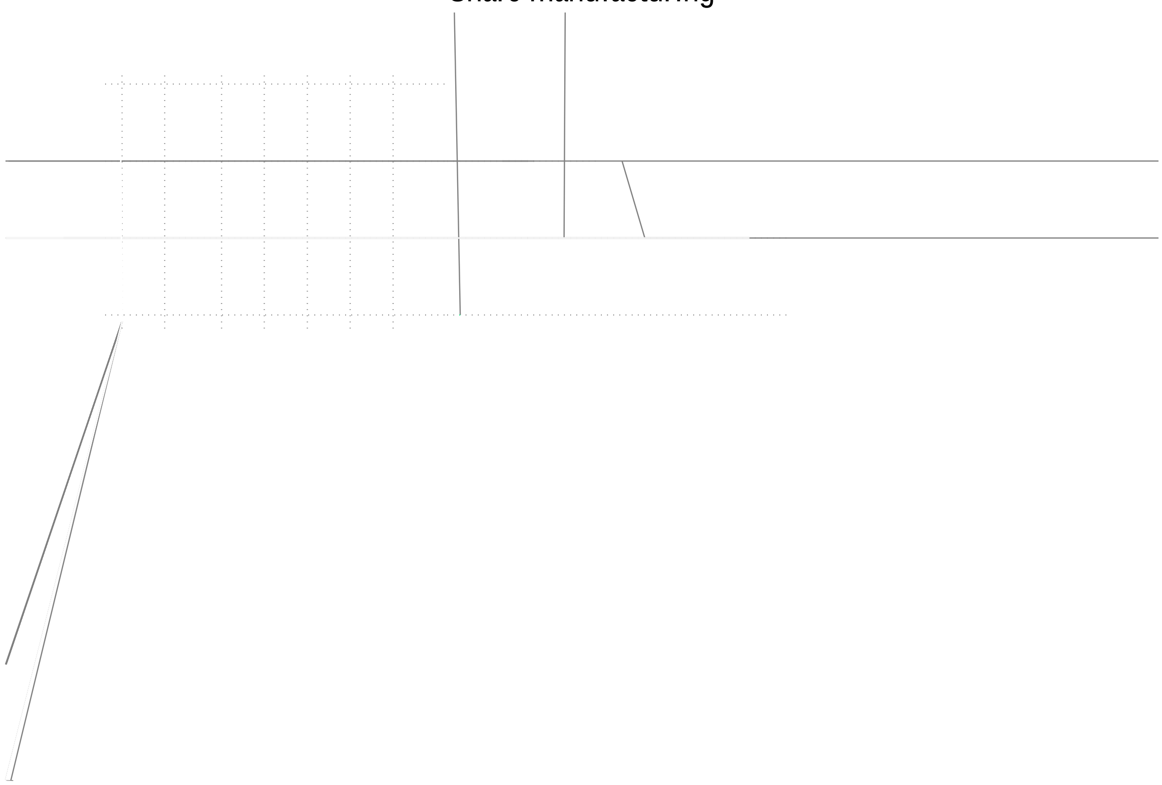
Panel (B): Industry share of employment

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 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).

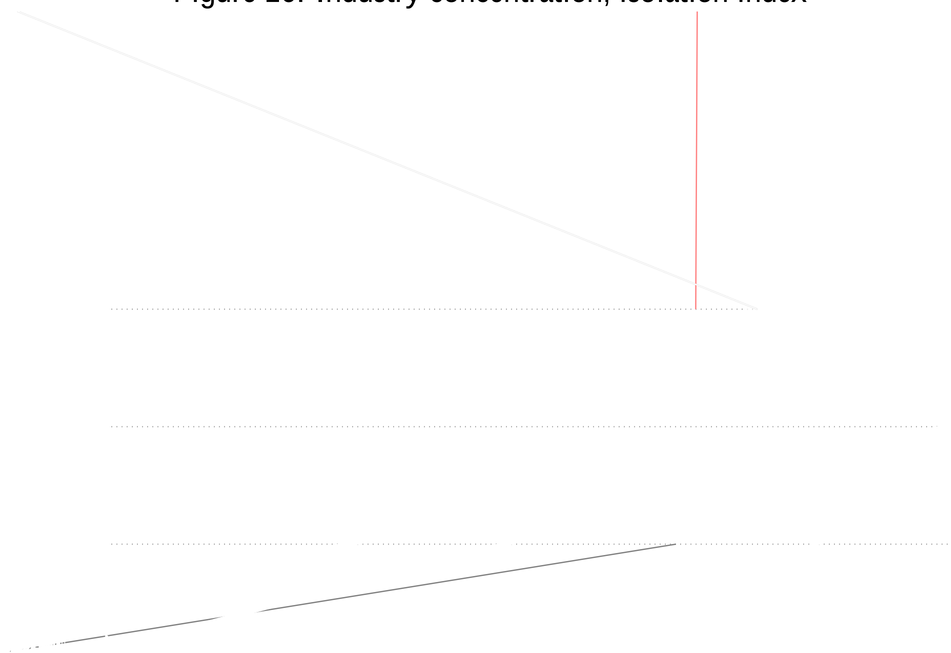
Figure 14: Sectoral share of GDP per worker inequality as a fraction of the Theil index, common deflator

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

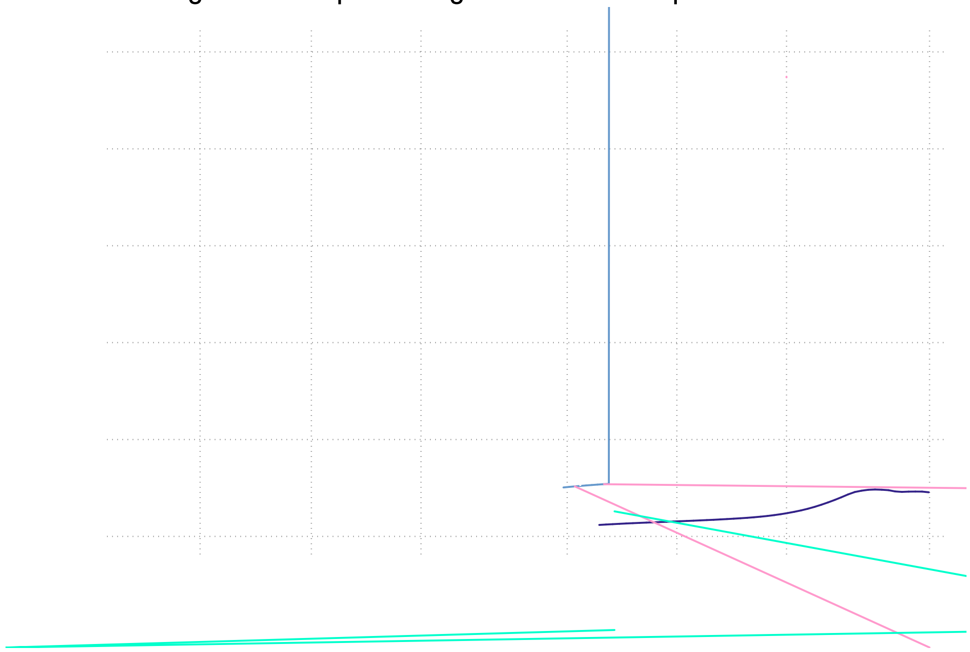


Notes: Main sample (excluding high mining and utility counties, and very small counties; see Section 2.3).

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

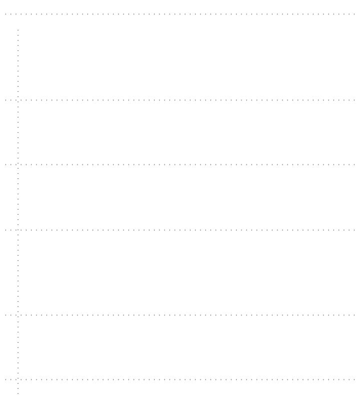
Notes: Productivity is industry deflated county industry GDP per worker. We cannon meaningfully calculate service productivity inequality before 1920, so it is not shown in the figure. We trim the top and bottom 1 percent of the distribution in each year. We note there is a change in data sources in 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).

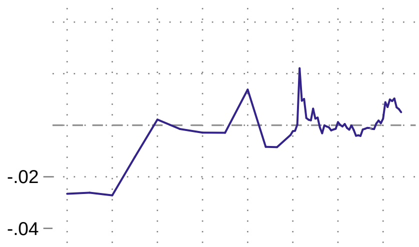
Figure A-3: GDP per worker of select metro areas

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 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

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

in ing

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

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

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 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 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

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:

$$E^j_{c;t}$$

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 com-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 (BIE)-255(ada)-294ydTdaY BIE ada 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 nonu5(percenriods.)

denoting the price of inputs p_t^I, the real quantity of inputs q_t^I

(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

Table A-1: Industry deflators: Notes and Sources 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

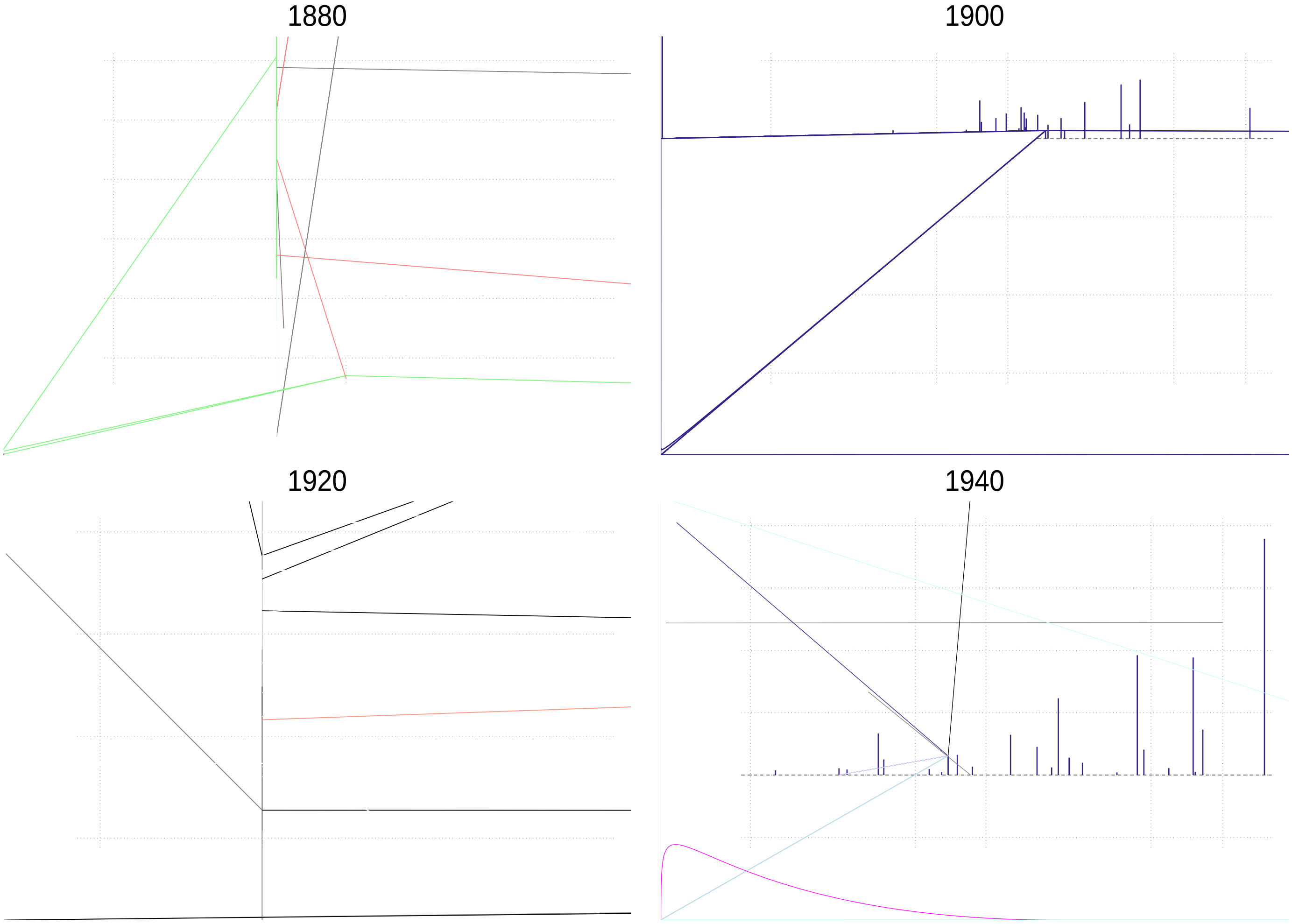
Figure A-10: Aggregate county GDP and estimates of U.S. GDP

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.

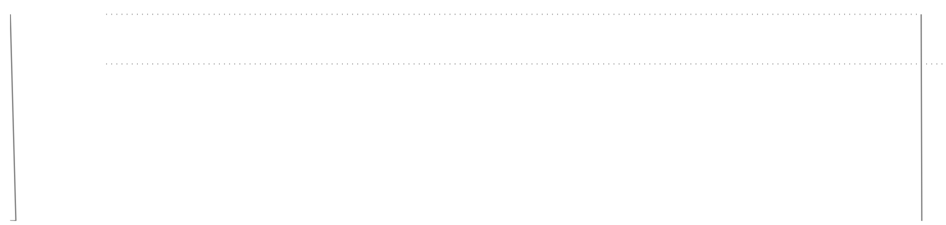
Table A-2 shows simple regressions with our measure of log GDP per person against the BEA measure from 2001–2019. With no exclusions for mining or utilities, our measure is highly correlated with the BEA estimates, with a slope coefficient of 0.829 and and R^2 of 0.78. Excluding the high mining and utility 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.