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Recent Changes in the Nature of Distribution Dynamics of US County Incomes*

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Abstract

Analysis of US county per capita incomes from 1970 to 2017 reveals the emergence of bipolarizing distribution dynamics from the early 1990s. This bipolarization process is characterized by the vanishing middle income counties mostly joining the high end of the distribution of county incomes. Cross-county differences in education and industry composition contribute to the bipolarization, but government transfers effectively reverse it. The results for these recent decades weakly support the *two-club convergence hypothesis*. A simulation of various nonlinear income growth dynamics and corresponding distributional dynamics reveals certain conditions on growth patterns for income bipolarization.

JEL Codes: D30, O11, O40, O51

Keywords: bipolarization, distributional dynamics, index, growth dynamics, transfers

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1 Introduction

This paper investigates the dynamics of the cross-sectional distribution of per capita income across United States (US) counties. Special attention is given to understanding and explaining the regularity of polarization, a characteristic of distribution dynamics that often features in the world income distribution. As is well summarized by Anderson (2004a,b) and Krause (2017), among others, polarization has been widely examined in both microeconomic analyses of income distribution that emphasize the diminution of the middle income class and the macroeconomic literature on growth and convergence issues.[1] This paper mainly concerns the latter. Despite the homogeneity of economic fundamentals across the US, which conventional wisdom suggests should lead to the convergence of regional incomes, we show new evidence that the distribution of county-level incomes has become significantly bipolarized since the early 1990s. Our research focuses on understanding the nature and driving forces of the recent bipolarization of US county incomes and the associated policy issues. While our primary concern lies in the US regional income distribution, our results are general enough to discuss two important related issues in the growth and convergence literature: testing the *club convergence hypothesis*[2] and existence of non-linearity in the growth-income relationship.

The advantage of using distribution dynamics to study convergence issues are well expressed by a series of studies by Quah (1993, 1996a,b,c, 1997), among others. Most importantly, compared to the traditional empirical approaches—cross-sectional linear convergence regressions, time series modeling, and panel data techniques—that capture the behavior of an *average* region, the distribution dynamics approach is better suited for addressing the main focus of the convergence hypothesis: whether poor regions catch up with the rich. Do *different* regions con-

[1]For the microeconomic studies of bipolarization of individual/household incomes, see Esteban & Ray (1994), Wolfson (1994), Gradín (2000), Gradín & Rossi (2006), Esteban et al. (2007), Hussain (2009), Foster & Wolfson (2010), Alichi et al. (2016), and Lee & Shin (2016), among others. For the macroeconomic studies of distribution dynamics, see Durlauf & Johnson (1995), Quah (1996a, 1997), Bianchi (1997), Jones (1997), and Azariadis & Stachurski (2003), among others. Also see Durlauf et al. (2005) for a more complete survey of the literature on growth and convergence.

[2]Galor (1996, p.1056, 1058) writes, "The *club convergence hypothesis* (*polarization*, persistent poverty, and clustering) – per capita incomes that are identical in their 'structural' characteristics converge to one another in the long-run provided that their initial conditions (initial *per capita* output levels) are similar as well."

verge to the same state regardless of initial condition? If not, what is the nature of regional income dynamics and what determines the fate of a region? These questions can be addressed with distribution dynamics which concern both mobility and shape dynamics in the whole distribution of regional incomes. The results inform policy-makers with interests in regional development and the geographic redistribution of income. Particular interest in the dynamics of US regions stems from the homogeneity of their economic and political fundamentals as well as the uniformity in variable definitions and the data collection processes, when compared to a collection of countries. Analysis of the US naturally controls for most, though not all, cross-region differences in 'structural' characteristics that are considered to be important growth determinants. By contrast, these determinants are not easily controlled for in a cross-country analysis due to data limitation (e.g., differences in the political system, preferences, technologies, and other institutional setups). This is important because the test of the conditional convergence vs. club convergence hypothesis, for example, assumes that regions are identical in their fundamentals and vary only in their initial conditions represented by output per capita. Interest in US regional incomes is also related to the recent bipolarization of individual/household incomes in the US (e.g., Foster & Wolfson, 2010; Alichi et al., 2016). To the extent that the bipolarization of individual incomes is connected to regional factors and that regional mobility is limited due to either asymmetric information or mobility costs, the bipolarization of regional incomes has important welfare implications: The persistent income gap between the rich and poor regions results in an 'un-equalizing difference' between their residents' utility. Although states are relatively more independent economic units compared to counties, we follow Higgins et al. (2006) in using county-level income data to study convergence issues. The county-level analysis allows us many more degrees of freedom (over 3,000), which facilitates more precise estimates in the analysis of conditional club convergence while controlling for as many as 40 county-specific variables. This is not feasible in the state-level analysis. More complete controls for region-specific characteristics are a top priority not only for a more thorough investigation of drivers of distribution changes but also for an effective test of the *club convergence hypothesis*.

This paper contributes to the literature on regional income convergence in several ways. First, most existing studies of the US (to be introduced in Section 3) cover only through the 1990s and consistently report evidence of income convergence across US regions, mostly states.[3] There are, however, reasons to suspect that the nature of distribution dynamics might have changed since this time. It is often hypothesized that the intensive IT-related investment during the 1990s (e.g., Beaudry et al., 2016) followed by China's joining the World Trade Organization in 2001 triggered or accelerated the industry restructuring process in many developed countries. This process involves the decline of traditional middle-income manufacturing and/or routine jobs held by workers with middle to relatively high education, leading to the labor market polarization observed since the early 1990s (e.g., Autor et al., 2006). To the extent that different regions are specialized in different industries, these forces drive divergence in the middle income range and promote the formation of two distinct income clubs, the rich and poor. Using an extended sample period of 1970–2017, this paper tests for and investigates the nature of changes in the distribution dynamics of US county incomes since the 1990s. Aside from providing the most up-to-date evidence in the literature, to the best of our knowledge, this paper is the first empirical paper that discusses bipolarization (or two-club convergence) of regional incomes in the US.

Second, while the distributional dynamics approach provides us with a complete picture of how an income distribution evolves over time, existing studies, both of the US and elsewhere, have made little in the way of statistical inference. This is mainly attributable to the inter-temporal and qualitative nature of the approach. To address this gap, we borrow the index-based approach developed in the micro literature, in which the extent of bipolarization at any given time is quantified in a single number. We use this approach to quantify the discussion of bipolarization and provide statistical conclusions. All the qualitative results obtained by the distribution dynamics analysis are statistically tested based on the corresponding changes in the index value. As discussed below, the two approaches work together in helping us understand the importance and nature of the bipolarization of incomes across US counties. This paper is

[3] Despite the proliferation of non-US empirical studies during the 1990s (discussing convergence of the world income distribution or regional income convergence within other countries), their sample periods are also centered from the 1940s to the 1990s. See Durlauf & Quah (1999) and Durlauf et al. (2005), among others, for surveys of these studies.

also the first that conducts a correspondence analysis between the distribution dynamics and index-based approaches in assessing the trends of bipolarization.

Third, using many conditioning variables and a large number of cross-sectional observations, we provide a detailed explanation of the nature and driving factors of the bipolarization in the US regional income distribution. While most cross-country studies are primarily interested in controlling for country-specific structural factors and focus on the *conditional* distribution dynamics, we also emphasize the roles played by these characteristics in making the *unconditional* distribution bipolarized. In general, interest in the unconditional distribution is higher when the analysis unit is a within-country region as compared to a whole country. Among other reasons, once some 'structural' factors are identified as drivers of the bipolarization process, making these factors converge to one another by appropriate policies is more meaningful within a country than across counties. We further investigate characteristics of the bipolarization process by asking whether the process is characterized by the vanishing middle class of counties joining the high-income club or the low. This is important, as welfare implications are different depending on the specific type of the bipolarization process, and no US evidence exists in this regard.[4] In addition to this 'structural approach,' we also test the effectiveness of government/business transfers as a means of mitigating the bipolarization of regional incomes. Lastly, by using more homogeneous units and further controlling for various county-specific characteristics, we expect to provide an effective test of the club convergence hypothesis.

Lastly, although our primary concern lies in the US regional income distribution, we further generalize our discussion of the bipolarization process by investigating how it is linked to nonlinearity in the growth-income relationship. As will be demonstrated subsequently, the results of our distribution dynamics analysis are directly translated into a specific nonlinear pattern of the growth-income relationship. In general, the presence of nonlinearities calls into question the contribution of estimates of the speed of convergence. In particular, this correspondence analysis between growth dynamics and distribution dynamics allows us to understand what

[4] In the literature on distributional dynamics of the world income distribution, existing studies often produce mixed results in this regard. While Bianchi's (1997) evidence supports a transition from middle income to poor, other studies suggest movement from middle to high (e.g., Kremer et al., 2001; Azariadis & Stachurski, 2003).

conditions on growth patterns govern which type of bipolarization process. This generalization is done by simulating various income growth patterns and examining their implications for distributional dynamics. The lack of evidence on the relationship between growth patterns and the findings from the distributional dynamics approach was previously noted by Durlauf et al. (2005, p. 598). We do not attempt to address the vast theoretical and empirical literatures on the effects of growth on distributions. Our investigation rather focuses on how a specific form of nonlinearity in the growth-income relationship governs the nature of the bipolarization *process*. In particular, we elaborate on Barro & Sala-i-Martin's (1999, pp. 51–52) argument that, for the existence of 'poverty traps,' it is necessary for the growth-income relationship to have a range of initial income levels where growth rates are increasing in the income level (henceforth, a phase of increasing returns), following a range of initial income with decreasing returns to the income level. As will be revealed in Section 3, not only the shape of the steady state distribution but also the process of bipolarization (e.g., whether the vanishing middle joins the high or low) differs depending on the specific location of the phase of increasing returns. This paper is also the first that discusses nonlinearity in the growth-income relationship in the US context, and one of a few studies in the whole literature on growth and convergence.[5]

Our major findings are as follows. Analysis of US county-level per capita income data for the period 1970 to 2017, while confirming the previous finding of income convergence across regions during the 1970s and 1980s, finds new evidence that the regional income distribution has been significantly bipolarized in an unconditional sense since the early 1990s. The recent bipolarization trend may surprise some who believe that US counties are much more homogeneous compared to countries and, therefore, are likely to converge to one another. Our correspondence analysis between the distribution dynamics and index-based approaches provides a dynamic explanation of the trends in the estimated bipolarization index: Only in the recent sub-period of increasing index values, we find that the estimated transition kernel shows a pattern of two-club

[5] Durlauf & Johnson (1995), Liu & Stengos (1999), Fiaschi & Lavezzi (2003), and Anderson (2004a) present evidence on nonlinearity in the growth-income relationship using country-level data. Romer (1986) previously provided a formal long-run growth model which assumed increasing marginal productivity of knowledge, which is an intangible capital good. According to the model, per capita output can grow without bounds, and the levels of per capita output in different countries need not converge.

convergence, and the steady state distribution generated by the transition kernel is bi-modal. The good news is that much, though not all, of the recent bipolarization of county incomes is explained by cross-county differences in education and industry mix, suggesting that policy should be aimed at reducing disparities in the structural characteristics. Consistent with the finding of our distribution dynamics analysis that the initial income level determines the fate of a county, simple government/business transfers are found to be effective in reversing the bipolarization process to a large extent. Another piece of good news is that the recent bipolarization process is characterized by the declining middle class mostly joining the high-income rather than the low-income club. This process is more desirable compared to a transition from the middle to poor observed by Bianchi (1997) in the dynamics of the world income distribution. Nevertheless, for the recent decades, our US results weakly support the *(conditional) club convergence hypothesis*: The distribution dynamics of US county incomes reveal evidence of two-club convergence even in a conditional sense, which is the case even for the post-transfer income variable. This is less desirable compared to the case where county incomes converge to one another regardless of their initial income levels.

Finally, our simulation of various nonlinear growth patterns and corresponding distribution dynamics finds that, when the phase of increasing returns is located above the national average income in the growth-income relationship, the steady state distribution is characterized as having one 'poor' income club slightly below the national mean and one rich club well above the mean. The bipolarization *process* takes the form of the vanishing middle income counties joining the high-income club. If, instead, the range of increasing returns is located below the national mean, the steady state distribution has one very poor club and one middle income club, and the bipolarization process is characterized by the shrinking middle joining the poverty club. As predicted by the simulation results and also by the results of the distribution dynamics, during the recent period of bipolarization, growth rates of county incomes appear nonlinear in the initial income level. These growth rates first show a phase of decreasing returns, followed by a phase of increasing returns, which in turn is followed by another phase of decreasing returns. In addition, the phase of increasing returns is located above the national average income. These nonlinear patterns are preserved even in the conditional growth equation, though they are stronger in the unconditional growth equation.

The organization of this paper is as follows. Section 2 introduces the data and discusses methodological issues. We briefly introduce and compare the index-based and the distribution dynamics approaches, highlighting the relative strength of each in understanding bipolarization trends. Section 3 presents our empirical results based on US county-level income data and reconciles them with related studies of the US. For brevity, our citations of empirical studies focus on the US evidence, leaving many important non-US studies out of the discussion. We use an instrumental variable approach in identifying the main drivers of bipolarization. Section 3 also provides a brief summary of our simulation-based results, leaving further details to Appendix C. We further conduct various robustness tests regarding our main results. Section 4 summarizes our findings and discusses some welfare implications.

2 Data and Methods

2.1 Data

Our analysis utilizes US county-level per capita income data administered by the Bureau of Economic Analysis (BEA) for the period 1970 to 2017. The BEA provides data on personal income and population size by county on a yearly basis across the entire sample period. Personal income is based on residence and is defined as the sum of wage and salary income, other labor income, proprietors' income (with inventory valuation and capital consumption adjustments), rental income (with capital consumption adjustment), personal dividend income, and personal interest income. It does not include government transfer income or military income. For each county, per capita income is the ratio of personal income (expressed in 2012 dollars) to county population. While we follow existing studies (see, among others, Barro & Sala-i-Martin, 1991; Johnson, 2000; Higgins et al., 2006) in using this income definition, we also test other definitions of per capita income in Sub-section 3.6 and find that our main results are quite robust to changing definitions. The original sample includes 3,138 counties from 1970 to 2017. In order to generate results that are not driven by outliers, our main analysis excludes the top 1% and bottom 1% of counties in each year's income distribution, resulting in 3,075 counties in total. To avoid changes in the distribution dynamics attributable to changing county compositions, we focus on a balanced sample of 3,026 counties which have valid per capita income data every year from 1970 to 2017 with no history of county births, deaths, divisions or mergers. In a later discussion, however, we find that our results are quite robust with respect to these sample restrictions as well. Appendix A contains the variables used in our analysis and their summary statistics for selected years. The first five variables are used to construct various types of county per capita income variables. The others are used as conditioning variables. These include, among others, education, the industry distribution of workers, age composition, race composition, median house price, and a natural amenities scale.[6]

This panel of county observations is appropriate for our analysis for a number of reasons. Most importantly, the county-level analysis has the advantage of having a large number of cross-sectional observations, facilitating our use of as many as 40 conditioning variables in the analysis and still allowing us precise estimates of their coefficients. In contrast, previous cross-country empirical studies, taken together, have considered about 145 different variables as potential growth determinants (e.g., Durlauf et al., 2005, Appendix B). Given that the sample sizes adopted by these studies are typically around 100, it is questionable whether country-level analysis can produce statistically meaningful conclusions about the conditional convergence hypothesis when a reasonable set of regressors are included. While US state-level analysis uses more homogeneous economic units and, therefore, dramatically reduces the 'right' number of conditioning variables required for the analysis of regional income convergence, 50 observations may not be enough to produce precise estimates of the coefficients of the still-remaining conditioning variables. This is precisely the reason Higgins et al. (2006) adopted county-level income data for estimation of

[6]The personal income and conditioning variables (except for the natural amenities scale) were previously examined by Higgins et al. (2006) and Young et al. (2008) in the contexts of the convergence speed and σ-convergence for the period 1970 to 1998. See Higgins et al. (2006, Data Appendix) for additional details of these variables.

the convergence speed. In addition, analyses of trend movements in bipolarization and associated distribution dynamics require longitudinal income data that are consistent over a long period. Ultimately, our sample is ideal for our analysis because the period of five decades is long enough to analyse trends in income polarization; the structure of yearly panel data is maintained throughout the period with little issue of attrition/non-response; and the definitions of per capita income and other control variables are fairly consistent across counties and over time as they are collected by a single institution (BEA).

All these advantages of using county-level data come at the cost of making the analysis unit a less independent economic unit, compared to states or countries. While the same argument could be used against all subnational levels of data including the state-level (e.g., Barro & Sala-i-Martin, 1991; Sala-i-Martin, 1996), a county is more weakly defined as an economic unit compared to a state. We believe, however, that this limitation is outweighed by the advantages of having a dramatically larger sample size and more degrees of freedom. Furthermore, it is recognized that industries are quite localized at the county level, and county governments have a certain degree of autonomy in developing policy in many areas, including education, housing, transportation, health, and welfare, among others.[7] Nevertheless, people may live in one county but travel to work in another county, and the volume of mobile workers is likely to be greater at the county-level than the state-level. This generates the question of whether county per capita income should be defined by residence or work place. A later discussion, however, finds that both the residence-based and work-place-based income variables lead to virtually identical results.

Controlling for cross-county differences in the cost of living and amenities is another important issue in the discussion of regional income convergence. The cost of living varies across

[7]In addition to the administrative mandates of their respective states, county governments also play additional independent roles such as the administration of mass transportation, airports, water supply and sewage disposal, hospitals, building and housing codes, public housing, stadiums, recreation and cultural programs, education, libraries, and consumer protection. Counties have also played a major administrative role in welfare programs such as Temporary Assitance for Needy Families (TANF) and Medicaid, and in state mandated environmental programs. These additional economic roles played by county governments have been growing over time. (https://www.encyclopedia.com/social-sciences-and-law/political-science-and-government/us-government/county-government.)

regions, and regions with relatively higher living costs offer higher wages to compensate, calling for adjustments of our county per capita income observations by the cost-of-living difference. A similar argument can be made regarding differences in amenities across counties. When studying regional income convergence using state-level data, Barro & Sala-i-Martin (1991) adopted population density as a proxy for housing costs, stating that the differences in housing costs are a major source of variation in the cost of living across states. We directly use the time-varying variable of median house price to control for the cost of living at the county level. To further control for possible cross-county heterogeneity in the cost-of-living and amenities, for each set of analysis, we include state dummies, a dummy for metro area and its interactions with state dummies, dummies for five broad regions (Northeast, Great Lakes, West, Plains, and South), and a variable measuring natural amenities (on a scale of 1 to 7) among the conditioning variables.[8] A later discussion, however, finds that our main results remain virtually identical whether or not these variables are controlled for. They are also robust to splitting of the whole sample into metro and non-metro areas.

2.2 Methods

We adopt two exiting approaches that have been developed independently: the distribution dynamics approach and the index-based approach. Below we briefly introduce the two, highlighting how they are related and complementary to each other in achieving our research goal.[9]

A series of studies by Quah (1993, 1996a,b,c, 1997) investigate the dynamics of income distributions by imposing a time-invariant first-order Markov structure in a sequence of income density functions. In particular, Quah (1996b, 1997) formulates the income distribution dynamics such that $f_{t+\tau}(y) = \int_0^\infty g_\tau(y|x) f_t(x) dx$, where $f_t(\cdot)$ and $f_{t+\tau}(\cdot)$ are the income density functions at time t and $t+\tau$, respectively, for some $\tau > 0$. In this framework, $g_\tau(y|x)$ is the

[8] Interaction terms of the metro dummy and state dummies are intended to capture the further localized amenity (cost-of-living) differences beyond the state-level that are not fully reflected in differences in natural amenities (the median house price).

[9] For more formal discussions of measuring income [bi]polarization, see Esteban & Ray (1994), Wolfson (1994), Anderson (2004a) Esteban et al. (2007), and Lee & Shin (2016), among others. See Quah (1993, 1996a,b,c, 1997) for a complete introduction of the distribution dynamics.

conditional density of the τ-period-ahead income y conditional on x, which is assumed to exist and be time-invariant. Hence, it can be interpreted as the homogeneous transition kernel (or stochastic kernel) of the time-invariant, first-order Markov process of the densities $\{f_t(\cdot)\}$. The transition kernel, $g_\tau(y|x)$, contains information on how each relative income level in the initial year changes to a relative income in the terminal year in terms of a probability distribution. We consider relative county per capita income, where each county per capita income is divided by the national average income in each t. We adopt Silverman's Rule-of-Thumb bandwidth when estimating the kernel density.

Eyeballing the estimated transition kernel and the corresponding contour map, however, does not always provide us with a clear impression of bipolarization or uni-modalization. Even when the estimated transition kernel appears twin-peaked, whether it works in the direction of bipolarizing the distribution also depends on many factors in a complicated way: the location of each pole, between-pole distance, height of each pole relative to the other, and the initial income distribution, among others. To better understand the nature of the distribution dynamics that appears in a sample, we focus on the pattern of expected income growth between t and $t+\tau$ that is generated by the estimated transition kernel. This sets up a bridge between the distribution dynamics and the growth dynamics and calls for a more formal discussion of correspondence between the two approaches. As we discuss in the next section, our simulation of various income growth patterns and corresponding distributional dynamics reveals that the bipolarization process of an income distribution is described by a specific form of nonlinearity in the growth-income relationship. Another way of understanding the nature of distribution dynamics is to evaluate whether the income distribution would be eventually bipolarized or unimodalized following the observed transition kernel. This corresponds to solving the following steady-state equation, $f_\infty(y) = \int_0^\infty g_\tau(y|x) f_\infty(x)dx$, for given $g_\tau(y|x)$, and predicting the ergodic (or steady-state) density $f_\infty(\cdot)$. All the factors mentioned above are simultaneously considered in predicting the ergodic distribution. In practice, the predicted $f_\infty(\cdot)$ is obtained by iterating the following equation: $\widehat{f_\infty^{|k+1|}(y)} = \sum_{i=1}^n \widehat{g_\tau(y|x_i)} \widehat{f_\infty^{|k|}(x_i)}$, for k=0,1,2,...,500. This corresponds to applying the same estimated transition kernel $\widehat{g_\tau(y|x)}$ successively to the terminal distribution from the previous step. We let the initial distribution $\widehat{f_\infty^{|0|}(\cdot)}$ be the predicted marginal density in the terminal year of the sample period. In a typical case, $\widehat{f_\infty^{|k|}(\cdot)}$ shows a converged distribution at approximately k=200 and onward. We are interested in not only the shape of the steady state distribution but also the process of evolution to the ergodic distribution.

This process raises the econometric question of whether the conventional assumption of stationarity is innocuous in estimating the transition kernel, $g_\tau(y|x)$. The stationarity assumption is relatively safe when our interest lies in the long run steady state distribution. While the stationarity assumption also facilitates comparisons of our results with existing studies, a recent study by Hierro & Maza (2009) points out that stationary estimation runs the risk of not accounting for changes in intra-distribution dynamics at intermediate times and, consequently, could generate spurious results. In a later discussion, we follow Hierro & Maza (2009) in providing the results of Anderson & Goodman's (1957) test of stationarity.

The distributional dynamics approach provides us with a complete picture of how an income distribution evolves over time in terms of both shape and mobility. Repeated and successive applications of the transition kernel to the terminal distribution of the previous step show us how the distribution converges to a steady-state distribution. For example, the process may show us whether the shrinking middle class joins the high- or low-income clubs. These distributional dynamics, however, do not allow us a quantitative assessment of income bipolarization that accrues during a sample period. The literature on distribution dynamics often emphasizes twin-peaks of the contour plot and bimodality of the ergodic distribution as evidence of bipolarization.[10] No decision rule, however, is applied to the location and size (relative height and population share) of each peak to conclude that the distribution is bipolarized during a sample period in a statistical sense. To provide a quantitative assessment of the bipolarization that progressed during a sample period, we exploit existing bipolarization indices, mapping a density $f_t(\cdot)$ at time t into a real value, $P_t(f_t)$. Then, by simply comparing P between t and $t+\tau$, we may evaluate whether the distribution has bipolarized or de-bipolarized between the

[10]The twin peaks phenomenon was repeatedly identified by a series of studies by Quah (aforementioned). For example, Quah (1997, pp 37–38) writes, "In Figure 5.1, a twin peaks property again manifests. The twin peaks in the stochastic kernel ... shows clearly the polarization dynamics."

two time points. Because the index value is based on the cross-sectional information contained in a density and because we compare the summary statistics between time t and $t+\tau$ without referring to the transition process, $g_\tau(y|x)$, the index-based approach primarily focuses on the shape, rather than mobility, dynamics that appear in a sequence of densities $\{f_t(\cdot)\}$.

Since the seminal paper by Love & Wolfson (1976), numerous studies have been devoted to developing the concept and measurement of income polarization (e.g., Esteban & Ray, 1994; Duclos et al., 2004; Esteban et al., 2007; Foster & Wolfson, 2010; Lee & Shin, 2016). Two types of polarization indices stand out, among others: the Esteban-Ray type polarization indices and the Wolfson-type bipolarization indices. Both types are based on the concept of between-group differences and within-group similarity. Recently, Lee & Shin (2016) developed a generalized polarization index that nests several existing polarization indices (e.g., Esteban & Ray, 1994; Wolfson, 1994; Duclos et al., 2004) and the group Gini index as its special cases. Precisely, Lee & Shin's generalized bipolarization index has the following form: $S(\alpha,\theta) = \frac{\mu_2-\mu_1}{\mu}\pi_1\pi_2\Big\{(1-\theta)\Big(\frac{\pi_1}{\delta_{11}/\delta}\Big)^\alpha + \theta\Big(\frac{\pi_2}{\delta_{22}/\delta}\Big)^\alpha\Big\}$, where μ_1 and μ_2 represent the mean income levels of low and high income groups, respectively, which are divided by the population mean (μ); π_1 and π_2 are their respective population shares such that $\pi_1+\pi_2=1$; δ_{kk} represents a measure of the within-group dispersion of group k, and δ is a measure of overall dispersion; $\alpha>0$ is a sensitivity parameter that distinguishes the within-group similarity (the term in braces) from the between-group difference $\Big(\frac{\mu_2-\mu_1}{\mu}\Big)$; and θ is the weight placed on the higher income group. The between-group income distance is normalized by the population mean (μ), and the within-group similarity is measured by the ratio of the group size to the within-group dispersion. The within-group dispersion is also expressed as a relative level. This bipolarization measure is general enough to include both statistical and psychological aspects of bipolarization. To focus on the statistical features of the index and obtain estimates more comparable to Esteban & Ray (1994) and Wolfson (1994), we set θ=0.5.[11] With this restriction, the only difference between Lee & Shin (2016) and Esteban & Ray (1994) lies in the inclusion of a measure of within-group

[11] Lee & Shin's generalized index allows for the possibility that the antagonistic feeling the poor have against the rich is greater than that the rich have against the poor ($\theta > 0.5$), which introduces a psychological aspect to the index.

dispersion in the former. As group clustering is the major feature of club convergence, we choose Lee & Shin's measure for our research purposes.[12] We use the standard deviation as a measure of dispersion. As in the distribution dynamics analysis, this analysis examines the relative county per capita income level, defined as the ratio of each county income to the national average.[13]

A concern with existing polarization indices is that they are designed for use with household-level data and may not be applicable to county-level data. Although these indices were developed to present changes in the income distribution *within* an economy, their focus on cluster formation also makes them widely used indicators of changes in the distribution of per capita income *across* different economies. For example, Anderson (2004a), Pittau et al. (2017), Anderson et al. (2012), and Krause (2017) all applied various indices including Esteban-Ray and Wolfson-type indices to country-level data to study polarization of the world income distribution. This is precisely the reason we use the index that focuses more on cluster formation by incorporating a direct measure of within-group dispersion. Duclos et al. (2004, p. 1758) also writes, " ... one might use our measures (Esteban-Ray type) to explore the "twin-peaks" property identified by a series of studies by Quah (aforementioned) for the world income distribution."

Testing for polarization is tricky as polarization (or club convergence) has an inter-temporal dimension, describing the dynamic nature of distribution changes. Because it represents a *tendency* towards the emergence of two or more separate bumps in a distribution over time, it can occur before these "bumps" and "dips" actually emerge in the distribution under consideration. For example, bipolarization or two-club convergence (or 'emerging twin peaks' as put by a series of the aforementioned Quah's studies) can characterize the nature of the distribution dynamics for a given sample period with no cross-sectional distribution showing bimodality. This renders bump-dip seeking tests less useful in detecting polarization between two time points (Anderson, 2004b). Given these difficulties, researchers have investigated ways to test polarization

[12]Following the literature, we also set α=1.6, which is the maximum value α can have to make Esteban-Ray type indices satisfy a set of reasonable axioms set up by Esteban & Ray (1994).

[13]In both Esteban & Ray (1994) and Lee & Shin (2016), group sizes play important roles. This is important for a quantitative assessment of bipolarization (or two-club convergence): The more asymmetric the rich and poor clubs become in their population shares (e.g., 0.001 vs. 0.999), the more diminished the importance of bipolarization. By dividing the distribution by its mean, we let the data choose the club size, making it play such a role.

vs. convergence (depolarization) that occurs during a sample period by comparing information contained in cross-sectional distributions, $f_t(\cdot)$ and $f_{t+\tau}(\cdot)$. For example, by combining non-parametric density function estimates with stochastic dominance arguments, Anderson (2004a) constructs a new indicator of polarization of the per capita GNP distribution and conducts a bootstrap test for significance of changes in the indicator. This is an effective way of testing for bipolarization in the absence of a distribution theory for the indices (ibid, p. 538). A recent study by Lee & Shin (2016) derives the asymptotic distribution of their general measure, which enables us to make direct statistical inferences about a change in the index.

A major argument in support of the index-based approach is that it is relatively easy to compute index values using cross-sectional data and, by simply comparing estimated index values between two points in time, make a quantitative statement regarding changes in the degree of income bipolarization. In addition, through a time series visualization of the index value, we can detect if there are trend changes in the extent of bipolarization within a sample period, which is one of our research concerns. With the income threshold level fixed, however, changes in the within-group income distribution may not be fully reflected in an index-based analysis. A whole picture of intra-distribution mobility is better captured by the distribution dynamics approach.

As evident from the above discussion, the two approaches have different strengths which are complementary to each other in achieving our research goal. As a result, we use both to study the nature and importance as well as trend movements of bipolarization of US county incomes.

3 Empirical Results

3.1 Trends in Estimated Bipolarization Index

We begin our discussion by displaying estimated (Lee and Shin's) bipolarization indices for the whole sample period, 1970–2017. County per capita income, defined as the ratio of personal income to county population, is used throughout the paper, unless otherwise specified. Figure 1 shows the results for the balanced sample of 3,026 counties. A pointwise confidence interval at the 95% level is shown by the dotted lines and is obtained by the Jackknife method described in Lee & Shin (2016, p. 470). The level of bipolarization in the distribution of US county incomes reveals a strong upward trend since the early 1990s. For example, over the period from 1995 to 2015, the estimated index increased by a statistically-significant 53 percent. Even for 1995–2006, which excludes the period of the Great Recession and its aftermath, the estimated index increased by about 34 percent, which is also statistically significant. From 1972 to 1995, however, the estimated index increased by only 5.3 percent which is insignificant in both statistical and empirical senses. The results remain similar when the whole unbalanced sample of 3,075 counties are used, and all extreme values (the top 1% and the bottom 1%) are further included in the sample (N=3,138): a 6.5 percent increase in the index value for 1972–1995 vs. a 58 percent increase for 1995–2015. Although not reported for brevity, usage of other income variables such as average earnings per worker (establishment-based or residence-based), division of the whole sample between metro and non-metro sub-samples, or usage of other popular indices such as Esteban & Ray (1994) or Wolfson (1994) produce similar results regarding trend movements of an estimated bipolarization index.[14]

3.2 Unconditional Distributional Dynamics

Because Figure 1 shows two different trends during our sample period, we split the whole sample period into two sub-periods, analyse the distribution dynamics separately for each sub-period, and examine how the nature of the regional income dynamics has changed between the two. To reduce the sensitivity of the estimation results due to the choice of the initial or the terminal year, we require all the initial and terminal years of the two sub-periods to be similar in terms of overall economic conditions as represented by the aggregate unemployment rate while also keeping the sample period similar between the two sub-periods. To further reduce the sensitivity

[14]For 1995–2015, our balanced sample produces an increase in the Gini index by 28 percent, compared to a 53 percent increase in the bipolarization index. For the same period, the standard deviation (a summary measure in σ-convergence) increased by 30 percent. These numbers seem to suggest that the distribution of US county incomes has been more bipolarized than unequal for recent decades.

of the results that may arise from measurement errors in the income variable, we repeat the analysis five times for each sub-period, using different starting and ending years each time, and average the results. These considerations lead us to choose the following three non-recessionary reference periods: 1970 to 1974, 1993 to 1997, and 2013 to 2017. The average unemployment rates in these three reference periods are 5.4 percent, 5.8 percent and 5.6 percent, respectively. In the first sub-period, 1970–74 to 1993–97 (henceforth Period One), we analyse the average of five 23-year distribution dynamics for 1970–1993, 1971–94, 1972–95, 1973–96, and 1974–97. Similarly, we investigate the average of the five 20-year distribution dynamics for the second sub-period, from 1993-97 to 2013–17 (henceforth Period Two). Consequently, τ=23 for Period One, and τ=20 for Period Two.

Figure 2 shows the results of the unconditional distribution dynamics of county per capita incomes. Each panel in Figure 2 contains the estimated transition kernel, the corresponding contour map, and the ergodic distribution generated by the estimated transition kernel. In each contour map, the vertical axis represents the relative income level at the initial point, and the horizontal axis stands for the relative income at the terminal point. The estimated kernel and the contour map represent stacked conditional density plots, containing information on how each relative income level in the initial year changes to a relative income in the terminal year in terms of a probability distribution. To provide a more clear picture of the nature of distribution dynamics, each contour plot is superimposed by the 45-degree line (black dashed) and the trajectory of the mean terminal income predicted at each level of initial income (red solid). When the red solid line crosses the 45 degree line from below (above), county per capita incomes tend to converge towards (diverge from) the point, with the slope of the red line determining the speed of convergence (divergence) in the vicinity of the crossing point. In the panels displaying the ergodic distributions, we also display how the predicted marginal density in the terminal year (lightest line) evolves to the steady state distribution (darkest line) as we repeatedly and successively apply the estimated transition kernel to the density obtained in the previous step.

The results reveal important features of the distribution dynamics of US county incomes.

The contour plot in panel A shows no clear pattern of forming two income clubs during Period One. The *relative* income of initially rich counties decreased significantly towards the terminal year, whereas the relative income of initially poor counties increased slightly. The trajectory of the red sold line crosses the 45 degree line only once and at around the national mean from below, suggesting convergence of income towards the center of the distribution. The ergodic distribution is single-peaked at around the national mean and is not much different from the predicted marginal density at the terminal point of Period One. The result is consistent with the index-based result in Figure 1: For 1972–1995, the estimated index increased by only 5.3 percent, which is statistically insignificant.[15]

In contrast, panel B shows strong evidence of two-club convergence in Period Two. There exists a clear tendency for persistence at both ends of the distribution. The estimated transition kernel is twin-peaked near the origin and the other end, and both peaks are located close to the 45 degree line. The red solid line in the contour plot crosses the 45 degree line three times: at the initial income level of around 0.7 from below; at around 1.7 from above; and at around 2.1 from below. (This red solid line is more clearly visualized by the same red solid line in Figure 6 which will be discussed later.) These patterns of income growth from t to $t + \tau$ suggest divergence of income among relatively middle income counties and formation of two convergence clubs, the rich and the poor. The ergodic distribution derived by the estimated transition kernel shows bimodality. This result is also in line with the index-based result in Figure 1: for 1995–2015, the index increased significantly by 53 percent. More specifically, the ergodic distribution of Period Two is characterized as having one large income club below the national mean (at around 0.7) and one relatively small rich club that is located well above the mean (at around 2.1), and the income threshold level of 1.7 that distinguishes the 'rich' from the 'poor' group is higher than the national mean in the steady state. To compare the two sub-periods in the steady state distribution, Appendix B1 displays the two cumulative ergodic distributions derived from Figure 2, with the dashed and solid lines representing Period One and Period Two, respectively.

[15] The red solid line is approximately linear with a slope slightly greater than the 45 degree line for the range of initial relative incomes level up to 1.3 and vertical thereafter, implying that rich counties converge to the center of the distribution faster than poor counties.

The takeaway result is that the size of the middle income counties is much thinner for Period Two than Period One, and a *majority* of the diminished middle class forms a very-high income club in a new income range that hardly exists in Period One.[16] The result for Period Two may surprise some who believe that US regions are more likely to converge due to their homogeneity. For example, Durlauf et al. (2005) summarize that unconditional β-convergence is typically supported when the data come from relatively homogeneous groups of economic units such as the US states, the OECD, or the regions of Europe. While the unconditional convergence also characterizes our early sample period, our analysis also points to a change in the distribution dynamics in recent decades.

Our discussion so far assumes stationarity in the transition kernel for each sub-period. Following Hierro & Maza's (2009) suggestion, we conduct Anderson & Goodman's (1957) test of stationarity and find supporting evidence for stationarity for each sub-period. For Period One, with 100 income support points and τ=23, the chi-square value, degrees freedom, and the corresponding p-value are 109,890; 217,800; and 1, respectively, strongly accepting the null hypothesis of stationary transition kernel. Respective numbers for Period Two are 100; τ=20; 78,946; 188,100; and 1. However, when applied to the whole sample period with τ=43, the same test produces the chi-square value of 3,311,800 with 415,800 degrees of freedom, and the associated p-value is less than 0.0001, rejecting the stationarity in the transition kernel at any conventional significance level. All these test results are consistent with our index-based results in Figure 1 and justify our within-sub-period stationary and between-sub-period non-stationary analyses.[17]

For Period Two, analysis of the distribution dynamics reveals additional information regard-

[16] The club size of rich counties whose relative incomes are higher than 1.7 is close to 27 percent for Period Two whereas the population share of the same income range is around 1 percent for Period One. In the 'middle' income range, the share of counties with relative incomes between 0.8 and 1.7, for example, is reduced from about 80 percent to 46 percent as we switch from Period One to Period Two. Concurrently, the share of counties with income levels below 0.8, for example, increases from 19 percent to 27 percent.

[17] Regardless of the test results, the stationarity assumption is relatively innocuous when our interest lies in the long-run equilibrium distribution and therefore when comparing ergodic distributions between the two sub-periods. Following the above test result, we also estimate the non-stationary transition kernel for the whole sample period (τ=43) using the Chapman-Kolmogorov equation. The results, though not reported to save space, show evidence of bipolarization of county incomes. Interestingly, even the stationary transition kernel estimated for the whole sample period also produces bimodality in the steady state distribution.

ing the bipolarization *process* as well as the shape of the bipolarized distribution in the steady state. As demonstrated in Figure 2B, the shrinking middle class tends to join the high-income club, as the line becomes darker. This finding seems at odds with Bianchi's (1997) evidence that supports a transition from middle income to poor in the distributional dynamics of the world income distribution, but is consistent with Kremer et al. (2001) and Azariadis & Stachurski (2003) who suggest movement from middle to high. This raises a question of what conditions on income growth dynamics govern which type of bipolarization process. This question arises from the observation that, in the contour plots of Figure 2, the trajectory of the mean terminal income for each initial income level corresponds to a specific nonlinear relationship between the growth rate and the initial income level. Precisely, the red solid line for Period Two is translated into an interesting growth pattern: a phase of 'decreasing returns' (where growth rates decrease in the initial income level) showing first, which is followed by a phase of 'increasing returns', which in turn is followed by another range of decreasing returns. In Appendix C, we further generalize our discussion by investigating how nonlinearity in the growth-income relationship is associated with the bipolarization process. This is done by simulating various income growth patterns and generating their implications for distributional dynamics. It turns out that the bipolarization *process* as well as the *shape* of the ergodic distribution differs depending on the location of the phase of increasing returns. When the above-average income group gets the 'benefits' of increasing returns (probably due to skill-biased technological progress), the ergodic distribution is characterized as having one relatively 'poor' income club below the national mean and one 'rich' club well above the mean. In this case, the bipolarization process takes the form of the shrinking middle class joining the high-income club, which is considered to be desirable. This is the case observed in the US distribution for Period Two. On the contrary, when the range of increasing returns is located below the national mean income level, the ergodic distribution has one 'very poor' club and one middle income club, and the bipolarization process is characterized by the shrinking middle class joining the 'poverty club,' which is considered to be undesirable. This is the case observed in the world income distribution.[18] See Appendix C for

[18]In the literature on convergence/divergence of the world income distribution, researchers often find evidence

a more detailed discussion.

This leaves us an empirical question of whether heterogeneous growth rates of US county per capita income follow the patterns suggested by the results of numerical simulations. In particular, we want to examine if the phase of increasing returns does appear above the US national mean income level. We estimate the growth equation nonparametrically as a function of the initial relative income level.[19] The results of this exercise are reported in Figure 3.[20] Focusing on the unconditional growth dynamics, as predicted by the simulation results, Figure 3Ab shows that the growth rate is nonlinear in the initial income level for Period Two, and more importantly, the phase of increasing returns appears above the national mean. In contrast, for Period One, the growth rate is approximately linear and negatively sloped, confirming our previous finding of the unconditional convergence in Figure 2A.

3.3 Can Government/Business Transfers Mitigate Income Bipolarization?

To test the effectiveness of government/business transfers in mitigating the bipolarization process, we include receipts of transfers from government and business in deriving county per capita income data and repeat the analyses of Figures 1 and 2.[21] As shown in Figure 4, the estimated bipolarization index is smaller when county-level per capita income is adjusted by government/business transfers (dashed line) than when pre-transfer income is used (solid line). The change from the pre- to post-transfer income in the estimated index is negative and statistically significant in all years. In addition, these transfers work in the direction of mitigating the

of nonlinearity in the growth equation, with the phase of increasing returns appearing below the world average. See, for example, Liu & Stengos (1999), Fiaschi & Lavezzi (2003), and Anderson (2004a).

[19]Precisely, the dependent variable is the annual average growth rate for each sub-period. Both the initial income and the growth rate are expressed relative to their respective national means. The nonlinear growth equation is estimated by the Nadaraya-Watson kernel method, and Silverman's Rule-of-Thumb bandwidth parameter is applied. Similar to the analysis of distribution dynamics, we analyse the average of five growth dynamics for each sub-period. For Period Two, for example, they are 1993–2013, 1994–2014, 1995–2015, 1996–2016, and 1997–2017.

[20]Figure 3 also reports conditional growth rates, which are discussed later.

[21]Current transfer receipts from government are from all levels of government, including county, state, and federal governments. Current receipts from business include liability payments for personal injury and corporate gifts to nonprofit institutions.

bipolarization trend. For Period One, the post-transfer income data show a slightly declining trend, whereas the pre-transfer variable reveals a slightly rising trend. For Period Two, the upward trend in the estimated index becomes weaker once transfers are included in the income variable. For the whole period (1972–2015), the estimated bipolarization index increased by 35 percent for the post-transfer income variable, compared to 61 percent for the pre-transfer income variable.

Figure 5 replicates the analysis of Figure 2 using the post-transfer income data. A comparison of Figures 2 and 5 suggests that the index-based observations in Figure 4 are supported by the distribution dynamics. For Period One, while there is a clear tendency for persistence at the lower end of the distribution, no such tendency exists at the upper end, suggesting that rich counties fail to form a separate income group. The ergodic distribution is more symmetrically distributed and less dispersed around the mean in Figure 5B than in Figure 2A. For Period Two, government/business transfers make the distribution less bipolarized. Although the high-income group still shows persistence in relative income, the between-group income distance is reduced compared to the pre-transfer distribution as the dynamics progress. While the ergodic distribution still shows some bimodality, the size of the high-income (middle) group is much smaller (larger) compared to the one based on the pre-transfer income variable. Ultimately, the tendency of the middle class shrinking to join the high income club becomes weak but still remains even in the post-transfer income variable. For Period Two, Appendix B2 compares the cumulative ergodic distribution of before-transfer incomes (dashed line) to that of after-transfer incomes (sold line). Transfers make the share of counties with relative incomes between 0.8 and 1.2 grow back to about 49 percent in the steady state, compared to the before-transfer case (about 25 percent). Concurrently, the size of the rich club (those counties with relative incomes higher than 1.7) is dramatically reduced from 27 percent to 5 percent, and the share of the 'poorest' counties is also reduced to some degree. If transfers are intended to make the after-transfer ergodic distribution less centrifuged, the goal is achieved.

3.4 Conditional

In this sub-section, we repeat all our previous analyses by controlling for various county-specific characteristics. This investigation is important for two reasons. First, while Figure 2 shows clear evidence of bipolarization of county incomes since the early 1990s, this evidence does not support the *club convergence hypothesis* by itself. Although counties are generally more homogeneous compared to countries in their structural characteristics, there may still exist some cross-county differences in many other structural factors that are responsible for the appearance of bipolarization. As put by Galor (1996, p. 1056, 1058), "The *club convergence hypothesis* (*polarization, persistent poverty, and clustering*) – per capita incomes that are identical in their 'structural' characteristics converge to one another in the long-run provided that their initial conditions (initial *per capita* output levels) are similar as well." By further controlling for about 40 county-specific characteristics, our analyses are intended to provide a reasonable test of the hypothesis. Second, by comparing the results from the unconditional and conditional distribution dynamics, we can sort out what factors have driven income bipolarization since the 1990s. Our results can inform policy-makers who are interested in helping the 'poor' counties—which would remain in the low income club permanently—to catch up with the rich club. This could be accomplished by making the driving factors converge between the two clubs. Compared to the aforementioned redistribution policy, this could be called a 'structural approach' to depolarization.

Figure 6 shows the results of the conditional distribution dynamics of county per capita incomes. Following Quah (1996b), after controlling for county-specific characteristics as of the starting point of each sub-period in the linear growth equation, we use the residuals to non-parametrically estimate the transition kernel. However, the literature (e.g., endogenous growth) often suggests that some of the conditioning variables in the growth equation, such as education and the industry distribution of workers, are endogenous. To avoid the potential inconsistency in the estimated coefficients generated by ordinary least squares (OLS), we instrument the education (industry mix) variable with the population-weighted average of the education (industry mix) variable among adjacent counties.[22] The results are reported in Figure 6. Appendix B3 additionally compares the cumulative ergodic distributions of the two sub-periods.

First, a comparison of Figures 2 and 6 shows that conditioning reduces the tendency of club convergence in Period Two. For example, while Figure 2B shows a clear tendency for persistence at both ends of the distribution, in Figure 6B, the tendency is strong only at the lower end of the distribution. In addition, the relative income of rich counties is reduced by a larger extent towards the terminal year in the conditional distribution dynamics. More transparent evidence comes from the trajectory of the mean terminal income predicted at each level of initial income. While the red solid line still shows a similar pattern of crossing the 45 degree line three times as in Figure 2B (evidence of a bipolarization process), the tendency is weaker when conditioning on the county-level characteristics. For a more clear comparison of the unconditional and conditional distribution dynamics in Period Two, we display the two predicted mean terminal income lines from Figures 2B and 6B in one large figure. As shown in Figure 7, compared to the red solid line (describing the unconditional distribution dynamics), the blue dotted line (conditional distribution dynamics) is closer to the 45 degree line in the middle range. In addition, the income distance between the first and the third crossing points (these are the two-club convergence points) is narrower in the conditional case, implying that the conditional distribution becomes less centrifuged towards the terminal year. As a result, once region-specific characteristics are controlled for, the ergodic distribution does not exhibit bimodality as strong

[22] The idea is that the educational environment of adjacent counties affects the educational level of the county under consideration without having a direct effect on the county's income growth. A similar argument can be made for the industry variable. To obtain information on adjacent counties for each of the 3,066 counties for the 48 contiguous US states, we use the data available at https://www2.census.gov/geo/docs/reference/county_adjacency.txt and create a 3,066×3,066 adjacency matrix with the $(i, j)^{th}$ element being one if the i^{th} and j^{th} counties share a geographical border and is zero otherwise. In total, there are 20 endogenous regressors (16 industry shares and 4 education variables) and 20 instrumental variables. Except for 2 out of 40 cases (20 cases for each sub-period) of the first stage regressions, $F_{20,\infty}$-tests reject the null hypothesis of zero coefficients on all the instrumental variables even at the 1 percent significance level. The $F_{20,\infty}$ values are generally greater than 10 except for 6 cases. The exceptions are construction, wholesale, federal, state, and local governments for Period One, and only federal government for Period Two. As a further robustness check, we also use lagged instrumental variables for the endogenous regressors. For example, a county's education level in 1970 is instrumented by the education levels of adjacent counties as of 1969 which are considered to have little to do with the county's income growth from 1970 to 1993. Little change, however, is made to Figure 6 by this additional exercise. In a previous version of this paper, we also conducted the conditional analysis using OLS residuals and found similar results as in the current version. All these additional results are electronically available upon request.

as in Figure 2B. This finding is further confirmed by a comparison of the cumulative ergodic distributions displayed in Appendix B4. We conclude that much, though not all, of the recent bipolarization of county per capita income is explained by cross-county differences in structural factors. Nevertheless, the tendency of the shrinking middle joining the high group still remains even in the conditional distribution dynamics, though the effect is weaker than the unconditional case.

Second, these results have different implications for the convergence hypotheses of the two sub-periods. For Period One, Figure 6A strongly supports the *conditional convergence hypothesis*: County per capita incomes converge to one another at the center of the distribution regardless of their initial income position. This is reconfirmed by the results of the conditional growth dynamics presented in Figure 3Ba: For Period One, the estimated conditional growth equation is approximately linear and negatively sloped. For Period Two, however, Figure 6B weakly supports the *club convergence hypothesis*: Once county-specific structural factors are controlled for, county per capita incomes converge to each other only when their initial income levels are also similar as well (or within the basin of attraction of the same steady-state equilibrium, as put by Galor, 1996). Figure 3Bb reconfirms this conclusion: The conditional growth rate is nonlinear in the initial income level with the range of increasing returns appearing above the national mean. We call the evidence's support for the club convergence hypothesis 'weak' based on our informal observation that the phase of increasing returns appears relatively brief and weak in Figure 3Bb compared to Figure 3Ab as well as based on the following formal test.

To provide a quantitative assessment of whether conditioning reduces bipolarization of county per capita income for Period Two, we adopt the same IV residuals used in the analysis of the distribution dynamics; derive the 'conditional cross-sectional distribution' at the terminal year by adding the residual growth rate to the initial income level; compute the index value associated with the conditional distribution; and compare it to the index value from the original unconditional distribution. For brevity, we take the middle point from each of five starting (1993–97) and ending (2013–17) years, obtaining residuals of 20-year income growth from 1995 to 2015. We conduct this exercise using both the before- and after-transfer income variables.

The results of this exercise are displayed in Figure 8. Each pair of bars indicates the 95 percent confidence interval for the corresponding circular data point. Focusing on before-transfer income, we previously noted from Figure 1 that, for 1995–2015, the index value increased from A to B (along the solid blue line) and that the increase is significant in both statistical and empirical senses. As demonstrated by the solid red line (from A to C), however, conditioning depolarizes the distribution significantly: The reduction in the index value generated by conditioning is large (from B to C) and statistically significant. Estimated index values in Figure 8 suggest that conditioning reverses about 82 percent of the increase in the bipolarization index from 1995 to 2015 that appears in the unconditional distribution. Consequently, once county-specific characteristics are controlled for, the increase in the estimated bipolarization index (from A to C) becomes small at around 10 percent and marginally significant.[23] All of these observations are preserved when using the post-transfer income variable.

For Period Two, we can further identify the main drivers of the bipolarization by considering the conditioning variables individually. A variable is considered an important contributor to bipolarization if controlling for the variable makes the bimodality of the unconditional ergodic distribution less distinct. For brevity, we categorize conditioning variables (6) to (21) in Appendix A as 'industry composition'; variables (22) to (25) as 'age composition'; variables (30) to (33) as 'education'; and variables (34) and (35) as 'race composition'. As shown in Figure 9, among the various conditioning variables considered in the current study, cross-county differences in education and the industry distribution of workers at the starting point contribute to the bipolarization of county incomes. Precisely, controlling for only education or industry composition 'over-explains' the change from the unconditional to fully-conditional steady-state distribution, as the partially-conditional ergodic distributions in C and D are closer to unimodality than the fully-conditional ergodic distribution in B.[24] In particular, controlling for education alone makes the ergodic distribution unimodal and almost symmetric. The large con-

[23] Using the five-year averages of the beginning and terminal years makes the increase in the 'conditional' bipolarization index slightly greater (12 percent). This 12 percent increase in the bipolarization index corresponds to what is observed in the conditional distribution dynamics in Figure 6B.

[24] Controlling for cross-county differences in the age distribution or miscellaneous characteristics makes the steady state distribution more bipolarized.

tribution of these two variables to income bipolarization is generally consistent with the evidence of job/labor market polarization suggested by Autor et al. (2006), Autor & Dorn (2013), and Mandelman (2016), among others. Interestingly, neither median house price nor the natural amenities scale contributes to bipolarization. Even when these two variables are simultaneously controlled for (not shown in a separate figure), the ergodic distribution becomes very similar to the unconditional ergodic distribution, implying that cross-county differences in the cost of living and amenities as represented by these two variables are not contributors to the bipolarization of county incomes. To further illustrate how education (the most important contributor) contributes to the bipolarization of county incomes, Appendix D examines if education itself has been bipolarized across US counties. For this illustration, we first derive years of education for each county by using the cell mid-points of the four categorized education variables (30) through (33) in Appendix A and calculating the weighted average of the four cell mid-point values, where the weight is the share of each group among the total. We then estimate the bipolarization index using the generated education variable for each of 1970, 1980, 1990, 2000, and 2010. The figure shows that the average education level has been significantly bipolarized across counties over the last several decades, providing a channel through which education contributes to the recent bipolarization of county per capita incomes.[25] These results suggest that making the education level of the 'poor' club catch up with that of the rich club can be a desirable structural policy to depolarization as it is expected to further accelerate the transition and eventually make all 'poor' counties join the high club.

3.5 Comparison with Existing US Studies

In this sub-section, we discuss how our results compare to related studies of the US. First, Johnson (2000) applies the unconditional distribution dynamics approach to state-level income data for the years 1948, 1963, 1978, and 1993 and finds a single-peaked ergodic distribution.

[25] Alternatively, for each year, we used the same generated education variable to compute the share of 'high-education' counties (whose education levels are greater than the national mean plus one standard deviation) and the share of 'low-education' counties (less than the national mean minus one standard deviation). The results show that both the high and low education counties increased their shares during our sample period.

To facilitate the comparison of our results to Johnson's, Appendix E uses per capita incomes for 48 contiguous states and produces the results for both sub-periods, noting that his sample period overlaps with our Period One. As in Johnson's results (2000), Period One shows no evidence of income bipolarization. For Period Two, however, even state-level income data show some evidence of bipolarization, although the tendency is weaker compared to our main results using using county-level income data. While the estimated transition kernel is approximately twin-peaked in panel B, the income distance between poor and rich states in the terminal year is much narrower, compared to the contour map derived from county-level data (Figure 2B). Therefore, Johnson's conclusion that there is no evidence of income bipolarization is based on two factors. His sample period overlaps our Period One when even our county-level data show little evidence of income bipolarization. Additionally, by averaging within-state variation of heterogeneous growth rates of county per capita income, the use of state-level income data attenuates the bipolarization process to some degree, compared to county-level data.

Second, the results of our index-based and distribution dynamics analyses are generally consistent with a series of studies that examine labor market polarization (previously cited) regarding the timing of trend movements in bipolarization. For example, Figure 3 of Autor et al. (2006) shows clear evidence of job bipolarization (more rapid employment growth in jobs at the bottom and top relative to the middle of the skill distribution) for the 1990s and no such pattern for the 1980s.

Third, using the same county-level income data as in the current study but for 1970–98 (Period One), Higgins et al. (2006) estimate the linear growth regression and find that conditioning increases the speed of β-convergence by a large extent: from an unconditional convergence rate of 0.7% per year to a conditional convergence rate of about 7% based on their 3-stage least squares method (2% based on their ordinary least squares).[26] This finding appears similar to our result that, for Period Two, conditioning attenuates the bipolarization of county incomes and tends to make them converge to the center of the distribution. However, some caution

[26]See Barro & Sala-i-Martin (1991, 1992) and Sala-i-Martin (1996) for the US state-level evidence. Using the same linear cross-sectional regression specification, we were also able to replicate Higgins et al.'s estimates of an absolute convergence rate of 0.7% per year and a conditional convergence rate of 2% based on OLS.

should be exercised when comparing these two studies. As emphasized by numerous researchers (e.g., Bernard & Durlauf, 1996; Quah, 1997), the conventional linear growth regression and distribution dynamics examine different aspects of income growth. The estimated coefficient on initial income in the cross-sectional growth-income regression represents the average behavior among the economies in the sample, informing us as to whether the average economy converges to the common steady-state growth. The coefficient is not, however, sufficient to ascertain which type of dynamics characterizes the sample. In particular, the coefficient does not admit a test of the hypothesis of conditional β-convergence hypothesis vs. the club convergence hypothesis, nor does it shed direct light on the main concerns of the convergence issue: whether and how poor economies catch up with rich ones. These issues are more effectively addressed by the distribution dynamics approach. For example, during Period One, Figures 2 and 6 show that, conditioned or not, not only do county incomes converge to one another, but also rich counties converge to the center of the distribution at a faster rate compared to poor counties. For Period Two, Figure 6B shows some evidence of two-club convergence even in the conditional sense while additionally showing that rich counties form their club at a relative income level of around 1.8 and that the shrinking middle income group joins the high. In terms of growth dynamics, Figure 3 shows that, both conditionally and unconditionally, there was a change in the nature of growth dynamics from 'approximately linear' for Period One to 'nonlinear' for Period Two. Even for Period Two, however, the estimated coefficient of the initial income *would* be negative, *were* the growth rate regressed against the initial income in a linear fashion, conditioned or not.

As noted in the introduction, the concept of polarization has also been used in microeconomic analyses of income distribution that emphasize the phenomenon of the shrinking middle class. In particular, these studies (cited in footnote 1) have developed various measures of [bi]polarization and reported trends in income bipolarization that appear in individual/household income data. Focusing on the US evidence, there is a general consensus that the distribution of the US household/individual income has been bipolarized in recent decades (e.g., Esteban et al., 2007; Foster & Wolfson, 2010; Alichi et al., 2016; Lee & Shin, 2016). To compare the existing micro evidence to our county-data-based result, we reproduce the bipolarization index using Panel

Study of Income Dynamics (PSID) data from the 1970 through 2017 surveys. To provide a more meaningful comparison between the PSID and BEA results in the estimated bipolarization index, we focus on labor earnings excluding all other sources of income and compare the BEA's county average earnings per worker to the PSID's individual labor income.[27] Both of these measures are before tax/deductions and transfers. Appendix F compares individual earnings and county-level average earnings per worker in their estimated bipolarization indices. The red dashed line uses individual earnings and corresponds to the right scale, while the black solid line uses county-average earnings and corresponds to the scale on the left. The takeaway from Appendix F is that, despite possible differences in the data collection process and income definitions, both the individual and county average earnings variables show similar trends, particularly since the mid-1990s.[28] This suggests the potential importance of the bipolarization of regional incomes as a source of the bipolarization of individual incomes.

3.6 Additional Robustness Tests

Our main analyses have used county per capita income defined as the ratio of personal income from all sources to county population. Here, we first test the robustness of our main results to different income definitions: dividing income by the number of workers instead of population as well as using earnings (as opposed to total income) both by place of work and place of residence. We further examine the results when splitting of the sample into metro and non-metro areas. For each of our various income measures—total income (Appendix G1), earnings by the place of work (Appendix G2), and earnings by the place of residence (Appendix G3)—we display results using both county population and county employment to calculate average income. In each case, we display figures that allow for comparison between metro and non-metro areas, between

[27]We use data from the nationally-representative Survey Research Center component of the PSID sample and include both household heads and wives in the sample. Since the PSID switched to biennial surveys starting in 1997 and each year's survey contains labor income for the previous year, the income observations run every year until 1996 and every other year since then. The PSID's labor income includes bonuses, tips, commissions, and the labor parts of business, farm, market gardening, and roomers/boarders income in addition to wages and salaries. The county average earnings include both the total compensation of employees and proprietors' income.

[28]Index values are generally lower for county incomes, reflecting that within-county income bipolarization is averaged out.

the two sub-periods, and between the unconditional and conditional approaches. To save space, the comparison is based only on the dynamics leading to the ergodic distributions derived from estimated transition kernels. The results presented in Appendix G1 through G3 show that, for all cases, metro counties show a stronger pattern of income bipolarization compared to non-metro counties.[29] For both metro and non-metro samples, however, the following three patterns remain consistent regardless of different definitions of county per capita income: (1) The tendency toward income bipolarization is stronger in Period Two than Period One, (2) conditioning mitigates income bipolarization, and (3) whenever county incomes are bipolarized, the process takes the form of the shrinking middle mostly joining the high income club. These observations lead us to combine the metro and non-metro samples for our main analyses.

Second, our analyses so far have used a national deflator to construct real personal income at the county level. It is further suggested that there may be large differences in the level and trends in inflation across counties that may affect the distribution of county incomes and its changes. Given that price deflators are not available at the county level, we use the time-varying variable of median house price to generate a 'county price deflator.' To do this, we select a county whose median house price is at the median in 1970 (Columbia, Washington); set the median value at 100; and adjust all other county-by-year median house prices accordingly. Because the BEA's conditioning variables are based on the 1970, 1980, 1990, 2000, and 2010 Decennial Censuses, values for other years are generated by interpolation/extrapolation. In Appendix H, we reproduce Figure 2 using county per capita incomes deflated by the generated 'county price deflator.' The results confirm our previous findings based on Figure 2. For example, once county-specific inflations and their trends are more fully considered, the bipolarization tendency becomes even stronger in Period Two, compared to the case of not considering them in Figure 2, and the convergence tendency towards the center of the distribution becomes more apparent in Period One.

Third, we examine if the results are robust to the exclusion of the Great Recession and

[29]Metro counties are those that contain large cities with populations of 100,000 or more, or border such counties. In our balanced sample of 3,026 counties, the share of metro counties grew from 464 (15.3%) for Period One to 719 (24.1%) for Period Two.

its aftermath from the sample. That is, we redefine the three reference periods dividing our sub-periods as 1970 to 1974, 1987 to 1991, and 2004 to 2008. The average unemployment rates in these three reference periods are 5.4 percent, 5.9 percent and 5.1 percent, respectively. In examining our first sub-period using these alternative definitions, 1970–74 to 1987–91, we analyse the averaged distribution dynamics for the five 17-year periods beginning in each of 1970 to 1974. Similarly, we analyse the average of the five 17-year distribution dynamics for the second sub-period, 1987–91 to 2004–08. The estimates in Figure 1 suggest that the estimated bipolarization index, while having maintained its level during the first sub-period, increased by 47 percent for the second sub-period, a change which is statistically significant. In Appendix I, we repeat the analysis of Figure 2 for the newly-defined sub-periods. For brevity, we report only the contour plot and the implied ergodic distribution. As in the results of Figure 2, while the first sub-period shows little evidence of forming two income clubs, the distribution dynamics for the second sub-period are characterized by a bipolarization process with the shrinking middle mostly joining the high.

Fourth, so far, our analyses of distribution dynamics and the bipolarization index have been based on a balanced sample of 3,026 counties which have valid per capita income data every year from 1970 to 2017. While we make this restriction to maintain the same sample composition between the two sub-periods and between the two approaches, it certainly neglects the 'extensive' margins of the distribution change between Period One and Period Two. We previously mentioned that the observed trend movements of the bipolarization index remain virtually identical even when the unbalanced sample of 3,075 counties are exploited. In Appendix J, we repeat the analysis of Figure 2 using the unbalanced sample. Because both the balanced and unbalanced samples are identical for Period One (N=3,026), we report the results of distribution dynamics only for Period Two with an extended sample (N=3,044). Once again, the resulting distribution dynamics indicate a bipolarization process with growth in the high-income club coming from the middle class.

Lastly, we repeat all previous analyses with the full sample of 3,138 counties without excluding extreme values (the top 1% and bottom 1% of counties in each year's income distribution).

Although not reported to save space, the results are robust with respect to inclusion of these extreme observations, implying that our results apply broadly even when these observations are included.[30]

4 Conclusion

Analysis of US county per capita incomes from 1970 to 2017, while confirming the previous finding of income convergence across US regions during the 1970s and 1980s, finds new evidence that the unconditional distribution of US county incomes has become significantly bipolarized since the early 1990s. While both absolute and conditional convergences characterize the sample until the early 1990s, there was a change in the nature of distribution dynamics toward bipolarization (or two-club convergence) in the early 1990s. Some good news is found in our results showing that much, though not all, of the recent bipolarization is 'explained' by cross-county differences in education and industry mix. This suggests that a 'structural' approach to depolarization can be sought by using labor and education policy to reduce disparities in these variables across regions. Additionally, consistent with the finding that the initial income level determines the fate of a county, government/business transfers are found to be effective in reversing the bipolarization process. A positive aspect of the recent bipolarization process is that the shrinking middle class has mostly joined the high-income group. This is a more desirable process compared to a transition from middle income to poor that is often observed in the evolution of the world income distribution. Nevertheless, the recent US evidence weakly supports the (conditional) club

[30] All our non-parametric estimations are based on the the Rule-of-Thumb bandwidth, $1.06 n\sigma^{-\frac{1}{5}}$, where σ is the standard deviation and n is the number of observations. While this Rule-of-Thumb bandwidth is easy to compute and optimal under the Gaussian assumption, Sheather & Jones (1991) and Botev et al. (2010) point out that it can produce inaccurate estimates when the underlying density is far from normal. To cope with outliers and multimodality of the density, these studies modify the original formula to $0.9 \times min\left(\sigma, \frac{IQR}{1.34}\right) \times n^{-\frac{1}{5}}$, where IQR is the interquartile range. This modified bandwidth becomes optimal when the underlying density is multimodal or there exist outliers. Multinormality is treated by reducing the proportionality factor from 1.06 to 0.9, while outliers are considered by replacing the standard deviation by a more robust measure of the spread, $min\left(\sigma, \frac{IQR}{1.34}\right)$. Application of this modified bandwidth, however, makes little change to our main results. Although the contour map becomes slightly more wiggly compared to the case of using the original Rule-of-Thumb formula, the shape of the distribution in the steady state as well as the nature of distribution dynamics remain virtually identical between the two choices.

convergence hypothesis, which is true even when the post-transfer incomes are considered. This is less desirable compared to the case where county incomes converge to one another regardless of their initial income levels, other things being held constant.

The finding that the declining middle income counties tend to join the high income club has additional welfare/policy implications. First, structural policies targeting depolarization should be directed in a way not to reverse this desirable aspect of the process. For example, by making the education level of the 'poor' club catch up with that of the rich club, we can further accelerate the transition and make all 'poor' counties join the high club. Such a process would produce depolarization of county incomes in a Pareto-improving way. In the long run, these types of active structural policies are considered to be more desirable compared to simple transfer policies that reverses the desirable parts of the bipolarization process with the aim of integrating regional incomes in a relatively short time period. Second, to the extent that regional factors are responsible for the bipolarization of individual/household incomes, the current finding of the US bipolarization *process* runs against the pessimistic view pervasive in the current policy debate on inequality/polarization of individual incomes. The pessimism may partly result from looking at *snap shot* income distributions without considering the *process* of distribution changes. That being said, the current study deviates from those studies that focus on the upper (e.g., top 1 percent) or lower (below the poverty line) end of the individual income distribution in that our discussion is more broad-based.

As a final remark, due to limitations of the current data set that abstract from within-county distribution changes, our discussion of regional bipolarization as a potential source of the bipolarization of individual incomes is limited, still leaving in a black box various issues such as the empirical importance of this 'regional effect' and appropriate interpretations of the effect in conjunction with regional mobility. An empirical assessment of these issues would require a rich data set that tracks a large number of individuals for each region (county in our case) for decades and a sophisticated econometric model that incorporates both intensive and extensive margins of distribution changes. In fact, regional mobility has been another important subject in the study of regional income convergence. Some studies find that labor mobility makes regional incomes converge at a faster rate (e.g., Evans & Karras, 1996a,b; Evans, 1997). However, Rappaport's (2005) theoretical discussion introduces labor mobility in the neoclassical growth model and finds that outmigration creates a disincentive for gross capital investment, and this disincentive at least partially offsets the positive and direct contribution of labor mobility to faster income convergence. To make the discussion more complicated, we believe that the effects of labor mobility on convergence or divergence of regional incomes also depend on the 'quality' of mobile workers in addition to the volume. For instance, if regional mobility is costly, only richer people will pay for the mobility costs and cluster in counties that confer the benefits of, say, a good education system. In this scenario, an increase in regional polarization may reflect spatial sorting rather than changes in the distribution of individual incomes. Whether mobility increases or decreases inter-regional income gaps is an empirical matter. More formally, we could apply Roy's (1951) equilibrium model of worker-sector matching to discuss how different regions are specialized by different sectors (industries); how sector-specific skills are correlated in the population; who moves to which region; and how the quantity and quality of mobile workers affect the observed income gap between the region workers leaves and the region they join in. This avenue of future research will set up a useful bridge between the microeconomic literature on income distributions and the macroeconomic literature on regional income convergence.

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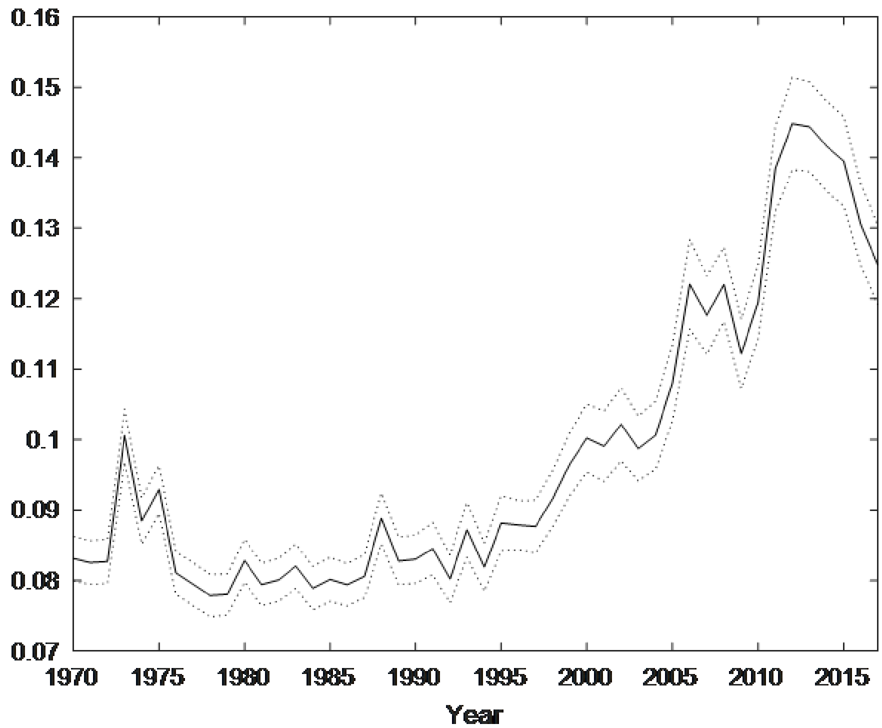
Figures

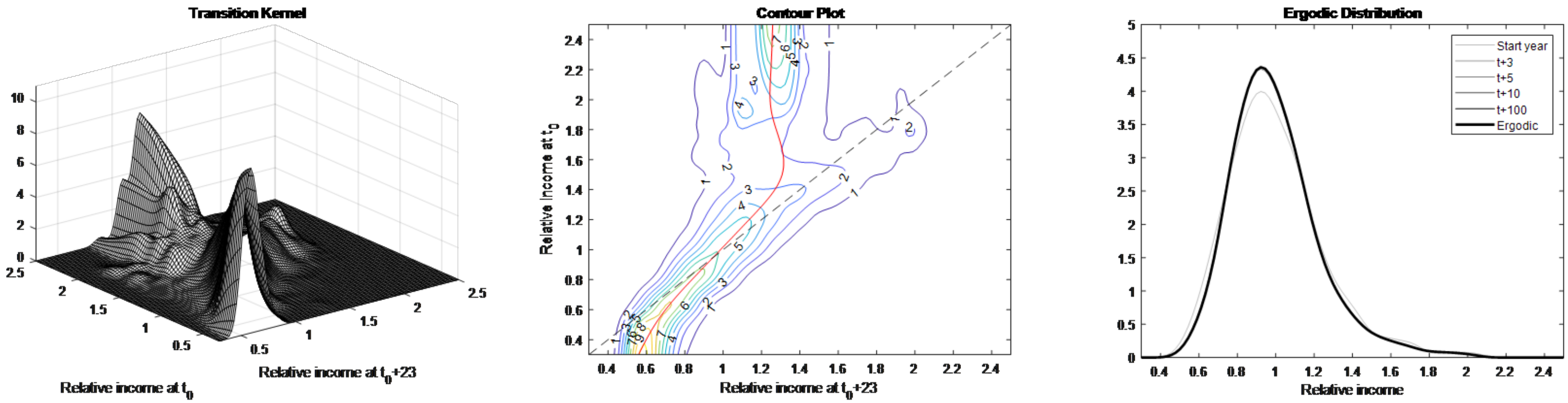
Figure 1: Trends in the Estimated Bipolarization Index in the US, 1970–2017



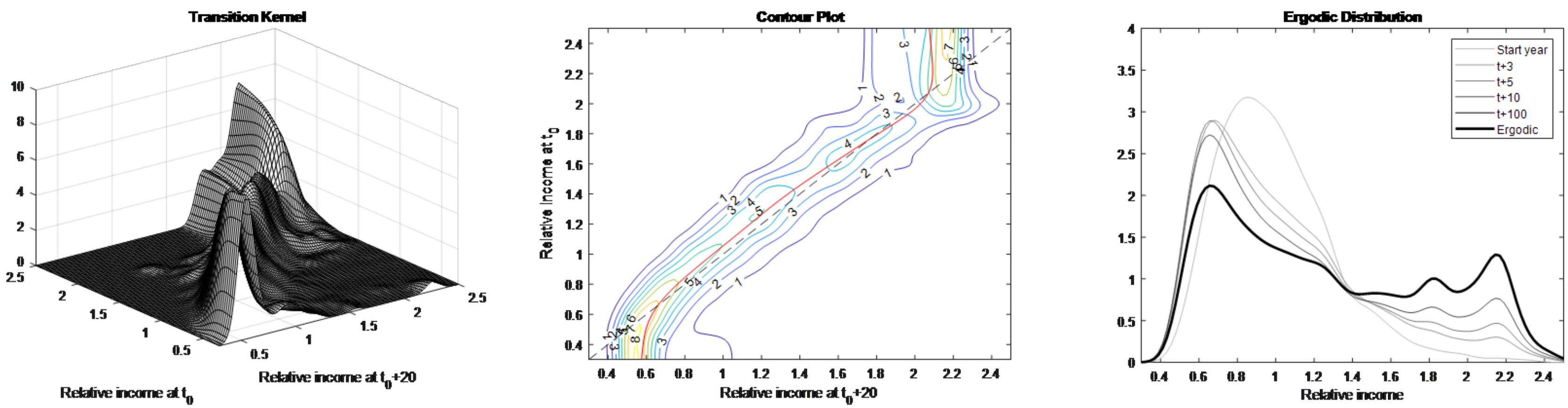
Data source: Bureau of Economic Analysis (BEA) Regional Economic Information System.
Notes: Produced using a balanced sample of 3,026 counties that appear every year from 1970 through 2017. For each county, per capita income is the ratio of personal income (expressed in 2012 dollars) to county population. Personal income is defined as the sum of wage and salary income, other labor income, proprietors' income (with inventory valuation and capital consumption adjustments), rental income (with capital consumption adjustment), personal dividend income, and personal interest income. It does not include government/business transfer nor military income. The solid line represents estimated index values. See the text for a brief introduction of the bipolarization index. A pointwise confidence interval at the 95% level is shown by the dotted lines which are obtained by the Jackknife algorithm described in Lee & Shin (2016).

Figure 2: Unconditional Distribution Dynamics of County Real Per Capita Income

(A) Period One (1970–74 to 1993–97): 3,026 Counties



(B) Period Two (1993–97 to 2013–17): 3,026 Counties



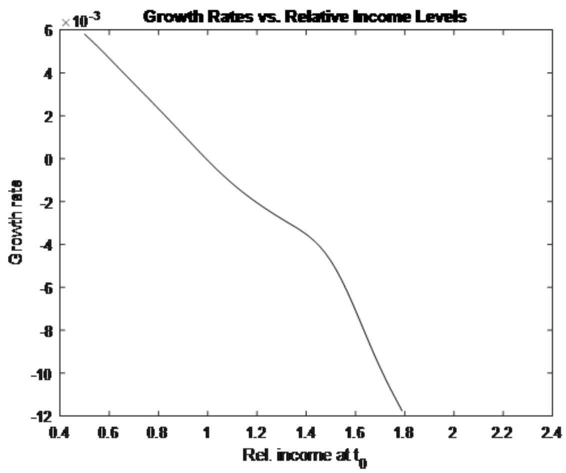
Data source: Bureau of Economic Analysis Regional Economic Information System.

Notes: See notes to Figure 1 for the sample used. Both the initial and terminal income levels are expressed relative to their respective national means. Each contour plot is superimposed by the 45-degree line (black dashed line) and the trajectory of the mean terminal income predicted at each level of initial income (red solid line).

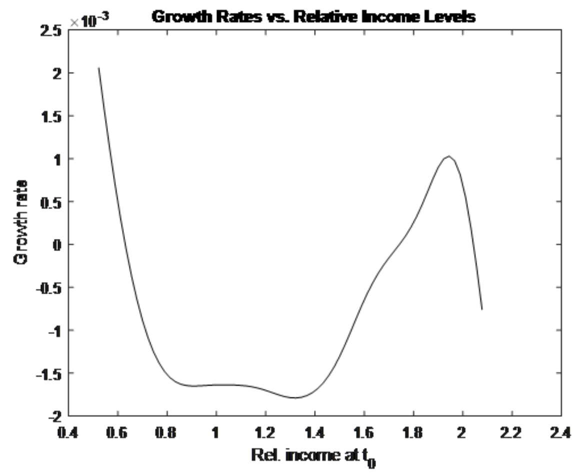
Figure 3: Nonparametric Estimation of Growth Equation of the US County Real Per Capita Income: Balanced Panel of 3,026 Counties

(A) Unconditional Growth

(a) Period One (1970–74 to 1993–97)

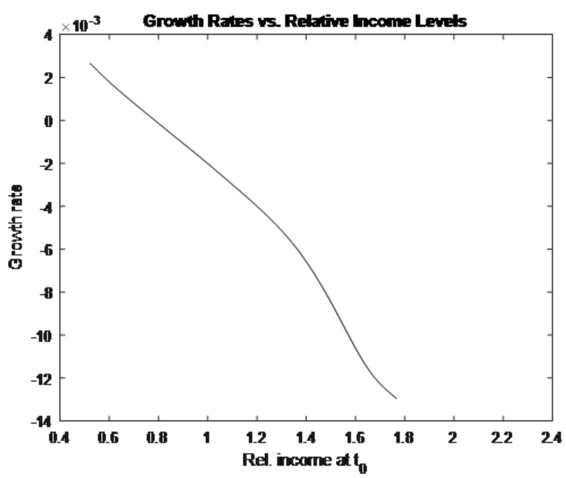


(b) Period Two (1993–97 to 2013–17)

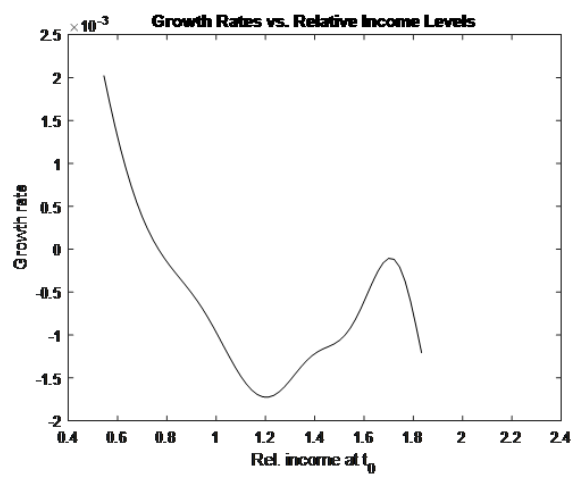


(B) Conditional Growth

(a) Period One (1970–74 to 1993–97)



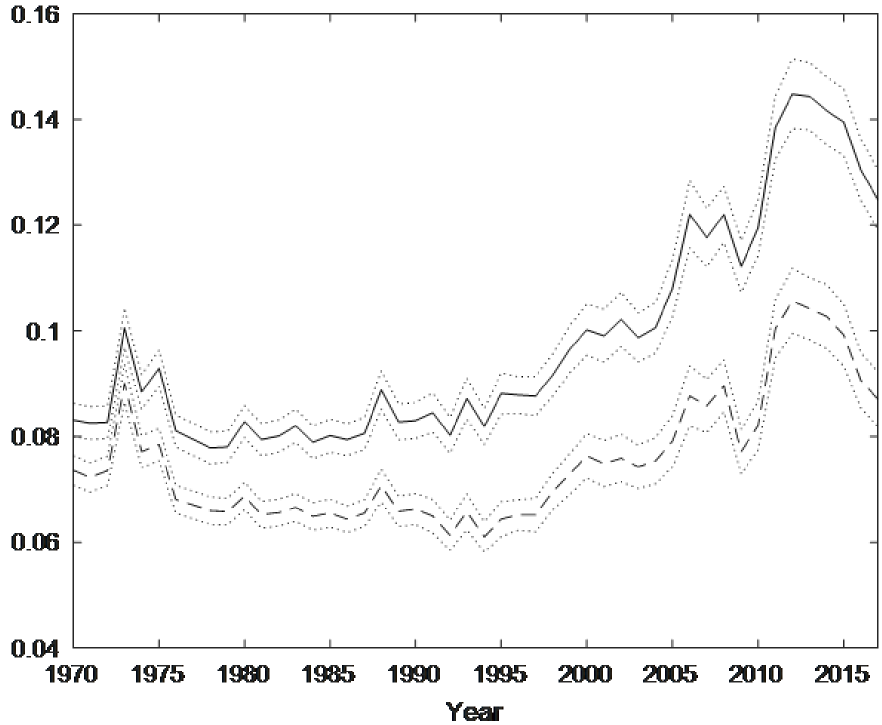
(b) Period Two (1993–97 to 2013–17)



Data source: Bureau of Economic Analysis Regional Economic Information System.

Notes:See notes to Figure 1 for the sample used. See footnote 19 for the estimation method. Both initial income levels and growth rates are expressed relative to their respective national means.

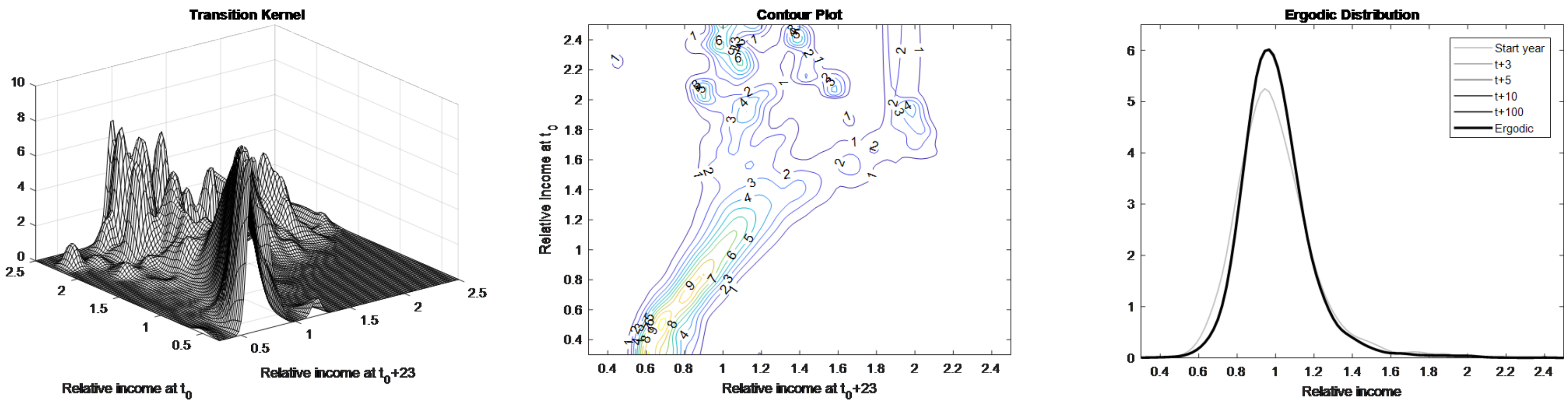
Figure 4: Effectiveness of Government Transfers



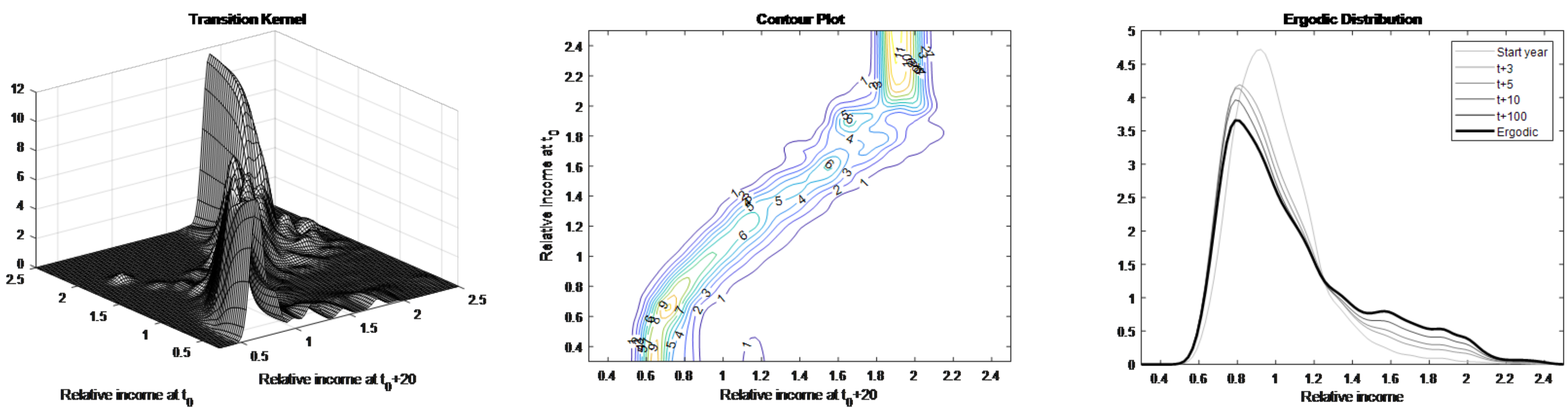
Data source: Bureau of Economic Analysis Regional Economic Information System.
Notes: The solid line represents the bipolarization indices estimated based on pre-transfer county real per capita income, and the dashed line stands for the index values based on post-transfer county per capita income. See notes to Figure 1 for the sample used and definition of pre-transfer income.

Figure 5: Unconditional Distribution Dynamics of County Real Per Capita Income: Government Transfer Income Added

(A) Period One (1970–74 to 1993–97): 3,026 Counties



(B) Period Two (1993–97 to 2013–17): 3,026 Counties

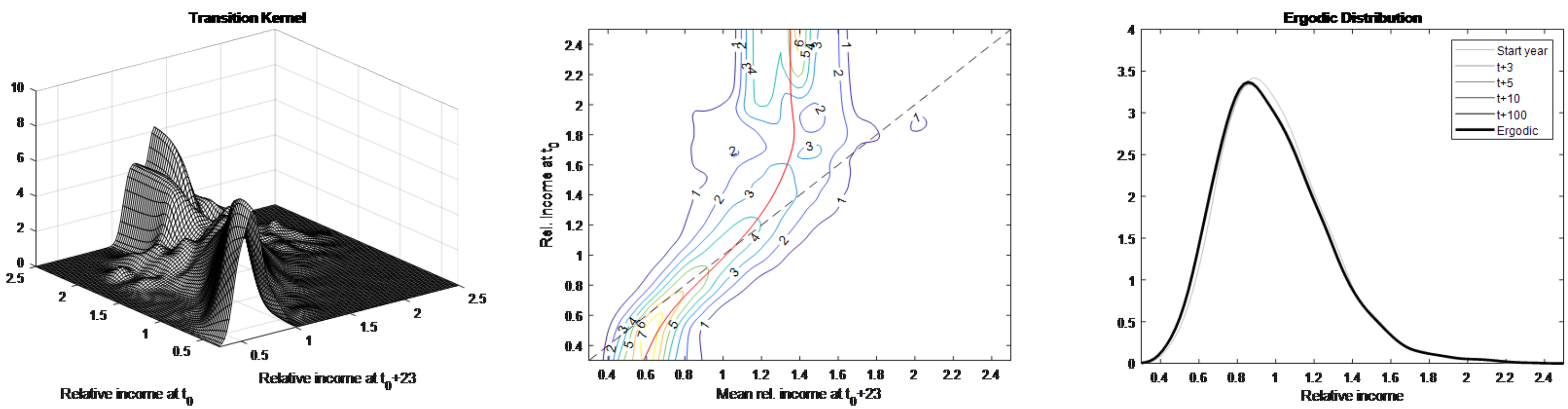


Data source: Bureau of Economic Analysis Regional Economic Information System.

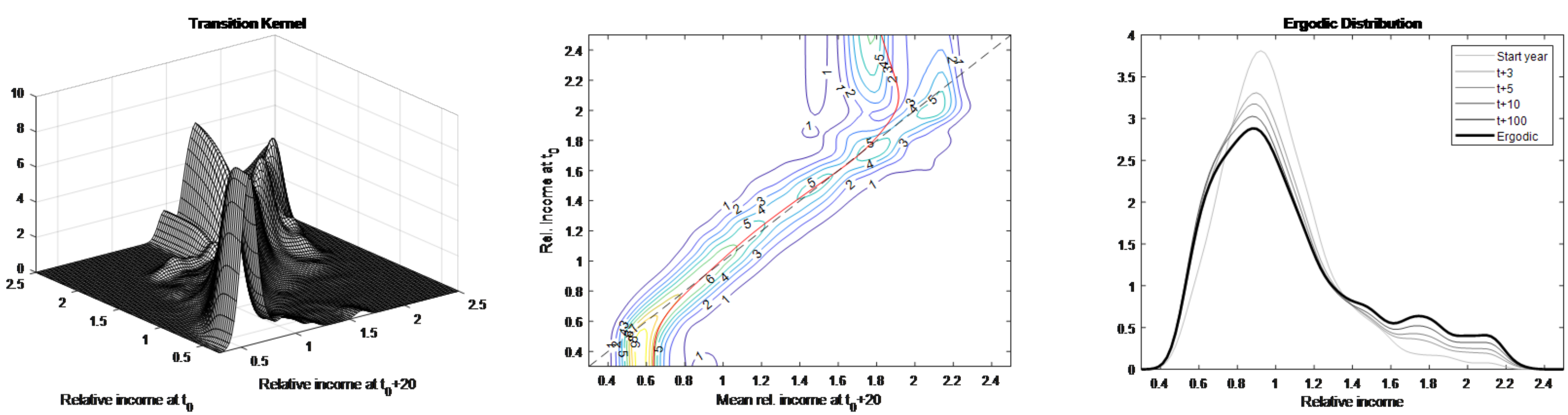
Notes: Figure 5 replicates Figure 2 using county per capita income adjusted by government/business transfers.

Figure 6: Conditional Distribution Dynamics of County Real Per Capita Income

(A) Period One (1970–74 to 1993–97): 3,026 Counties



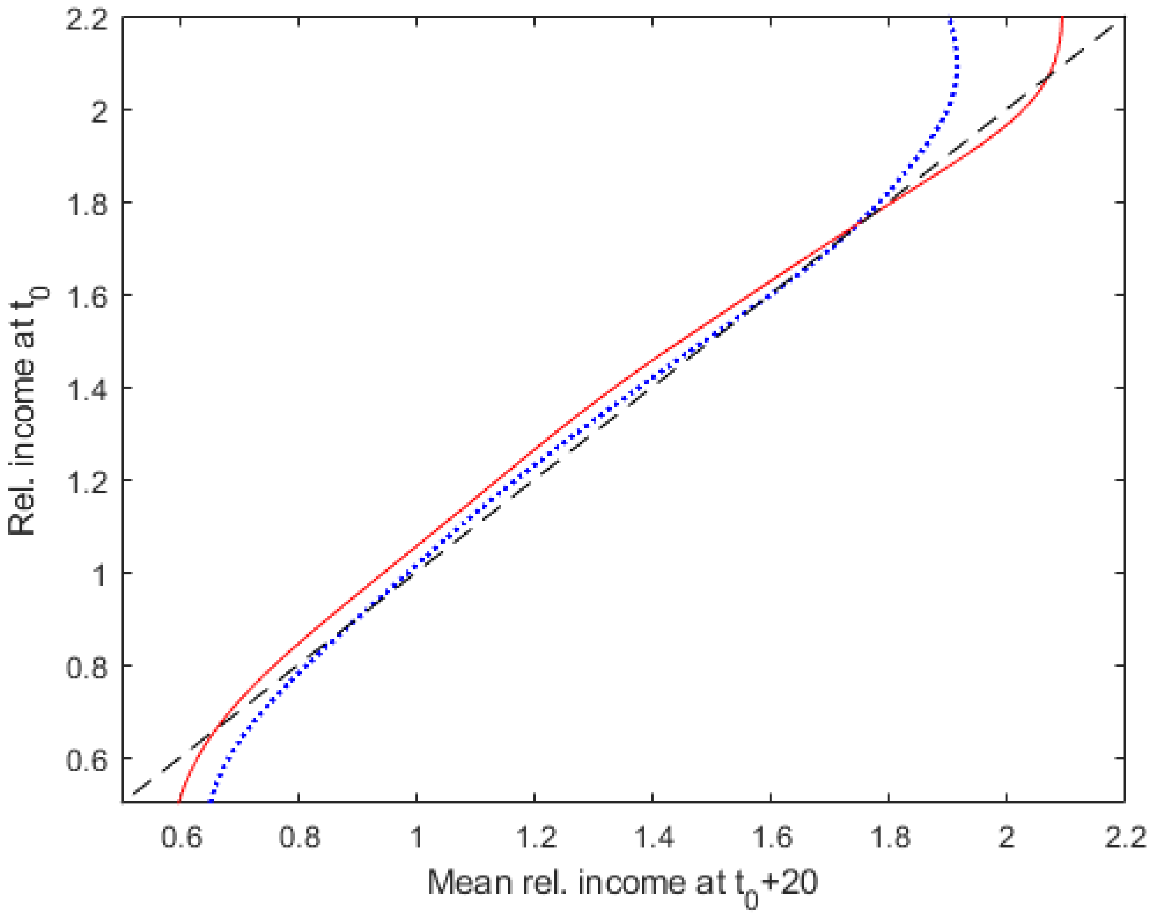
(B) Period Two (1993–97 to 2013–17): 3,026 Counties



Data source: Bureau of Economic Analysis Regional Economic Information System.

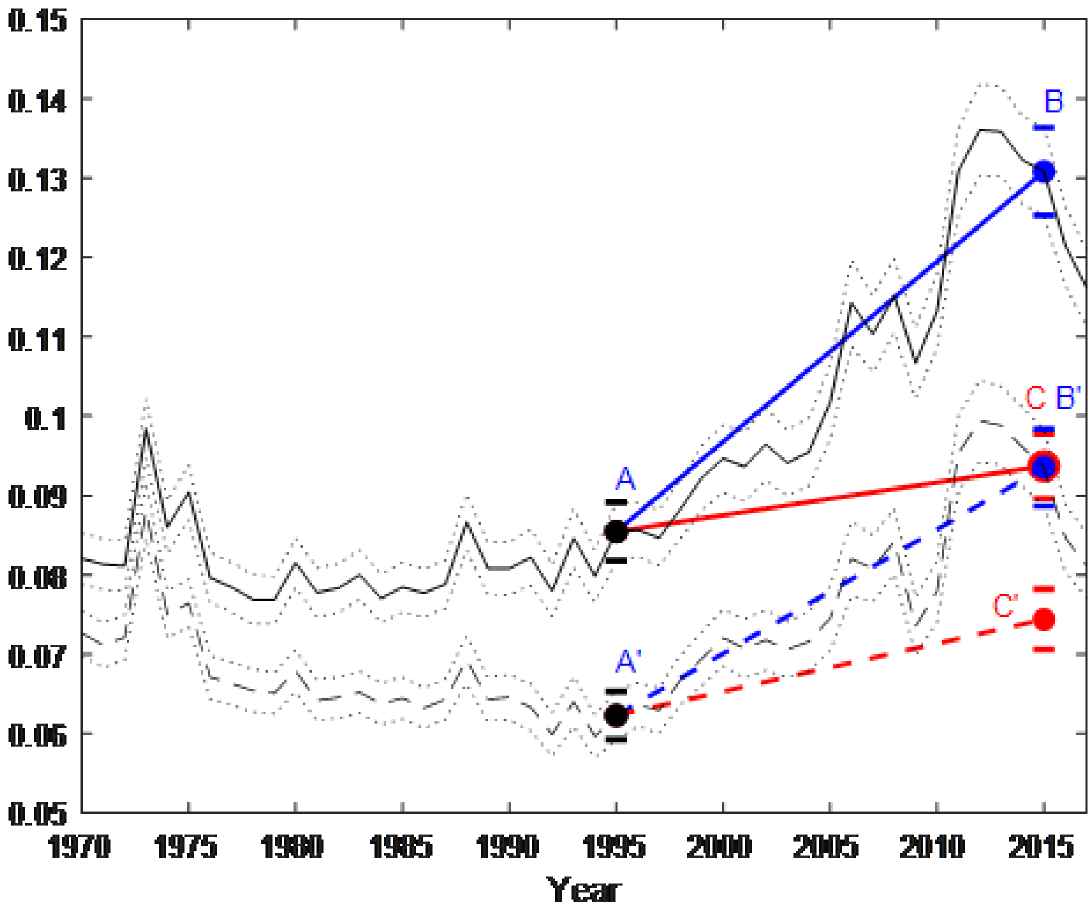
Notes: Figure 6 replicates Figure 2 using the IV residuals obtained from the estimated conditional growth equation. See the text for the IV approach. See Appendix A for the conditioning variables. Each contour plot is superimposed by the 45-degree line (black dashed line) and the trajectory of the mean terminal income predicted at each level of initial income (red solid line).

Figure 7: Comparison of Unconditional and Conditional Distribution Dynamics



Data source: Bureau of Economic Analysis Regional Economic Information System.
Notes: The red solid and blue dotted lines represent the trajectories of the mean terminal income predicted at each level of initial income for unconditional and conditional distribution dynamics, respectively. These are borrowed from 2B and Figure 6B, respectively.

Figure 8: Does Conditioning Mitigate Bipolarization of County Incomes for Period Two? A Quantitative Analysis

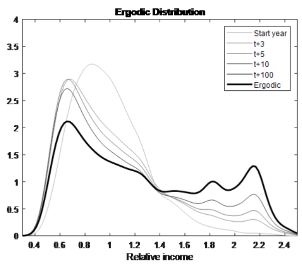


Data source: Bureau of Economic Analysis Regional Economic Information System.

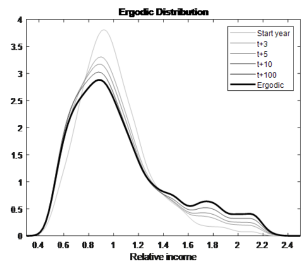
Notes: The solid line represents the bipolarization indices estimated based on pre-transfer county real per capita income, and the dashed line stands for the index values based on post-transfer county per capita income. The blue sold line from A to B represents the 'unconditional' increase in the bipolarization index for Period Two, and the red solid line from A to C indicates the 'conditional' increase for the same period. Corresponding figures for the post-transfer income variable are represented by dashed lines and A', B' and C'. Each pair of bars represent 95 percent confidence interval for the corresponding circular point.

Figure 9: Drivers of Bipolarization

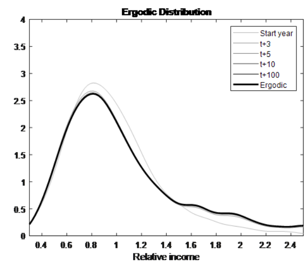
(A) Unconditional



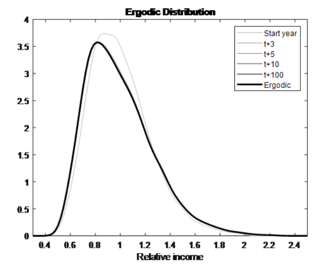
(B) Fully conditional



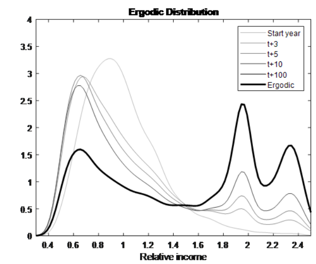
(C) Industry composition only



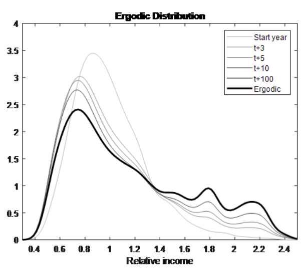
(D) Education only



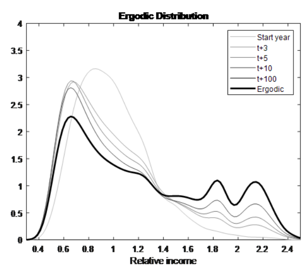
(E) Age composition only



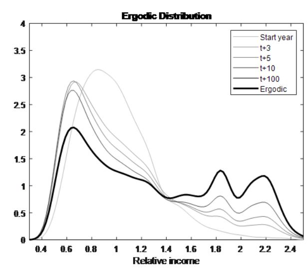
(F) Racial composition only



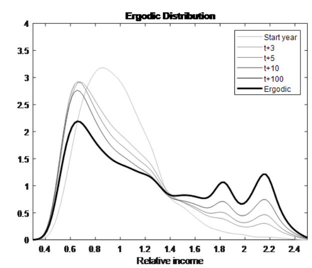
(G) Land/Water area only



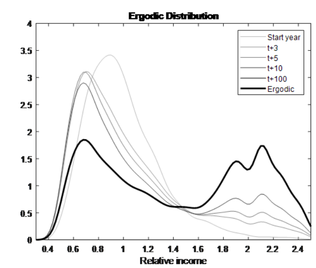
(H) Median house price only



(I) Natural amenity only



(J) Miscellaneous only



Data source: Bureau of Economic Analysis Regional Economic Information System.

Notes: Figures 9A and 9B are borrowed from Figure 2B and 6B, respectively. A variable is considered an important contributor to the income bipolarization if controlling for the variable makes the bimodality of the unconditional ergodic distribution less distinct. For brevity, we categorize conditioning variables (6) to (21) in Appendix A as 'industry composition'; variables (22) to (25) as 'age composition'; variables (30) to (33) as 'education'; and variables (34) and (35) as 'race composition'.