What Makes Economic Growth Inclusive?

Evidence on the Role of Ethnicity from Native Americans

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Abstract: Does the ethnic purity, or polarization, of a society predict whether income inequality will narrow or widen with economic growth? We study this question by comparing the growth-inequality relationships on Native American reservations with U.S. states and other countries. To do so, we first construct a new data set of Gini coefficients and variables measuring ethnic assimilation and polarization for a panel of reservations spanning 1945 to 2010. We find that assimilated and polarized reservations have tended to follow the same trend of exclusive growth – i.e., rising inequality - found elsewhere in the United States. After isolating the contributions of polarization from that of assimilation, we find that polarization has been the key driver of exclusive growth, as reservations with ethnically homogenous populations prior to 1945 have experienced inclusive growth. The effect of polarization is strongest during 1990-2010 and appears to be driven by uneven distribution of tribal casino gaming returns. The findings provide new evidence on the relative role of ethnically-endowed preferences vs. ethnic polarization in driving inequality.

JEL Codes: D31, O57, P25, P52, C14

Key words: Inequality, growth, ethnicity, assimilation, polarization, Native Americans, indigenous economies

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1. **Introduction**

When does economic growth raise income inequality and when does it lower inequality? This question receives significant attention in the economics literature, with oft-cited contributions ranging from Kuznets (1955) to Piketty (2013). Yet there is still no agreement about what factors determine whether growth will narrow or widen a society’s income distribution. So the question remains — are there key characteristics of a society that determine if its growth will be inclusive or exclusive?\(^1\)

Two concepts, developed in the literature, suggest ways in which a society’s culture, and ethnicity, might constrain growth to be inclusive. One posits that preferences towards equality and redistribution vary systematically across ethnic groups in ways that are transmitted, fairly unchanged, from generation to generation (Guiso et. al 2006). This view implies that a political jurisdiction comprised of ethnic Group A (e.g., Native Americans) will maintain lower inequality than a jurisdiction comprised of ethnic group B (e.g., Americans of European origin) if ancestors of Group A had stronger cultural intolerance for inequality.

Another view posits that ethnic heterogeneity influences a jurisdiction’s tolerance for inequality and hence its willingness to redistribute income (see Benabou 2000, Alesina and Glaeser 2004, Ashraf and Galor 2013, Fenske and Zurimendi 2017). Research suggests that ethnic heterogeneity and inequality are positively related because of *in-group bias*—people tend to be more altruistic towards others in their own ethnic group (Dahlberg et al. 2012). In-group bias implies that a more ethnically heterogeneous society will prefer less redistribution across the entire population, because this population contains groups outside one’s own. This view implies a jurisdiction comprised of ethnic groups A and B (e.g., Native Americans and whites) will maintain higher inequality than a jurisdiction comprised entirely of Group A or Group B, even if cultural preferences are endowed through ethnicity and identical across the two ethnic groups.

To disentangle the relative importance of ethnically endowed preferences vs. ethnic heterogeneity in determining if economic growth is inclusive or exclusive, we assess the role of ethnicity in a novel empirical setting. We analyze growth-inequality relationships within and across approximately 100 Native American reservations and contrast those relationships with growth-inequality relationships across U.S. states and international nations. We focus on 1945-2010, which is a period during which U.S. per capita income growth was robust and

\(^1\) Throughout this paper, we refer to inclusive growth as increases in income per capita associated with lower income equity. Exclusive growth is associated with higher income inequality.
exclusive on a national scale, at least since the 1970s (see Piketty and Saez 2003, Frank 2008, Piketty 2013, Boustan et al. 2013). Much less is known about the growth-inequality relationship on Native American reservations, as our study is the first to quantify reservation inequality over a long period of time. As shown in Section 2, there has been significant growth in per capita income within and across reservations since 1945. We can therefore compare inequality across several income points, thereby controlling for overall levels of development, which may be systematically related to inequality (see Kuznets 1955, Barro 2000, Forbes 2000, Frazier 2006, Sarigiannidou and Palivos 2012, Barro 2008, Gallup 2012, Berg et al. 2018).

Studying the growth-inequality relationship on Native American reservations is illuminating because they are sovereign political jurisdictions with governments that are empowered to directly affect income distributions, and because ethnic composition varies across reservations for historical reasons. One key difference is the extent of average assimilation with whites, based on Bureau of Indian Affairs (BIA) blood quantum reports collected during the late 1930s. The data measure the percentage of the reservation’s American Indian population in different bins of percent Native American blood. The bins are: greater than zero but less than 25%, 25% to 49%, 50% to 99%, and 100%. From this information, we construct a measure of average assimilation for each reservation, which is the weighted mean of blood quantum mix.

The BIA’s detailed collection of blood quantum data during the 1930s allows us to focus on variation in average assimilation that is predetermined with respect to growth-inequality relationships over 1945-2010. As Guiso et al. (2006) note, using ethnic characteristics that are predetermined helps to overcome the reverse causality problem that economic outcomes can affect ethnicity and culture. Our historical measure correlates strongly with modern percentages of Indian populations fluent in a Native American language, suggesting that average historical blood quantum is a meaningful predictor of cultural strength today.

We also construct a measure of ethnic heterogeneity from the blood quantum data. Reservations with a high variance in blood quantum have high levels of heterogeneity, which peaks on reservations where half of the population had 25% or less Native blood and half the

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2 Ethnic diversity endogenously evolves in many settings as new groups search for resources (see Ahelrup and Olsson 2012). These forces were also at work in determining white settlement on and around Native American reservations, but US Government policies that played the most explicit role in this process concluded during the 1930s.
population had 100% Native blood. Our measure is conceptually similar to concepts of ethnic polarization, developed in the cross-national literature, that also peak when a single minority ethnic group is almost as large as the majority group (see Montalvo and Reynal-Querol 2005, Esteban and Ray 2011). A key difference is that our measure is based on the degree of assimilation of one group into another through process more akin to immigration dynamics (Kuhn and Sweetman 2002). In our case, polarization in ethnic assimilation is a direct cause of polarization in tribal citizenship, because tribal membership is often determined by blood quantum as discussed below.

There is a high but imperfect correlation between our measures of ethnic assimilation and ethnic polarization. A reservation compromised entirely of full-blooded Native Americans is neither assimilated nor polarized. A reservation comprised entirely of individuals with less than 25% Native American blood is highly assimilated, but not polarized. A reservation comprised entirely of half-blooded Native Americans will have roughly the same average assimilation as a reservation whose population is split equally between full-blooded Native Americans and Natives Americans with 25% or less blood quantum. The former reservation will have minimal polarization whereas the latter will have maximal polarization.

Our empirical methodology evaluates how changes in reservation-level income inequality (of the Native American population) correlates with reservation-level income growth (of the same population), when interacted with the assimilation and polarization variables. The most parsimonious empirical model indicates that, at low levels of income per capita – generally from 1945 to 1980 - reservations experienced rising inequality with income growth regardless of ethnic assimilation or polarization. At higher levels of income, the growth-inequality relationship on reservations is sensitive to assimilation and polarization. Reservations with low average levels of assimilation started to experience inclusive growth over 1980 to 2010, sharply diverging from the overall trend of rising inequality in the broader United States.

This finding appears to affirm the importance of ethnically endowed preferences in steering inclusive growth. It is consistent with evidence elsewhere indicating that, historically, most Native American tribes redistributed income prior to being confined to reservations (Jorgensen 1980) and that, today, the average Native American has stronger preferences for equality when compared to the average white ancestor of European colonists, even after controlling for differences in income, age, and other factors (Guiso et al. 2006).
Our other empirical results, however, suggest that ethnic polarization is a much more important factor. Once we control for polarization, we fail to detect an independent effect of assimilation on the growth-inequality relationship. Reservations with low levels of polarization started to experience inclusive growth over 1980 to 2010, and this effect is robust to a suite of other controls. The finding that polarization did not matter before 1980 is interesting because the post-1980 period is a self-determination era in which tribes transitioned from being viewed as merely “administered communities” to more autonomous governments that can, among other things, operate casinos and distribute earnings to tribal members (Stull 1990, Kalt et al. 2008).

Consistent with the interpretation that polarization exacerbates the effects of income shocks on inequality, we find that increases in the number of slot machines per Native American – which is our measure of casino gaming intensity – translates into exclusive income gains on ethnically polarized reservations and inclusive income gains on reservations that are ethnically homogenous. This finding supports our interpretation that citizenship polarization is a key mechanism through which ethnic polarization operates, although we cannot rule out other channels.

2. Background, Literature Review, and Implied Hypotheses

2.1 Income Growth on Reservations

The disparity between the modern per capita income of American Indians living on reservations and the U.S. national average is large, but so too is the disparity in income growth rates since the 1940s. The per capita income for Native Americans living on reservations over 2006-2010 was $11,454, compared with $17,981 for Native Americans living off reservations and $27,344 for the total U.S. population. From 1945 to 2010, however, the per capita income on reservations converged towards the U.S. average as shown in Table 1. During this period, annualized income growth per capita was 2.52 percent on reservations compared to 1.69 percent for the total U.S. population.

Throughout this paper the term reservation refers to federal American Indian Reservations. Our analysis does not include off-reservation trust lands, state designated tribal areas, and Alaskan Native village areas. These data come from the U.S. Census, which beginning in 2000, gave survey respondents the option to select a single race or multiple races. Throughout our analysis, we employ data for respondents who reported a single American Indian race.

The relatively strong growth on reservations preceded the recent growth in tribally owned casinos, which began to flourish in the 1990s (see Cookson 2010, Akee et al. 2015b).
Table 1:
Annualized Growth Rates in Real Per Capita Income

<table>
<thead>
<tr>
<th></th>
<th>1918-1942</th>
<th>1942-2010</th>
<th>Pre-Casino Era 1942-1979</th>
<th>Casino Era 1989-2010</th>
</tr>
</thead>
<tbody>
<tr>
<td>American Indians on Reservations</td>
<td>0.25%</td>
<td>2.52%</td>
<td>3.87%</td>
<td>1.80%</td>
</tr>
<tr>
<td>Total U.S. Population</td>
<td>2.29%</td>
<td>1.69%</td>
<td>1.79%</td>
<td>1.34%</td>
</tr>
</tbody>
</table>

Notes: Income data were converted to 2010 $s prior to calculating growth rates. The pre-1970 data used for the reservation calculations come from Bureau of Indian Affairs (BIA) statistical reports, and the data for later years come from the Census Bureau. The 2010 income data are for self-identified American Indians who reported a single race on the Census questionnaire. In the 1980 Census, respondents were not given the option to check multiple races. American Indians were identified by BIA agents in the annual BIA reports. Per capita GDP data from 1918 to 2010 for the total U.S. population are from Bolt and van Zanden (2013).

Per capita income growth for American Indians has been far from uniform across reservations, as shown in Figure 1. Twenty-four percent of the reservations in our sample experienced growth rates in excess of 2.5 percent, while nine percent experienced growth rates below 1.0 percent. By contrast, per capita income growth in all U.S. states fell in the range of 0.98 to 2.19 percent indicating that across-reservation inequality in income growth has been large relative to cross-state inequality in growth. The cross-sectional variation in growth across reservations more closely resembles the variation across countries as shown by the overlapping histograms in Figure 1.

Figure 1
Annual Growth Rate in Per Capita Income

Notes: The country-level per capita GDP data are from Bolt and van Zanden (2013). The U.S. state-level per capita income data come from the Bureau of Economic Affairs (BEA) regional tables.
The wide variation in growth across reservations, coupled with the fact that tribes are sovereign entities with differing governance structures (see Cornell and Kalt 2000, Akee et al. 2015a), has motivated empirical research investigating the causes of this variation that is more similar to the cross-country growth literature than it is to studies of local income growth within the U.S. The empirical papers have identified several factors associated with income growth including governance institutions, geographic location, natural resource endowments, casino gaming, and historical trauma.5

Most of the literature on reservation-level income growth does not attempt to estimate the role of culture or ethnicity, perhaps because both are difficult to measure and perhaps because they may endogenously evolve with income growth. But Cornell and Kalt (1992, 227) discuss and rebut the notion that Native American culture is somehow antithetical to markets and wealth creation and conclude that “evidence suggests that indigenous culture, in and of itself, is not the obstacle to development that it is often portrayed to be.” Dippel (2014) finds evidence of lower income growth on reservations for which multiple tribes were forced to coexist when reservations were established in the late 19th century. This is suggestive evidence that cultural and ethnic cohesiveness may assist development on reservations.6

2.2 Culture, Ethnicity, and Inequality

We are not aware of research that has analyzed the extent to which the growth-inequality relationship on reservations is conditioned by ethnic or cultural traits,7 but the topic has received considerable attention in cross-country analyses and in studies of the rising inequality within the United States. In much of the political economy literature, redistributive policies are a major determinant of income inequality. Benabou (2000) suggests that history-dependent political equilibria, called social contracts, determine whether a society will

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6 The role of indigenous culture, ethnic diversity, assimilation, and acculturation in the growth process are complex and not well understood. For an overview of the potential role of some these factors, see Cornell and Kalt (1992), Pickering and Mushinski (2001), and Anderson and Parker (2009). For specific empirical research on how assimilation and ethnicity might affect wages and earnings of Native Americans, see Patrinos and Sakellariou (1992), George and Kuhn (1994), Kuhn and Sweetman (2002), Gitter and Regan (2002), and Pendakur and Pendakur (1998).

7 Mushinski and Pickering (2000) and Pickering and Mushinski (2001) study the relationships between pre-reservation cultural characteristics and 1990 income and income inequality using a cross-section of reservations. Their study informs our research but it is different because it does not dynamically assess how inequality has evolved with income growth.
maintain a low redistributive scheme with high inequality or a high redistributive scheme with low inequality. He highlights the differences between the policies of the U.S. and those of the “welfare states” of Western Europe. While these countries share high incomes and relatively similar political systems, their societal choices with respect to redistribution differ significantly. The U.S. has higher inequality and is less redistributive, whereas the European states have lower income inequality and redistribute more.

Alesina and Glaeser (2004) suggest there is a relationship between a country’s ethnic homogeneity and its choice of a social contract, noting that the European countries are more ethnically homogenous than the United States and also more willing to redistribute income. The reluctance to redistribute in ethnically fragmented societies may manifest as lower provision of public goods (Alesina et al. 1999, Miguel and Gugerty 2005, Glennerster et al. 2013). Fewer public goods could raise inequality in the long run because poorer families benefit more from public education, libraries, and infrastructure.\(^8\)

More closely related to our study, Fenske and Zurimendi (2017) push this idea further, providing evidence that ethnic heterogeneity may affect not only the overall level of redistribution, but also the inequality of government distributions. In the context of oil development in Nigeria, they show that citizens of certain ethnic groups benefitted to a greater extent than citizens of other ethnic groups. This is a fairly direct path through which ethnic (and religious) heterogeneity can raise inequality. In their case, shocks to the value of a country’s natural endowment increased the relative standing of specific ethnicities and amplified pre-existing differences in welfare across ethnic groups.

There is an even more direct path through which ethnic heterogeneity may raise inequality, especially in the context of positive value shocks to a country’s resource endowment. Ethnic heterogeneity may create heterogeneity in national or regional citizenship if such citizenship hinges on ethnicity. Heterogeneity in citizenship can lead to higher inequality when governments make payments, monetary or in-kind, to citizens but not to non-citizens. This can lead to a type of “citizen rent” as described in a different context by Milanovic (2016).

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\(^8\) A few studies also point to the potential role of ethnicity and ethnic heterogeneity in affecting regional income inequality within the U.S. (see Partridge et al. 1996, 2005 and Panizza 2002). Notably, inequality in the racially diverse Northeast and the South tended to be higher than the national average, whereas inequality in the less diverse Midwest and West tend to be lower than average. Nielsen and Alderson (1997) find that racially diverse U.S. counties tended to have higher levels of inequality. Fallah and Partridge (2007) also examine U.S. counties and find evidence that the growth-inequality relationship is conditional on whether a county is urban or rural. They suggest that, in more rural counties, close communal ties and a lack of anonymity imply social constraints which limit conspicuous wealth and high income inequality.
2.3 *Implied Hypotheses*

The previous literature hints at reasons why the growth-inequality relationship on reservations may differ from the broader U.S. population, and why that relationship may vary with ethnic assimilation and heterogeneity across reservations. Here we note three specific potential links between Native culture, ethnic polarization, and tolerance for inequality.

First, with respect to history-dependent preferences, there is evidence that Native Americans are generally more accepting of redistributing income than Americans who are of British, Northern European and German descent as shown in Figure 2 which comes from Guiso et al. (2006). These survey results are consistent with evidence from anthropologists that, prior to the establishment of reservations, American Indian tribal societies generally reciprocated and redistributed goods among their members (Jorgensen 1980). According to their data, 79% of 172 surveyed tribes traditionally redistributed goods among members in their local residence group, prior to the establishment of reservations.

Second, there is also qualitative evidence that social norms on some Indian reservations are such that individual economic prosperity, and hence income inequality, is often discouraged. In his book discussing economic development, Miller (2012) argues that many Native Americans on reservations have experienced “resistance for seeming to have pushed ahead of others.” If it is the case that reservation communities are less accepting of conspicuous wealth and of an unequal distribution of income, then we expect these social sanctions to limit income inequality on reservations.

Third, with respect to ethnic polarization, we emphasize again that tribal membership typically depends on Native ethnicity, often through precise blood quantum rules. In this way, ethnicity defines the class of persons entitled to share in tribal resources and participate in tribal politics. According to data presented in Gover (2009), 70% of tribes had blood rules as of 2006, with other rules based on lineage (i.e. descendent of a tribal member) and parental

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9 There are a couple of reasons why U.S. citizens with ethnically European origins may not share the average preferences of their respective European “home” countries with respect to income redistribution. Generally respondents are several generations separated from the ancestors who originally emigrated from Europe. Furthermore, these immigrant families chose to live in the U.S. rather than in their home country, suggesting their preferences are more in line with that of U.S. society.

10 Redistribution here means that individuals would redistribute their food and chattel among people in their local residence group – both kin and non-kin. Of course, it is difficult to know if these customs of redistribution differed from those in the broader U.S. We do note that the U.S. did not institute a federal income tax until the beginning of the 20th century. In 1862, an income tax was implemented to fund war expenses. The first peacetime federal income tax was instituted in 1894 but was quickly repealed as unconstitutional by the Supreme Court. In 1913, the 16th amendment was ratified, making a federal income tax constitutional (IRS Website: “Brief History of IRS”).
residency. Blood rules imply that ethnic fragmentation can directly lead to membership fragmentation. If the reservation is ethnically polarized such that half of the Native American residents are greater than 25% Native blood and half are less than 25%, then a blood membership rule requiring a 25% minimum will maximally polarize membership.

**Figure 2**

*Ethnic Origin and Preferences for Redistribution*

![Ethnic Origin and Preferences for Redistribution](image)

Notes: This figure comes from Guiso et al. (2005). The source of the data is the General Social Survey. The bars represent estimated coefficients of an ethnic dummy (the omitted group is people with ancestors from Great Britain) divided by the average value of the dependent variable. To identify ethnic origin of the ancestors it uses the answer to the question “From what countries or part of the world did your ancestors come?” and grouped together several countries of origin. The dependent variable is the answer to the question “Some people think that the government in Washington ought to reduce the income differences between the rich and the poor, perhaps by raising the taxes of wealthy families or by giving income assistance to the poor. Other think that the government should not concern itself with reducing this income difference between the rich and the poor. […] What score between 1 and 7 comes closest to the way you feel?” A higher number means stronger preferences for redistribution. The regression includes demographic controls (health, gender, age, education, and race), religious affiliations (the omitted category is no religion and atheists) and dummy variables that indicate the origin of the ancestors of the respondent.

To summarize, there are two main arguments for why income growth on Indian reservations may be conditioned by ethnic composition. First, more inclusive growth might result from ethnically endowed differences in preferences towards equality. If ethnically endowed preferences are a dominant explanation, then reservations without ethnically assimilated populations should have growth that is more inclusive than reservations with ethnically assimilated populations. Second, more inclusive growth might result from more homogenous ethnic composition on reservations. As reservation populations become more
ethnically polarized, they should experience less inclusive growth even when holding constant the average level of assimilation.

Whatever effects ethnic assimilation and polarization have on income equality, we expect those effects to be conditioned by a tribal government’s ability to influence income distributions. Research suggests this ability was weak prior to self-determination policies of the late 1970s, which arguably converted tribal governments from paternally managed units to sovereign governments (see Stull 1990, Kalt et al. 2008, Dippel 2014, Frye and Parker 2016). With greater autonomy, we expect a tribe’s governmental decisions – which are constrained by democratic elections (Cornell and Kalt 2000, Akee et al. 2015a) - to be more representative of its members’ preferences. As Kalt et al. (2008) note, “sovereignty and self-determination allow local desires, preferences, needs, and ways of doing things to be more accurately perceived and acted upon.”

In order to affect the distribution of income, tribal governments need more than political self-determination; they also need public funds. In the case of Indian reservations, taxation is unlikely to be a major mechanism of redistribution because poverty on reservations implies a small tax base. In recent years – since the 1990s – casinos enterprises operated by tribal government have become a new and major budgetary source for some tribes (Cookson 2010, Akee et. al 2015b). Because casinos are tribal enterprises, decisions regarding the allocation of revenues and jobs must be made by the tribal government thereby providing a clear mechanism through which ethnic composition might influence changes in income distributions.

3. Measuring Inequality and Ethnic Composition

3.1 Estimating Gini Coefficients

To conduct the analysis, we must construct reservation-level measures of income inequality. We accomplish this in three steps. First, we collected historical (1943-1945) reservation-level data on family incomes from BIA reports housed at the U.S. National Archives. The reports estimate reservation-level Native American populations, aggregate incomes, and the distribution of families within ten income bins (e.g., under $100, $100-$199, etc.). Second, we collected reservation level data spanning 1970 to 2010 from decadal

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U.S. Census reports. The census reports provide the same information as the BIA reports except the distribution of families is reported in different sized bins in the different years (e.g., under $5,000, $5,000 to $7,500, etc). Third, we use non-parametric techniques to estimate lower and upper bounds of Gini coefficients and then use the mid-point.

We measure inequality with the Gini Index, because this is the most feasible measure of inequality to estimate, given our data structure. The data report the $K$ intervals with specific income boundaries $0 = y_1^U < y_2^U = y_2^L < y_3^U < \ldots < y_{K-1}^U = y_K^L < y_K^U = \infty$ and the number of families ($n_k$) within each income interval. The data also report the mean income of the entire population. An example of this type of frequency table from the 1980 census is shown in Table 2.

### Table 2: Example of Grouped Income Distribution Data

<table>
<thead>
<tr>
<th>INCOME IN 1979</th>
<th>Fond du Lac, MN</th>
<th>Fort Apache, AZ</th>
<th>Fort Belknap, MT</th>
<th>Fort Berthold, ND</th>
</tr>
</thead>
<tbody>
<tr>
<td>Families</td>
<td>110</td>
<td>1 248</td>
<td>353</td>
<td>453</td>
</tr>
<tr>
<td>Less than $5,000</td>
<td>14</td>
<td>379</td>
<td>122</td>
<td>107</td>
</tr>
<tr>
<td>$5,000 to $7,499</td>
<td>18</td>
<td>92</td>
<td>50</td>
<td>62</td>
</tr>
<tr>
<td>$7,500 to $8,999</td>
<td>5</td>
<td>147</td>
<td>22</td>
<td>49</td>
</tr>
<tr>
<td>$9,000 to $11,499</td>
<td>23</td>
<td>254</td>
<td>52</td>
<td>104</td>
</tr>
<tr>
<td>$11,500 to $15,999</td>
<td>13</td>
<td>159</td>
<td>32</td>
<td>58</td>
</tr>
<tr>
<td>$16,000 to $24,999</td>
<td>11</td>
<td>103</td>
<td>24</td>
<td>50</td>
</tr>
<tr>
<td>$25,000 to $34,999</td>
<td>14</td>
<td>81</td>
<td>31</td>
<td>41</td>
</tr>
<tr>
<td>$35,000 to $44,999</td>
<td>10</td>
<td>22</td>
<td>-</td>
<td>11</td>
</tr>
<tr>
<td>$45,000 or more</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Median (dollars..)</td>
<td>14 265</td>
<td>10 123</td>
<td>8 011</td>
<td>11 045</td>
</tr>
<tr>
<td>Mean (dollars..)</td>
<td>16 113</td>
<td>11 530</td>
<td>10 890</td>
<td>12 663</td>
</tr>
</tbody>
</table>

Notes: The table is a scanned directly from the 1980 U.S. Census.

Table 3 summarizes the structure of the BIA family income data (for 1945) and the U.S. Census income data (for 1970 through 2010). For each year, we have converted the data into 2010 dollars using CPI adjustments. The number of bins ranges from 9 to 16 and the lower limit for the terminal income group ranges from $24,228 (in 1945) to $253,258 (in 2000). We emphasize that, in all cases, the income measures are for Native Americans on reservations and do not include incomes of non-Natives (e.g., people zero percent Native blood).

12 Other inequality measures include the coefficient of variation, the Atkinson index, the Theil Index and various quantile-based measures (e.g., share of income within 10th percentile, 90-50th percentile gap, etc.).
Table 3:
Summary of Grouped Family Income Categories

<table>
<thead>
<tr>
<th>Year</th>
<th>Number of Bins (K)</th>
<th>Lower limit of terminal bin (2010$)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1945</td>
<td>10</td>
<td>$24,228</td>
</tr>
<tr>
<td>1969</td>
<td>14</td>
<td>$148,539</td>
</tr>
<tr>
<td>1979</td>
<td>9</td>
<td>$150,176</td>
</tr>
<tr>
<td>1989</td>
<td>9</td>
<td>$175,852</td>
</tr>
<tr>
<td>1999</td>
<td>16</td>
<td>$261,772</td>
</tr>
<tr>
<td>2010</td>
<td>10</td>
<td>$200,000</td>
</tr>
</tbody>
</table>

Notes: The table data from the 1970, 1980, 1990, 2000, and 2010 U.S. Census as well as data from 1943-1945 income reports from the U.S. Bureau of Indian Affairs, which are housed at the U.S. National Archives in Washington D.C.

To estimate Gini coefficients from the data we use nonparametric methods because we do not want to impose a specific distributional functional form on the grouped income data.\(^\text{13}\) Our nonparametric method is typical in that it employs optimization techniques to find the upper and lower limits of the Gini subject to the informational constraints inherent in the grouped data.\(^\text{14}\) In our case, we know the number of families in mutually-exclusive, non-overlapping income intervals with an unbounded top income group. We also know the mean income across all families, but we do not know the mean family income within each group. We follow the optimization technique described in Murray (1978), which is a blueprint for finding upper and lower bounds of Gini coefficients from grouped data that has the same structure and information as ours. Part A of Appendix 1 provides more detail on the optimization procedure we employ.

The final step, after calculating the upper and lower bounds, is to assign weights to each in order to generate a point estimate of the Gini. In this paper we choose the midpoint between the upper and lower bounds (i.e., weights of 0.5) but our key results are invariant to small to moderate modifications in this choice of weights. We also find that optimized

\(^{13}\) Based on visual inspection of the empirical distribution of income for various reservations, we find that many reservations have multi-modal income distributions and take forms that would be poorly approximated by the unimodal, right skewed parametric distribution functions commonly used in estimation of county-level income distributions, e.g., log-normal or Singh-Maddala.

\(^{14}\) For general description of nonparametric estimation techniques, see Cowell and Mehta (1982), Gastwirth and Glauberman (1976) and Cowell (2000). Depending on what information is available, slightly different methods are available for calculating the bounds of inequality measure (see Gastwirth 1972, Cowell 1991, McDonald and Ransom 1981, and Murray 1978).
weights, using an approach developed by Wu and Perloff (2007), are very close, at 0.48. Part B of Appendix 1 provides a fuller description of the Wu and Perloff approach.

Although we have estimated a Gini coefficient for all reservations in all years for which income distribution data are reported, the focus here is on the 91 reservations for which there were data for at least 5 of the 6 years spanning 1945-2010. These 91 reservations constitute the slightly unbalanced panel of data that we employ in most of the econometric analysis although we present some statistics for the 43 reservations for which data are available for all 6 time periods. Table 4 summarizes the (midpoint) Gini coefficients (scaled from 0 to 100) and provides international comparisons for context.

<table>
<thead>
<tr>
<th>Year</th>
<th>Minimum</th>
<th>Mean</th>
<th>Maximum</th>
</tr>
</thead>
<tbody>
<tr>
<td>1945</td>
<td>18.95</td>
<td>35.66</td>
<td>55.71</td>
</tr>
<tr>
<td></td>
<td>(Hoopa Valley, CA)</td>
<td>(Salt River, AZ)</td>
<td>(Ute Mountain, CO)</td>
</tr>
<tr>
<td></td>
<td>[≡ Sweden]</td>
<td>[≡ Cambodia]</td>
<td>[≡ Guatemala]</td>
</tr>
<tr>
<td>1970</td>
<td>27.42</td>
<td>39.81</td>
<td>62.39</td>
</tr>
<tr>
<td></td>
<td>(Menominee, WI)</td>
<td>(White Earth, MN)</td>
<td>(Fort Belknap, MT)</td>
</tr>
<tr>
<td></td>
<td>[≡ Romania]</td>
<td>[≡ Burkina Faso]</td>
<td>[≡ South Africa]</td>
</tr>
<tr>
<td>1980</td>
<td>28.94</td>
<td>42.04</td>
<td>51.63</td>
</tr>
<tr>
<td></td>
<td>(Menominee, WI)</td>
<td>(Mescalero Apache, NM)</td>
<td>(Hopi, AZ)</td>
</tr>
<tr>
<td></td>
<td>[≡ Kazakhstan]</td>
<td>[≡ China]</td>
<td>[≡ Panama]</td>
</tr>
<tr>
<td>1990</td>
<td>35.39</td>
<td>44.70</td>
<td>52.05</td>
</tr>
<tr>
<td></td>
<td>(Warm Springs, OR)</td>
<td>(Spirit Lake, ND)</td>
<td>(Navajo, AZ)</td>
</tr>
<tr>
<td></td>
<td>[≡ Jordan]</td>
<td>[≡ Venezuela]</td>
<td>[≡ Chile]</td>
</tr>
<tr>
<td>2000</td>
<td>31.87</td>
<td>43.55</td>
<td>55.52</td>
</tr>
<tr>
<td></td>
<td>(Oneida, WI)</td>
<td>(Standing Rock, SD)</td>
<td>(Crow Creek, SD)</td>
</tr>
<tr>
<td></td>
<td>[≡ Bangladesh]</td>
<td>[≡ Uruguay]</td>
<td>[≡ Bolivia]</td>
</tr>
<tr>
<td>2010</td>
<td>33.60</td>
<td>44.82</td>
<td>54.82</td>
</tr>
<tr>
<td></td>
<td>(Nez Perce, ID)</td>
<td>(Flathead, MT)</td>
<td>(Rosebud, SD)</td>
</tr>
<tr>
<td></td>
<td>[≡ Croatia]</td>
<td>[≡ Malaysia]</td>
<td>[≡ Brazil]</td>
</tr>
</tbody>
</table>

Notes: In parenthesis is the name of the reservation having the minimum and maximum gini or having a gini coefficient closest to the mean value. In brackets is the name of the country having a gini coefficient close in value to a particular summary statistic. The country level gini coefficients come from World Bank Indicators at http://wdi.worldbank.org/table/2.9# and span 1994 to 2010. In all cases except for Sweden in 2000, the international comparisons are approximately equal to associated reservation’s gini. Hoopa Valley’s 1945 gini of 18.95, however, is significantly less than the gini for any other nation during 1994 to 2010. The lowest gini reported is 25; for Sweden, Denmark and a few other countries. The comparisons here are based on the balanced panel of N= 48 reservations for which income data are available in all 6 years spanning 1945-2010.

15 We also limit the reservations in our sample to those with measures of ethnicity developed in section 3.2.
16 By using the unbalanced panel of reservations with at least 5 time periods of data, we more than double the number of reservations included in the analysis. Using a balanced panel for the last four time periods, we increase the number of reservations to 124.
In 1945, the Hoopa Valley reservation had the lowest inequality with a Gini of 18.95. For international context, this degree of inequality is close to Sweden. The average Gini coefficient across all reservations in 1945 was 35.66, which was closest in magnitude to the Salt River reservation’s Gini in 1945. For international context, Cambodia’s Gini coefficient was 36.0. The rest of statistics in Table 4 have similar interpretations.

3.2 Characterizing Ethnic Assimilation and Polarization

In order to explore the potential relationship between inequality and historical ethnic make-up, we construct two measures, one for how ethnically assimilated a reservation was and another for the degree of ethnic polarization. Both measures are constructed from blood quantum data collected by the Bureau of Indian Affairs, which we collected from the U.S. National Archives. The quantum data estimate the percentage of the American Indian population on reservations with 100%, 50-99%, 25-49%, and 0-24% American Indian blood in 1938.

From these data, we construct a measure called Less Blood Quantum Assimilation (LBA) and calculate it as

\[ \text{LBQA} = BQ_{100\%} + 0.50 \times BQ_{50\%} + 0.25 \times BQ_{25\%}, \]

where \( BQ_{p\%} \) is the percentage of population with \( p\% \) American Indian blood. A reservation whose population was entirely comprised of people with 100% American Indian blood would have an LBQA equal to 1. To gain inference on whether or not this measure of historical assimilation persists over time, we examine how the LBQA correlates with the percentage of the reservation population that speaks an American Indian language in recent years based on U.S. Census data. When we regress the percentage of American Indian language speakers in 1980 on LBQA, we find a positive and statistically significant relationship.\(^\text{17}\) This result suggest the LBQA variable captures differences that persist over time.

We also quantify the extent to which a reservation is ethnically homogenous or ethnically fragmented. The following measure, Blood Quantum Polarization, serves as a proxy for the degree of ethnic polarization on a reservation:

\(^\text{17}\) The coefficients on the intercept and LBQA respectively are -0.35 and 0.95, both significant at \( p<0.01 \). Correlations for regressions using other years of the dependent variable, i.e., the percentage of American Indian language speakers in 1990, 2000, and 2010, are similar.
\[ BQP = (BQ_{100\%} + BQ_{25\% \text{ or less}}) - (BQ_{100\%}^2 + BQ_{25\% \text{ or less}}^2) \]

where \( BQ_{25\% \text{ or less}} = BQ_{25\%} + BQ_{0\%} \). A \( BQP = 0 \) corresponds to a very ethnically homogenous reservation in which the entire population has either 100% American Indian blood or the entire population has 25% or less American Indian blood. A \( BQP = 0.5 \) implies the reservation was ethnically polarized with half of the population having 100% American Indian blood and the other half 25% or less.

Figures 3 and 4 show that the least assimilated and least polarized reservations tend to be in the Southwest, but there are exceptions to this general pattern. For example, the Yavapai-Apache Nation and the Colorado River Reservation, both located in Arizona, have assimilation and polarization measures near the mean values. Additionally, the Sac and Fox reservation in Iowa and the Mississippi Choctaw Reservation in Mississippi both have \( LBQA = 1 \) and \( BQP = 0 \). From this map it is also apparent that the two measures are negatively correlated, with a Pearson correlation coefficient of -0.65. While the two measures are correlated, there is still variability between the two. For example, the \( BQP \) for the Mille Lacs Reservation in Minnesota and the Southern Ute Reservation in Colorado are both roughly equal to 0.22; however, the \( LBQA \) for Mille Lacs is 0.44 and for the Southern Ute it is 0.88. So, while these reservations have roughly the same degree of polarization, they differ a great deal in terms of our measure of historical assimilation.

Much of the cross-reservation variation in our measures of assimilation and polarization is determined by U.S. land allotment policies that concluded before the 1945-2010 period of our analysis. Under the Dawes Act in particular, millions of acres of reservation land were privatized and opened for white settlement and farming during 1887-1934 (Carlson 1981, Anderson 1995). Ethnic assimilation tended to be less pronounced on reservations that were neither allotted nor opened for white settlement, or that were allotted late in time, close to 1934. These reservations concentrate in the arid southwest, which has poor rainfall conditions for agriculture. This explains why assimilation is low in the Southwest and higher in the better farming regions of the Midwest and Northwest.

\[ ^{18} \text{Empirical research shows that privatization and settlement was more likely on reservations in densely populated and states with rapid population growth over 1880 to 1930. Privatization and settlement was also more likely on reservations near railroad lines in the late 19th century, and on reservation with good rainfall conditions for agriculture (Carlson 1981, Leonard et al. 2017).} \]
Figure 3
Map of Assimilation Prior to 1945

Assimilation
- Least Assimilated
- Less Assimilated
- More Assimilated
- Most Assimilated
- No Data

Northwest

Midwest

Southwest
Figure 4
Map of Polarization Prior to 1945

Polarization
Least Polarized
Less Polarized
More Polarized
Most Polarized
No Data

Northwest

Midwest

Southwest
In addition to being less ethnically assimilated and polarized, the Southwestern reservations also tend to have more land in tribal ownership. For these reason, we control for geography and land tenure mix in empirical estimates in an attempt to isolate the role of ethnicity. We find that, in general, the relationships between ethnicity and growth-inequality patterns are robust to these controls as we discuss in more detail below.

3.3 Summarizing Growth-Inequality Patterns

To highlight variation in whether growth has been inclusive or exclusive, and if these patterns are correlated with ethnicity, we being by condensing the income and inequality data for qualitative assessment.\(^\text{19}\) We order each of the 91 reservation income and Gini coefficients observations by per capita income, from lowest to highest.\(^\text{20}\) Next, we partition each of the observations into three groups (tritiles) that contain the lowest, middle, and highest third of that reservation’s income observations for those reservations with 6 observations. For those reservations with 5 observations, the first “tritile” contains the lowest two income observations, the second contains the middle income observations, and the third contains the two highest income observations. We then compute the mean income and mean Gini coefficient for each tritile. This process generates three inequality-income points for each reservation. Appendix 3 shows the plots for each reservation.

Grouping the data into three categories suppresses some of the quantitative information in the original time series but there are advantages. A minimum of three points is required to trace out any single peaked curve, so a smaller number would not be sufficient. As shown in the appendix figures, only four shapes are possible with three points. They are: monotonically increasing, monotonically decreasing, single-peaked (inverted-U), and single-troughed (U-shaped).

The top row of Table 5 summarizes the occurrence of shapes. The increasing and single-peaked shapes are the most common, each occurring in 62 of 91 reservations. This pattern indicates that, at low levels of income, income growth has most commonly been exclusives. Moving from tritile 2 to 3, however, there is a less dominant relationship. Between these two points there are 40 of 91 reservations that exhibit a pattern of decreasing

---

\(^\text{19}\) Our method is inspired by time-series tests of the Environmental Kuznets Curve in Deacon and Norman (2006) and by the longitudinal analysis of income and inequality in Deininger and Squire (1998).

\(^\text{20}\) Here we include reservations for which we have six data points (43 reservations) and those for which we have five data points (48 reservations). We include those reservations with only 5 data points because this significantly increases the sample size and makes the analysis more robust.
inequality, and 51 reservations exhibit a pattern of increasing inequality. This comparison of shapes suggests that any effect of ethnicity on exclusive vs. inclusive growth will more likely reveal itself at medium to high levels of income, where there has been more qualitative variation in the shape of growth-inequality relationships.

The bottom rows of Table 5 hint at the potential importance of ethnicity. Reservations with decreasing inequality were less ethnically assimilated and less polarized than reservations with the other shapes. Reservations with increasing inequality were the most ethnically assimilated, and the second most ethnically polarized.

Table 5:

Mean Characteristics of Reservations, Based on Income-Inequality Shapes

<table>
<thead>
<tr>
<th></th>
<th>Decreasing</th>
<th>Increasing</th>
<th>Peak</th>
<th>Trough</th>
</tr>
</thead>
<tbody>
<tr>
<td>Frequency of Shape Gini</td>
<td>9</td>
<td>31</td>
<td>31</td>
<td>20</td>
</tr>
<tr>
<td></td>
<td>Tritile 1</td>
<td>42.2</td>
<td>35.9</td>
<td>36.9</td>
</tr>
<tr>
<td></td>
<td>Tritile 2</td>
<td>40.0</td>
<td>41.4</td>
<td>44.8</td>
</tr>
<tr>
<td></td>
<td>Tritile 3</td>
<td>33.4</td>
<td>44.4</td>
<td>40.4</td>
</tr>
<tr>
<td>Per Capita Income (2010$s$)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Tritile 1</td>
<td>$8,083</td>
<td>$5,260</td>
<td>$6,289</td>
</tr>
<tr>
<td></td>
<td>Tritile 2</td>
<td>$11,747</td>
<td>$8,989</td>
<td>$9,908</td>
</tr>
<tr>
<td></td>
<td>Tritile 3</td>
<td>$14,642</td>
<td>$12,053</td>
<td>$13,433</td>
</tr>
<tr>
<td>Less Blood Quantum Assimilation</td>
<td>0.889*+</td>
<td>0.693</td>
<td>0.749</td>
<td>0.761</td>
</tr>
<tr>
<td>Blood Quantum Polarization</td>
<td>0.163</td>
<td>0.224</td>
<td>0.274</td>
<td>0.213</td>
</tr>
</tbody>
</table>

Notes: The asterisk (*) indicates statistically significant differences (p<0.05) between the means across the Decreasing and Increasing categories, based on t-statistics calculated assuming both equal variance of means. The notation (+) indicates statistically significant differences based on t-statistics assuming unequal variation of means. There are a total of 91 reservations (N = 91) with Gini, income, and ethnicity data in this sample.

Although suggestive, the ethnicity relationships are confounded by many factors, and they are based on qualitative changes in inequality rather than quantitative changes. With respect to confounding factors, reservations with decreasing inequality also had the highest starting income, at $8,083. Reservations with increasing inequality had the lowest starting income, at $5,260. With respect to quantitative changes, reservations with decreasing and peak shapes both experienced declining Gini from tritile 2 to 3, but of different magnitudes: -6.7 vs -4.4. Reservations with increasing and trough shapes both experienced increasing Gini, but also of different magnitudes: +3.0 vs. +9.0.
In the next section, we begin to isolate the role of ethnicity using a semi-parametric assessment of growth-income relationships across reservations. In addition to controlling for income levels, the semi-parametric analysis is based on quantitative, rather than qualitative, information on inclusive vs. exclusive growth.

4. **Estimation of Growth-Inequality Relationships**

To further motivate the potential relationships between growth, inequality, and ethnicity, we also compare the growth-inequality across reservations, international countries, and U.S. states. The semi-parametric panel regression model is given in equation (1)

\[
(1) \quad gini_{it} = \varphi_i + f(y_{it}) + \varepsilon_{it}
\]

where \(\varphi_i\) an economy-specific fixed effect and \(f(y_{it})\) is an unknown smooth function of income \(y_{it}\) that we estimate with cubic regression splines. This method differs from much of the early cross-country research in that it identifies correlations from within-jurisdiction variation in income rather than across jurisdiction variation. This type of semi-parametric regression allows us to estimate how the variable \(y_{it}\) relates with the Gini within an economy while placing minimal assumptions on the functional form of the relationship.\(^{21}\) We follow widely used methods (Wood 2006 and Takezawa 2006) by estimating the cubic regression splines through the minimization of penalized least squares and by selecting a smoothing parameter through generalized cross-validation (GCV) procedures.

Figure 5 plots estimation results. Panel A plots family mean income against the function \(f(y_{it})\) for the sample of Indian reservations, holding constant the reservation specific fixed effects. Changes along this curve describe how the Gini changes with increases in family mean income. To aid in the ease of interpreting the Y-axis, we have added the median fixed effect into regression equation (1) before plotting. The shaded area represents the 95 percent confidence region around the predicted values. For context, we have also plotted Gini-family income data points for the entire United States.

Panel A shows that inequality on reservations increased with income at low levels of income. Beginning with an income level of around $45,000 per family, the relationship flattens out and inequality does not change in a precise way with income at higher levels. By

---

\(^{21}\) Essentially, a cubic spline function is a piecewise function with various sections being comprised of cubic polynomials. The polynomials are joined together at the end points of each section (called knots) such that the first and second derivative of the spline function is continuous across its entire domain.
contrast, the U.S. Gini-Income data points show that inequality was effectively flat for levels of income less than $50,000, and then inequality began to increase with income at levels above $50,000.

Figure 5

Income-Inequality Relationships for Reservations, Countries and U.S. States

Notes: U.S. Gini and family mean income data are from the U.S. Census Bureau and are for years 1947-2010. Country-level Gini data are from the UNU-WIDER World Income Inequality Database (WIID): http://www.wider.unu.edu/research/Database. The inequality data were collated with PPP-adjusted GDP per capita data from the Penn World Table (PWT) 8.0 which are adjusted and present in 2010 USD: https://pwt.sas.upenn.edu/. Gini data at the state-level comes from individual tax filing data available from the Internal Revenue Service (IRS) (see Frank 2009). State per capita personal income data are from the Bureau of Economic Analysis (BEA). Deininger and Squire (1996) find that Gini coefficients calculated from per capita measures are systematically higher than those from family or household measures.

Panel B shows the results for Indian reservations based on per capita income rather than family mean income. The growth-inequality pattern is similar to Panel A in that inequality increases with growth for low levels of income per capita. Inequality flattens and perhaps decreases in the range of $12,000 to $20,000. The relationship is indeterminate at levels of income exceeding $20,000. The X-axis shows the density of data points along the income distribution, indicating the majority of data points lie at income levels less than
$20,000. This is one reason why the estimation error is greater at income levels exceeding $20,000. Despite the substantial number of observations between income levels $13,000 and $20,000, however, we also observe a widening of the confidence interval in this region. This result suggests that heterogeneity in income-inequality relationships, rather than estimation error, may explain the insignificance of the growth-inequality relationship at higher levels of income. We return to this issue of heterogeneity below.

For purposes of comparison, Panel C shows estimates of equation (1) for an unbalanced panel of 144 countries for years spanning 1950 to 2006. The graph shows that inequality rises until GDP per capita of about $12,000, and then inequality begins to fall. At higher levels of development - GDP per capita greater than $27,000 - the inequality-growth relationship is neither positive nor negative in general. The Panel C results are similar to those in Frazier (2006), who uses the same data sets (with GDP per capita logged) and a partially linear model, but does not control for country-specific fixed effects. The Panel C results are also similar to Barro (2000) and Barro (2008), who, after controlling for fixed country effects and conditioning on other demographic characteristics, finds the relationship between inequality and income level to have somewhat of an inverted-U shape.

Panel D shows the regression results for U.S. states and the District of Columbia for the years 1929 – 2011. The state level dataset is annual and has the most data points and the smallest estimation error of the four estimates. Similar to reservations and countries, we see that within U.S. states, inequality rose with income growth at low levels of income. At a per capita income level of around $9,000, the relationship becomes relatively flat until roughly $20,000. For incomes exceeding $20,000, there is a strong positive relationship between inequality and income growth. This positive relationship between inequality and income growth for U.S. states is consistent with much of the literature on state and U.S. inequality.22 Comparing the results for U.S. states in Panel D with the data points for the U.S. as a whole in Panel A we see that they are largely consistent despite the fact that the data come from different sources and reflect different sources of income.

The comparisons in figure 5 raise questions about why inequality on American Indian reservations has not risen as consistently as in the broader United States. Have differences in ethnicity helped guide more inclusive growth on Indian reservations? To shed light on this question, we begin by estimating the semi-parametric panel model above with subsamples

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22 Piketty and Saez (2003), Frank (2008), and Boustan et al. (2013) all find that inequality is generally increasing with income growth among U.S. states.
segmented by the ethnic assimilation and polarization variables. The subsamples identify reservations as more assimilated if their \( LBQA \) variable is less than the mean (0.746). Similarly, the sub-samples identify a reservation as more ethnically fragmented if its \( BQP \) is greater than the mean (0.233).

Figure 6 shows the semi-parametric panel regression results. Panels A and B demonstrate how the growth-inequality relationship differs between reservations which are more ethnically distinct from the U.S., and those that are ethnically more similar to the U.S. The results for both sub-samples show a positive relationship between income and inequality for lower levels of income, i.e., $5,000 to $12,000. At higher levels of income this relationship across the two subsamples appears to diverge; the relationship is flat among the more assimilated reservations and decreasing among the less assimilated reservations. This difference represents preliminary evidence that reservations which are more ethnically distinct from the broader U.S. have experienced decreasing inequality with growth.

**Figure 6**

**Income-Inequality Relationships for Sub-Samples of Reservations**

A. Less Ethnically Assimilated  
B. More Ethnically Assimilated  
C. Less Ethnically Polarized  
D. More Ethnically Polarized

**Notes:** The number of reservations for the sub-samples A, B, C and D are respectively 45, 46, 40 and 51.
Panels C and D of Figure 6 compare the growth-inequality relationships of less ethnically fragmented reservations with those that are more ethnically fragmented. The set of reservations with less ethnic fragmentation experienced decreasing inequality after reaching a peak at around $12,000. By contrast, the more ethnically fragmented reservations did not have a clear turning point.

To summarize the results in Figures 5 and 6, they provide initial evidence that growth has been more inclusive on reservations that are less ethnically assimilated and fragmented. We examine these relationships in more detail in the sections that follow. Before proceeding, we note that the relationships are not simply explained by differences across geographical regions. As shown in Appendix 2, all three regions – the Midwest, Northwest, and Southwest – display overall growth-inequality relationships that resemble inverted U-shapes despite variation across those regions in terms of ethnic composition. These results suggest that income-inequality relationships are better explained by ethnic composition, which is an issue we examine in more depth in the following section.

5. **Empirical Framework: Panel Estimation**

To complete the analysis, we now focus on the growth-inequality relationship from decade to decade. Here we employ a panel model with reservation and time period fixed effects to examine how decade-to-decade changes in income relate to decade-to-decade changes in inequality. To test whether or not the level of ethnic assimilation and polarization affects inequality, we employ the following empirical model:

\[
(2) \log (gini_{it}) = \alpha_i + \phi_t + \theta_1 \log (\text{per capita inc}_{it}) \\
+ \theta_2 LBQA_i \times \log (\text{per capita inc}_{it}) \\
+ \theta_3 BQP_i \times \log (\text{per capita inc}_{it}) \\
+ \theta_4 (LBQA_i \times BQP_i) \times \log (\text{per capita inc}_{it}) \\
+ \sum_{k=1}^{K} \beta_k x_k + \sum_{j=1}^{J} \delta_{jt} (x_j \times \phi_t) + \epsilon_{it},
\]

where \(i\) is the reservation and \(t\) is the year for a balanced panel of 100 reservations covering each decade from 1980 to 2010.\(^{23}\) Focusing on these time periods has two advantages. First, it significantly increases the number of reservations usable in a panel because gaps in data

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\(^{23}\) In the Appendix, we run the main specification for our slightly unbalanced panel of 91 reservations. The results are very similar.
availability are concentrated in 1945 and 1970. Second, it allows us to focus on identifying the role of ethnicity on inclusive vs. exclusive growth during the period in which most reservation economies had reached middle income status. Our analysis in sections 3 and 4 showed that much of the heterogeneity in the growth-inequality relationship comes at higher levels of income, which were generally observed in these later years.

The coefficients of interest are the set of $\theta_i's$, where the interaction terms in the model allows the relationship between inequality and income to vary with blood quantum assimilation and polarization. The parameters $\alpha_t$ and $\phi_t$ denote reservation fixed-effects and year fixed-effects, respectively. The year fixed-effects, which we do not include in prior analysis, helps to isolate relationships between income and inequality without confounding those relationships with time trends.24

The set of $x_i$'s contains time-varying covariates which may impact inequality and are related to changes in per capita income, including state per capita income and adjacent county per capita income. Neighboring income provides potential spillover benefits and also can affect selective migration patterns and the composition of workers on the reservation. These may both have effects on reservation inequality.

The set of $x_t$'s contains time-invariant factors, including measures of land tenure, political and legal governance institutions, and distance to the nearest major metropolitan area. The literature on reservation development has established these as important characteristics for economic growth and industry development. We include them here because the covariates may be correlated with inequality.25 Land tenure, in particular, may be correlated with our ethnicity variables because reservations where land was allotted and privatized before and during the Dawes Era of 1887-1934 were more likely to have contact with white settlers prior to the 1930s (see Carlson 1981, Anderson 1995). We interact these time-invariant controls are interacted with year fixed-effects to account for changes in their impact over time. Standard errors are clustered at the reservation level to account for serial correlation. Appendix 4 and Table A.4.1 provides definitions and summary statistics.

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24 In other estimation results, not shown here, we allow each geographic region to have its own time effect. The results are similar in both cases.
25 The covariates are used in studies of reservation-level income growth, including research by Anderson and Parker (2008), Dippel (2014), Akee et al. (2015a), Frye and Parker (2016), and Brown et al. (2016).
6. Main Results

6.1 Inequality and Per Capita Income

Table 6 show the results from estimation of the panel model spanning from 1980-2010, where the various columns correspond to different ways in which per capita income interacts with $LBQA$ and $BQP$. Column (1) describes the basic relationship between income and income inequality. The coefficient estimate is consistent with the findings in panel B of figure 5, which shows a gradual positive relationship between income and income inequality on reservations.

Table 6:
Panel Model Estimates of Relationship between of Income and Inequality, 1980-2010

<table>
<thead>
<tr>
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<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ln(Income Per Capita)</td>
<td>0.028</td>
<td>0.448**</td>
<td>-0.190</td>
<td>0.046</td>
<td>-0.436**</td>
</tr>
<tr>
<td></td>
<td>(0.076)</td>
<td>(0.145)</td>
<td>(0.115)</td>
<td>(0.137)</td>
<td>(0.211)</td>
</tr>
<tr>
<td>Ln(Income Per Capita) × $LBQA$</td>
<td>-0.575**</td>
<td>-0.246</td>
<td>0.314</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.204)</td>
<td>(0.146)</td>
<td>(0.286)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Ln(Income Per Capita) × $BQP$</td>
<td>0.850***</td>
<td>0.632**</td>
<td>2.857***</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.286)</td>
<td>(0.289)</td>
<td>(0.998)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Ln(Income Per Capita) × $LBQA$ × $BQP$</td>
<td></td>
<td></td>
<td></td>
<td>-3.059*</td>
<td>(1.531)</td>
</tr>
<tr>
<td>Reservation Fixed-Effects</td>
<td>x  x</td>
<td>x  x</td>
<td>x</td>
<td>x</td>
<td>x</td>
</tr>
<tr>
<td>Year Fixed-Effects</td>
<td>x  x</td>
<td>x  x</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Time-Varying Controls</td>
<td>x  x</td>
<td>x  x</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Historic Time-Trend Controls</td>
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<td>Number of Observations</td>
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<tr>
<td>R-Squared</td>
<td>0.363</td>
<td>0.385</td>
<td>0.392</td>
<td>0.393</td>
<td>0.399</td>
</tr>
</tbody>
</table>

Notes: * p < 0.10, ** p < 0.05, *** p < 0.01. Standard errors, reported in parentheses, are clustered at the reservations level. Time-Varying controls include state per capita income and adjacent county per capita income. Historic Time-Trend controls include a dummy variable for whether the reservation adopted the IRA, a dummy variable for whether Public Law 280 applied to the reservation, log distance from the closest MSA, and controls for the share of reservation land held in tribal trust and individual trust. All of these variables are interacted with time period. The null hypothesis is that all the coefficients in the model are equal to zero.

The subsequent panels sequentially control for the ethnicity interactions. Column (2) adds the interaction term with ethnic assimilation ($LBQA$). The coefficient on the interaction term indicates that higher levels of income are associated with falling inequality for those reservations that are less assimilated. This result is consistent with the literature, discussed above, documenting that jurisdictions which are more ethnically homogenous, are more likely to lower levels of inequality.
In column (3), income is interacted with blood quantum polarization (BQP). The positive coefficient on the interaction term indicates that income gains are associated with rising inequality when the population is more ethnically polarized. Again this is consistent with the implied hypotheses outlined in section 2, and the literature on ethnic polarization.

Columns (4) and (5) include both measures of blood quantum, assimilation and polarization, allowing us to identify how inequality is affected by both measures simultaneously. Column (4) includes both of the previous ethnicity and income interactions, thereby isolating conditional correlations. Both ethnicity measures maintain their sign and significance. Column (5) introduces a fully interacted model with income and both ethnicity measures. This specification enables more flexibility in accounting for the correlation between the two ethnicity measures. The results suggest that the inclusion of the interaction term is important for understanding how the relationship between economic growth and inequality is conditioned by ethnic composition.

To demonstrate in a more intuitive way how these ethnicity measures interact with the growth-inequality relationship, Figure 7 plots the direction of the marginal effect of income for different values of LBQA and BQP. It shows the range of LBQA and BQP values for which the model predicts inequality to be increasing or decreasing with income growth, based on the model specification in Column (5) at a 90% confidence level.

**Figure 7:**
Marginal Effect of Income across Assimilation and Polarization Measures

![Figure 7: Marginal Effect of Income across Assimilation and Polarization Measures](image)

**Notes:** Transparent shaded values are not statistically significant at a 90% confidence level.
Figure 7 indicates that reservations that were more ethnically polarized ($BQP$ above 0.3) have tended to experience exclusive growth on a decade-by-decade basis since 1980. Those reservations which have lower levels of fragmentation ($BQP$ below 0.1), in general, tend to have experienced inclusive growth. From the coefficient estimates in Table 6 and the illustrated marginal effects of Figure 7, ethnic assimilation appears to play a smaller role in determining inequality. The findings here are generally consistent with Alesina and Glaeser (2004), which implies that ethnically homogenous societies prefer low inequality, and ethnically fragmented societies are more tolerant of high inequality.

The 1980-2010 panel analysis just described is noteworthy because a series of self-determination policies, beginning in the late 1970s, progressively gave elected tribal governments more control over reservation commerce. As Kalt et al. (2008) note, “sovereignty and self-determination allow local desires, preferences, needs, and ways of doing things to be more accurately perceived and acted upon.” Moreover, the Indian Gaming Regulatory Act of 1988 ushered in casino gaming on some reservations thereby creating a clear way for tribal governments to affect income distributions by directing casino jobs, profits, or public goods in progressive ways (Akee et al. 2015b). For both reasons, we have greater confidence that relationships between growth and inequality after 1980 reflect preferences and constraints at the tribal level, rather than top-down micro-management by the federal government.

6.2 Inequality and Casino Gaming

Given the growth in gaming as a source of tribal income and the mechanisms for redistribution possessed by tribal governments, a natural extension to our panel model explores the interaction between the rise in gaming, ethnicity, and inequality. Building on the previous framework from model (2), we replace income per capita with the number of slot machines per capita. This publicly available measure, used by Anderson and Parker (2008) and Cookson (2010), proxies for the (confidential) gaming income available to tribal governments. Appendix Table A.4.1 gives summary statistics of the slot machines per capita variable. The mean increased from 0.008 in 1990, to 0.319 in 2000, to 0.734 in 2010 demonstrating growth in gaming across reservations, over time.

Table 7 presents the estimation results for various specifications where reservation gaming is interacted with $LBQA$ and $BQP$. The results convey a similar relationship between gaming, ethnicity, and inequality to relationship identified with respect to overall income, in Table 6. When we include both ethnicity measures in the specification, as shown in column
(5), the relationship between slot machines per capita, ethnicity, and inequality mirrors the relationship with income, ethnicity, and inequality. This result suggests that the way in which tribal distribute income to reservation Native Americans, in this case from casino earnings, is a key mechanism through which ethnicity leads to inclusive or exclusive income growth.

Table 7:  
Panel Model Estimates of Relationship between Slot Machines and Inequality, 1980-10

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
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<tr>
<td>Y = Log(Gini_t)</td>
<td></td>
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<tr>
<td>Slots Per Capita</td>
<td>0.060***</td>
<td>0.023</td>
<td>0.076**</td>
<td>0.029</td>
<td>-0.304**</td>
<td>-0.270**</td>
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<td></td>
<td>(0.016)</td>
<td>(0.032)</td>
<td>(0.037)</td>
<td>(0.061)</td>
<td>(0.122)</td>
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<td>Slots Per Capita × LBQA</td>
<td>0.055</td>
<td>0.051</td>
<td>0.446***</td>
<td>0.372**</td>
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<tr>
<td></td>
<td>(0.049)</td>
<td>(0.053)</td>
<td>(0.160)</td>
<td>(0.168)</td>
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<tr>
<td>Slots Per Capita × BQP</td>
<td>-0.059</td>
<td>-0.012</td>
<td>1.437***</td>
<td>1.216**</td>
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<td></td>
<td>(0.138)</td>
<td>(0.156)</td>
<td>(0.507)</td>
<td>(0.540)</td>
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<tr>
<td>Slots Per Capita × LBQA × BQP</td>
<td>-1.975***</td>
<td>-1.538**</td>
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<tr>
<td></td>
<td>(0.734)</td>
<td>(0.760)</td>
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<td>Reservation Fixed-Effects</td>
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<tr>
<td>R-Squared</td>
<td>0.394</td>
<td>0.394</td>
<td>0.393</td>
<td>0.392</td>
<td>0.407</td>
<td>0.450</td>
</tr>
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</table>

Notes: *p < 0.10, **p < 0.05, ***p < 0.01. Notes: *p < 0.10, **p < 0.05, ***p < 0.01. Standard errors, reported in parentheses, are clustered at the reservations level. Time-Varying controls include, state per capita income and adjacent county per capita income. Historic Time-Trend controls include a dummy variable for whether the reservation adopted the IRA, a dummy variable for whether Public Law 280 applied to the reservation, log distance from the closest MSA, and controls for the share of reservation land held in tribal trust and individual trust. The endogenous controls include the share of the American Indian population that completed high school and the log of the American Indian population on the reservation. The null hypothesis is that all the coefficients in the model are equal to zero.

Figure 8 plots the results from Table 7 using the same approach as Figure 7. Here we see the region on the upper left – where assimilation is high but especially where polarization is high – is when the model predicts that increases in gaming increase inequality.
Figure 8:
Marginal Effect of Slot Machines across Assimilation and Polarization Measures

Notes: Transparent shaded values are not statistically significant at a 90% confidence level.

To summarize, the findings in Table 6 and Table 7 - that income growth was more inclusive on less assimilated and, especially, less polarized reservations - provide evidence that ethnicity plays an important role in guiding the growth-inequality relationships in democratic jurisdictions empowered to act upon majority preferences. Ethnic polarization, in particular, has played a key role in guiding income distributions in recent years. Ethnic polarization has plausibly caused tribal membership polarization, and this would explain why casino activity has widened inequality. As the proportion of non-member Native Americans on reservations grow, which is more likely on ethnically polarized reservations, we expect payouts to tribal members from gaming to exacerbate inequality.

6.3 Inequality and Migration

Selective migration, due to changes in income, may alter the distribution of income on reservations and contribute to the pattern of our empirical findings. If this selective migration is related to the historic ethnicity mix on reservations, then selective migration may be a channel driving our results. To understand the extent to which migration could be influencing the results we observe in Sections 6.1 and 6.2, we perform two additional tests.

First, we replicate model (2) with some additional covariates that account for changes in population and education levels. These models extend the main panel regression models presented in Table 6 by adding a set of potentially endogenous controls: American Indian
population on the reservation and the Share of the Indian population that completed High School. Both of these characteristics could be changing as a result of growth and inequality changes on the reservation, so they are excluded from our preferred model. They are potentially important, however, because the two measures are correlated with migration and migration selection. Table A.4.2 in the Appendix shows that adding these two controls does not change the main findings in Table 6. We take this as evidence that neither total migration, nor selective migration on educational ability, are driving our findings.

Second, we isolate the share of the American Indian population that moved from either out of the state or another country.\textsuperscript{26} We add this additional control to our preferred model from Table 6, column 6. Columns 1 and 2 in Table A.4.3 compare the specification with and without the additional migration control. The inclusion of the migration share variable does not influence our results. Additionally, we run an alternative model where the outcome of interest is the migration share. The results in Column 3 of Table A.4.3 indicate there was no correlation between long distance mobility and income-ethnicity interactions. Based on these results, it does not appear that our findings are driven by changes population or educational composition, or from individuals moving larger distances to return to the reservation.

7. Conclusions

Does the ethnic composition of a society determine the extent to which income growth in that society will be inclusive? We study this question in the context of Native American reservations, which are unique ethnic enclaves within the US because tribes have sovereign government powers. To do so, we first estimate Gini coefficients for a large panel of reservations and document how Ginis have evolved since the 1940s. We also create empirical measures of ethnic assimilation and polarization for each reservation relying on historical measures of blood quantum mixes. Hence, our first contribution is in providing original empirical variables that we hope other scholars will also use to better understand Native American economies.

Based on two different empirical methods - a semi-parametric panel regression and a decade-by-decade panel regression analysis - we conclude that growth-inequality relationships across reservations do systematically relate to ethnic composition. The strongest

\textsuperscript{26} These measures are available by race in the Census in 2000 and 2010. In 2000, the question asks where the respondent lived five years ago and in 2010, the question asks where the respondent lived one year ago.
result is that Native American nations with lower levels of ethnic polarization have tended to experience more inclusive income growth, meaning Gini coefficients decreased as per-capita income expanded. Although reservations with lower levels of ethnic assimilation also experienced more inclusive growth, this effect weakens once we control for our measure of polarization.

We emphasize the correlations between ethnicity and growth-inequality patterns do not simply result from differences across reservations in terms of geographic location, geographic isolation, and land tenure mix. To us, these findings suggest that ethnicity has likely played a causal role in guiding the extent to which income growth has been inclusive. We do not study every pathway from ethnicity to inclusive growth, however, and hence cannot claim to have identified a single, driving mechanism.

We do, however, find evidence that increases in casino gaming returns – measured by the number of slot machines per Native American – exacerbate inequality on ethnically polarized reservations. These results are consistent with recent findings by Fenske and Zurimendi (2017), who show that oil development has raised inequality in economic outcomes between ethnic groups in Nigeria. On Native American reservations, casino gaming has raised the stakes of tribal membership, and ethnic polarization has, as a consequence, caused meaningful polarization in membership and attendant access to gaming proceeds, in-kind or monetary.

In broad terms, our results shed light on the relative importance of ethnically endowed preferences vs. ethnic polarization. If preferences are hard-wired to ethnicity and relatively unmalleable, we would expect large differences in growth-inequality relationships on reservations comprised of mostly full-blooded Native Americans vs. reservations compromised of mostly assimilated individuals (i.e. 25% or less Native blood). Although these relationships are present, they are more fragile than relationships between ethnic polarization and exclusive vs. inclusive growth. These findings suggest that preferences for equality, if hard-wired through ethnicity, may not extend to others outside of one’s ethnic group.

We hope the findings and limitations of this study will stimulate further research on ethnicity and inequality. In terms of limitations, our study focuses on income inequality rather than consumption or wealth inequality, which may differ significantly from income inequality (see Norris and Pendakur 2015, Krueger and Perri 2005, Pendakur 2002). To our knowledge, historical data on consumption and wealth are unavailable for a large set of Native American reservations, but research on these outcomes is important where possible as
documented by Akee et al. (2016). Our study also employs measures of ethnicity that are fixed at a point in time – prior to World War II – but research on how ethnicity has evolved on Native nations could help improve understanding of the co-evolution of incomes, inequality, and ethnicity. We leave these important issues for future research.

8. References


9. **Appendices**

See Dustin Frye’s website at: [https://pages.vassar.edu/dustinfrye/](https://pages.vassar.edu/dustinfrye/)