The Short and Long Run Dynamics of the Great Gatsby Curve.*

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Abstract

The strong evidence in support of the Great Gatsby Curve (i.e. the negative cross-sectional relationship between intergenerational mobility and inequality) seems to be at odds with the fact that large increases in inequality in the US have not resulted in decreases in mobility. We solve this puzzle by measuring, for the first time, a dynamic version of the "Great Gatsby Curve" that relates *changes* in inequality to *changes* in intergenerational income mobility. We find that across US counties and during the last century the relationship is weak and unstable over relatively short intervals of two decades, but negative and significant over a longer period of almost a century. The historical record suggests that if the large increase of inequality observed in the US does not reverse, this may result in substantially lower socioeconomic mobility in the long term, even if mobility has not decreased yet. We complement our analysis with a study of the relationship between income inequality and the intergenerational mobility of education finding a stable dynamic correlation over the short run, suggesting that the process of human capital accumulation is a significant driver of the empirical relationship between inequality and intergenerational income mobility.

JEL classification: J62, N12, N52, R11

Keywords: Intergenerational Mobility, Inequality, Great Gatsby Curve.

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1 Introduction

This paper aims to resolve the apparent contradiction between two salient stylized facts documented by the literature on intergenerational mobility. On the one hand intergenerational mobility correlates negatively with inequality, a fact that has been called the "Great Gatsby Curve"(GGC for short)[1]. On the other hand, the significant increase in inequality observed in the US during the last few decades seems not to have been accompanied by a significant drop in intergenerational mobility. To resolve this puzzle we build a very long panel (over 120 years) of intergenerational mobility and inequality at the level of US counties and study the comovement of these variables. We show that increases in inequality are not systematically related to decreases in socioeconomic mobility over relatively short intervals of two decades, but they do lead to reductions in intergenerational mobility in the very long run. Thus, in light of history, one can worry that the current upsurge of inequality might be foretelling a more stratified society.

The relationship between inequality and intergenerational socioeconomic mobility has been the object of a sizable academic literature[2]. The presence of a strong negative relationship between inequality and mobility, captured by the GGC, is perhaps the most salient and robust finding in this literature. This negative relationship has been documented not only across countries, but also across regions or geographic units wherever it has been measured.

The GGC has naturally attracted a great deal of attention even beyond the academic debate, as it has been interpreted to have troubling implications.[3] Specifically, given the fact that more unequal societies tend to display a greater degree of socioeconomic persistence, it may be natural to expect that the large increase in income inequality over the last decades (particularly in the US) may be heralding future decreases in mobility. The mere fact that society becomes more unequal may anticipate that inheritance will become more prominent, reducing the "prospect of upward mobility" and producing a more sclerotic society where differences in wellbeing are not only more salient, but also more inheritable across generations.

We may call this the "naive" dynamic prediction of the GGC. "Naive" because it relies on an extrapolation that is met with both empirical and theoretical counterarguments. On the

[1]Alan Krueger was the first to refer to the empirical association between inequality and intergenerational income persistence as the "Great Gatsby Curve" referring to the work of Corak.

[2]See for instance, Hassler et al. (2007); Andrews and Leigh (2009); Bjorklund and Jäntti (2012); Blanden (2013), Corak (2006), Corak (2013); Ermisch et al. (2012); Durlauf and Seshadri (2018); Fan et al. (2021); Güell et al. (2018); DiPrete (2020); Nybom and Stuhler (2024). A great survey of the literature is Durlauf et al. (2022)

[3]See Council of Economic Advisers (2012), Krueger (2012)

empirical side, at least 40 years have passed since inequality started its significant upward surge in the US,[4] and yet we have not observed the expected decrease in mobility. Albeit measuring *changes* in mobility is notoriously difficult, the existing evidence points towards at most small decreases in mobility in the US during the last decades (see Aaronson and Mazumder (2008), Lee and Solon (2009), and Chetty et al. (2014a)).[5] Given the large scale of the increase in inequality, the slope of the GGC curve would have suggested that a large decrease in mobility should have materialized, and this has not been observed.

Moreover, on the theoretical side, Becker et al. (2018) have pointed out that a correlation of inequality and mobility in levels does not necessarily imply that *changes* in inequality will correlate with *changes* in intergenerational mobility. Whether such a correlation arises will critically depend on the causes of the increases in inequality. They present a model that reproduces the existing evidence on mobility (including the GGC) but where a dynamic form of the GGC (correlating changes in inequality with changes in intergenerational mobility) fails to materialize for specific (and reasonable) drivers of increases in inequality. Thus, putting both things together, they conclude that the predicted decrease in mobility may fail to materialize.

However, to the best of our knowledge, the relationship between *changes* in inequality and *changes* in socioeconomic mobility, something that henceforth we call the "dynamic GGC", has not been directly studied in the existing literature. This is likely due to significant empirical barriers: to perform such an exercise one requires consistent measures of changes in mobility and changes in inequality across meaningful economic units not only over one or two generations, but also over very long periods of time covering several generations. This is because the dynamics of intergenerational mobility are complex and take shape over very long periods of time (see Nybom and Stuhler (2024)). To assemble a panel dataset suitable for this type of analysis requires the linking of earnings information across a minimum of three generations, and preferably more for longer-run study. This has been impractical to do for most countries until very recently.

The key contribution of this paper, thus, is the direct measurement of the dynamic relationship between inequality and socioeconomic mobility. We provide what is, to the best of our knowledge, the first systematic empirical study of the *dynamic* relationship between inequality and socioeconomic mobility. We directly measure the dynamic GGC across US

[4]For a documentation of this rise in inequality, see for example Piketty and Saez (2003), Autor et al. (2008) and Acemoglu and Autor (2011)

[5]There is more evidence of a decline in *absolute* income mobility (see Chetty et al. (2017)), but this is a consequence of the decline of growth and the documented decrease in lifetime income by the median American during the last cohorts (see Guvenen et al. (2022)) and it is beyond the scope of our paper.

counties at both "short" intervals of two decades, and over a longer period of over a century.

We overcome the barriers that have precluded the study of the dynamic GGC in the past by making use of recently made available linked historical censuses for the US. We link the 1880-1900, 1900-1920, and 1920-1940 censuses and locate pairs of fathers and sons, observing outcomes of the parents in the older census and that of the sons in the newer census.[6] For each individual, we impute historical income based on occupation, race, age, and residence and use this to calculate inequality and intergenerational mobility at the level of US counties for a period spanning the years 1880 to 1940.[7] We also measure educational achievement as reported in the 1940 census. Our unit of observation is the county[8], and we compute county-level measures of intergenerational persistence as the average correlation of father-son outcomes at the county level, both for income and for education. We further measure county-level inequality as the dispersion in individual incomes as reflected by each county's Gini coefficient.

This allows us to perform the exercise in the 1880-1940 period, but in order to evaluate the dynamics of the GGC over the long run we need to merge our panel with contemporaneous data, at least at the county level. To this aim we make two additional contributions to the existing literature. Firstly, we develop a methodology that allows us to study the dynamic GGC over the long-run. In particular, we develop new unit-less measures of inequality and socioeconomic mobility that allow us to align historical census data with the modern county level mobility and inequality data assembled by Chetty et al. (2014b). Given that the inequality and mobility measures we are able to construct with our historical data are different than those constructed by Chetty et al. (2014b) with modern data, we propose to use county-level ranks within the US for both inequality and socioeconomic mobility as alternative measures of county-level inequality and socioeconomic mobility,[9] allowing us to extend our analysis from 1880 to 2010. We validate these alternative measures against more traditional measures by using them to study the static and short-run dynamic GGC, and then employ them to study the long-run dynamic GGC.

Secondly, to shed some light on the drivers of our results concerning the relationship between inequality and intergenerational mobility, we also study the relationship between

[6]For other recent contributions on within-country intergenerational mobility, see Dodin et al. (2024), Berger et al. (2023), Buckles et al. (2023), Tan (2023), Ward (2023), Jácome et al. (2022), and Feigenbaum (2015).

[7]Had the Great Gatsby been a real-life person, instead of a fictional one, he would be part of our micro-data.

[8]Specifically, the county where the son grew up, i.e. the one where we observe both father and son in the earlier census.

[9]Thus, when we use the rank-rank correlation as the measure of mobility at county level, our unit-less measure of mobility for the county is the rank-rank rank.

income inequality and *educational* intergenerational mobility. This presents fewer estimation difficulties than our measurement of the intergenerational mobility of income, as the censuses contain information on the number of years of schooling. We estimate the intergenerational mobility of education at the county level as the average father-son correlation of years of schooling, and relate it to income inequality at the county level.

Our findings paint a subtle picture of the relationship between inequality and socioeconomic mobility. We show that across the universe of US counties, changes in inequality over 20 years do **not** correlate in a systematic way with changes in intergenerational income mobility, which aligns with the current US experience and the explanation by Becker et al. (2018). Over the long run, however, (changes over a period of up to a century), we document a significant negative relationship between changes of inequality and changes of socioeconomic mobility, which is reminiscent of the static GGC. This would seem to provide additional support to the naive and pessimistic interpretation of the GGC: over the broad historical record, increases in inequality do tend to predict future decreases in mobility, albeit only in the very long run. Moreover, our results suggest that the mechanism hinges on the manner in which human capital is accumulated: although the relationship between changes in inequality and changes in intergenerational income mobility is flat in the short run, the relationship between changes in inequality and changes in intergenerational educational mobility is negative. More inequality translates to higher intergenerational persistence of educational achievement over the span of a single generation. The overall picture is, thus, pessimistic: the fact that mobility has not fallen *yet* is perfectly consistent with the historical record, but this record suggests that the rise of inequality may already be affecting the dynamics of human capital accumulation, and its effects are likely to eventually materialize in lower intergenerational income mobility unless the increase of inequality is reversed.

The rest of the paper is organized as follows. In section 2 we present our data sources, while in section 3 we describe our methodology and the construction of our novel unit-less measures of inequality and intergenerational mobility. In section 4 we outline our main results, while in section 5 we discuss their implications. Section 6 concludes.

2 Data

To measure our key variables of interest, income inequality and intergenerational socioeconomic mobility, we link men across censuses using the full count censuses available for the late 19th and early 20th centuries from IPUMS (Ruggles et al. (2021)). We draw on two different methods for linking people across censuses developed in the literature. The first, developed by Abramitzky et al. (2020) uses a fully automated approach that creates links based on standardized first and last names, as well as age.[10] The second method, developed by Helgertz et al. (2023) uses a probabilistic approach that employs machine learning techniques and also incorporates information on birthplace and family/household characteristics. Perhaps surprisingly, the overlap between the links identified by the two approaches is not large. Because of this, using matches created via both procedures results in a much larger sample size.[11] It should also be noted that both linking approaches that we employ use the last name as key information. Because of this, we omit females from our analysis as their surnames typically changed upon marriage, making it difficult to link them across censuses. A recent paper by Buckles et al. (2023) manages to link also women and finds that mobility patterns for married men and married women are very similar.

We create links across three 20-year intervals: 1880 to 1900, 1900 to 1920, and 1920 to 1940. In each interval, we link sons to their fathers, obtaining a dataset capturing the outcomes of fathers in the earlier census period and the corresponding outcomes of their sons 20 years later. We always restrict the sample to parents and children aged 25-50 in their respective adult census observations.

A key challenge we face in conducting our analysis is that US censuses before 1940 do not report any information on income, with the 1940 census being the only one in our data for which wage income information is available. To overcome this challenge, we employ an imputation procedure developed by Collins and Wanamaker (2022)[12], to construct an individual-level income measure. We regress 1940 (log-) wage income on dummies that interact occupation with state of residence, race[13] and age (measured in 5-year bins), and use the estimated relationship to predict wages for our whole sample based on their state of residence, race, occupation, and age. This gives us a granular measure of predicted wage income for most of our sample. However, this approach of predicting wage income is not a good income measure for farmers, who derive most of their income from non-wage sources and also represent a substantial fraction of our sample. We address this concern by following an imputation procedure for farmers' incomes that also draws on Collins and Wanamaker (2022) and Abramitzky et al. (2021). We use data on the total income of farmers and farm

[10] Specifically, we use less conservative *abe_nysiis_standard* matching procedure that merges based on NYSIIS-standardized names.

[11] However, we drop cases where the Abramitzky et al. (2020) and Helgertz et al. (2023) approaches have different linking results for the same individuals.

[12] Similar imputations based on occupation and other variables have also been used by Abramitzky et al. (2021) and Tan (2023). Authors sometimes also adjust income for self-employment in a way similar to our farmer adjustment. We do not do this, as data on self-employment is only available from the 1920 census onward.

[13] Black, White, and Other

laborers for the year 1960 and calculate the average ratio of farmers' total income to farm laborers' total income within every product of age-bin, race, and census region cell.[14] We then predict farmer total income by multiplying farm laborers' predicted wage income as calculated above by their cell-specific total income ratio. In the Appendix , we show that our results are robust to also including farm ownership or industry in our wage predictions. Ward (2023) points out that historical estimates of intergenerational mobility in the US can be severely affected by measurement error and not accounting for race. In the Appendix , we therefore also show that we get the same qualitative results when restricting the analysis to whites and when addressing measurement error in a strategy similar to Solon (1992).

For education, the 1940 census contains an almost ideal measure: years of schooling. We use this to create a restricted sample of father-son-pairs for the intervals 1900 to 1920, and 1920 to 1940, where both the father and son are matched to their 1940 outcome. For a 1920-1940 matched pair, this requires that the father is still alive and matched to the 1940 census. For a 1900-1920 pair, it requires that both father and son are still alive and matched in 1940.[15] Additionally, we need to assume that schooling does not change anymore after men enter the labor market. We find this a plausible assumption in our period of analysis.

For modern outcomes, we draw on measures of intergenerational persistence and inequality calculated by Chetty et al. (2014b). Using federal income tax data of parents over the years 1996-2002 and their children in 2011 and 2012, Chetty et al. (2014b) compute county-specific rank-rank correlations between father and sons, as well as Gini coefficients for the fathers.

3 Methods

3.1 Measuring county mobility and inequality.

Using the measures of income and education described above we proceed to construct measures of intergenerational socioeconomic mobility at the county$\times$interval level (where intervals represent the 1880-1900, 1900-1920 and 1920-1940 periods for income mobility, and the 1900-1920 and 1920-1940 periods for educational mobility). When constructing our measures of intergenerational mobility we assign each father-son pair to the county where they were initially observed sharing the same household (i.e. the county where the sons "grew up").

[14] We use census regions here, since for 1960 we only have a 5% of the sample and want to avoid having many small cells. Full count data for 1950 would be available, but only in a preliminary form, for which IPUMS cautions that personal income and education is still often erroneous. We therefore do not use it.

[15] We do not extend this to the 1880-1900 period, as it would give us only those few fathers who were adults in 1880 and still alive in 1940.

We then compute our county-level measures of socioeconomic mobility by correlating, for each county, fathers' outcomes in the early year of each interval with sons' outcomes in the late year, separately for income and education.

$$y^s_{ict} = \beta_c + \rho^{IGE}_{ct} \times y^f_{ic,t-20} + \epsilon_{ict} \tag{1}$$

where i denotes the father-son pair, y^s_{ict} is the log of income of the son, and $y^f_{ic,t-20}$ is the log of the income of the father twenty years before (in the previous census). ρ_{ct} is the intergenerational elasticity of income of county c at time $t \in \{1900, 1920, 1940\}$. In addition, following Chetty et al. (2014b), we also estimate rank-rank correlations. We calculate the father's rank in the national income distribution in his cohort, do the same for the son in his cohort and then correlate the ranks of sons and fathers within a country. Akin to the county-time specific intergenerational elasticity of income, this approach produces a county-time specific rank-rank correlation ρ^{RR}_{ct}. For education, we compute the correlation between the education of parents and sons. In the Appendix, we show that our results are robust to controlling for fathers' and sons' ages in the regressions that produce the county-level persistence measures.

To construct our novel county-level measures of intergenerational mobility, that are suitable for long-run analysis, we note that any period t can be characterized by a distribution of the persistence coefficients ρ across counties. We rank counties by their persistence coefficients for each time period to construct a unitless and time-varying index of socioeconomic persistence. We denote by $rank\rho_{ct} \in [0, 100]$ the county-rank of county c by each of the measures of persistence (ρ_{ct}) at time t. This county-ranking procedure is applied to the intergenerational correlation of income, the intergenerational elasticity of education, and the rank-rank correlation.

To measure inequality, we calculate the (income) Gini coefficient among fathers for each county c and each time t.[16] We also calculate an analogous unitless measure of inequality for the purposes of long-run analysis: the rank of counties by inequality at each point in time.

[16]Given that we impute earnings based on the procedure discussed above, one can worry how much inequality in imputed earnings reflects actual earnings inequality. We can assess this for 1940, when we observe wage income. To do so, we calculate the gini of wage income among sons and correlate it with the gini coefficient of the sons' imputed income. We find a correlation coefficient of 0.82, indicating a very close relationship between the two measures. In addition, we use data from Goldin and Katz (2010) that allow us to calculate Gini coefficients based on actual income for 13 counties in Iowa in 1915. We do so for males aged 25-50 and compare the resulting Gini coefficients to a similar measure based on earnings imputed via our procedure for males aged 25-50 in the same counties in the 1920 census. In spite of the low number of observations, we again find a sizeable correlation coefficient of 0.55.

	Mean	Standard dev	Obs
IGE 1900	0.397	0.152	2,272
Gini fathers 1900	0.240	0.077	2,272
IGE 1920	0.396	0.154	2,661
Intergeneration correl educ 1920	0.289	0.230	2,421
Gini fathers 1920	0.249	0.070	2,661
IGE 1940	0.365	0.125	3,008
Intergenerational correl educ 1940	0.377	0.115	3,054
Gini fathers 1940	0.271	0.071	3,008
Δ IGE 1920-1900	0.014	0.115	2,268
Δ Gini Fathers 1920-1900	0.014	0.047	2,268
Δ IGE 1940-1920	-0.026	0.098	2,655
Δ Gini Fathers 1940-1920	0.026	0.040	2,655
Δ Interg correl educ 1940-1920	0.088	0.228	2,418

Table 1: Summary statistics

We denote this inequality measure $rankI_{ct} \in [0, 100]$. In the Appendix, we show robustness to using other measures of inequality such as the variance of log income or the difference between the log of the 90th percentile and the log of the 10th percentile.

Table 1 shows summary statistics for our key variables. In Figures 1 - 3, we use shape files from Manson et al. (2023) to show the geographic distribution of social mobility (as measured via the IGE) and inequality (measured via the gini coefficient in the father's generation 20 years earlier) for 1900, 1920, and 1940. Notice the stark geographical variation of both variables, and the similarity with maps drawn using modern data.

3.2 Measures of the GGC

We empirically verify the presence of the GGC by measuring the cross-county correlation between measures of intergenerational persistence at time t and measures of inequality twenty years prior, i.e. among the fathers. We denote the regression coefficient between these moments γ_t. The GGC relationship is then estimated via

$$\rho_{ct} = \alpha + \gamma_t \times I_{c,t-20} + \epsilon_{ct} \tag{2}$$

We run this regression for three different measures of ρ: The intergenerational correlation in earnings, the rank-rank coefficient in earnings, and the intergenerational correlation

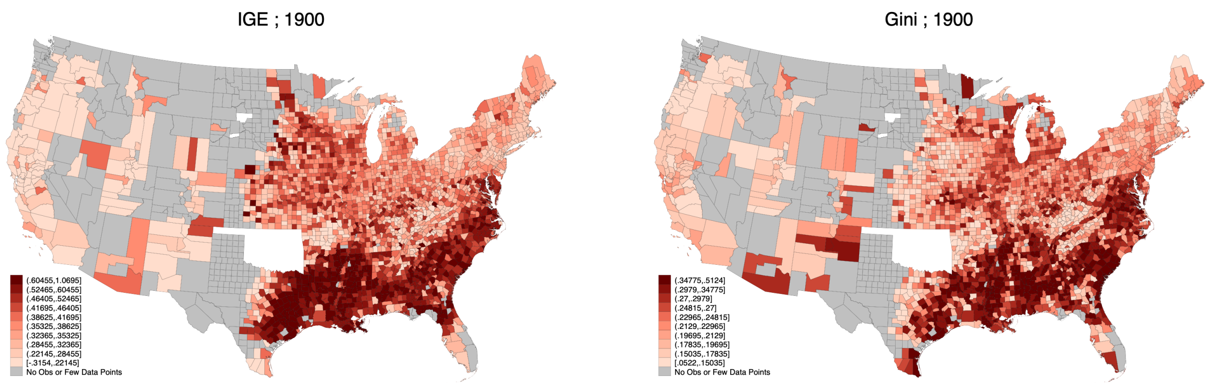


Figure 1: Geographical distribution of social mobility (measured via the IGE between fathers in 1880 and sons in 1900) inequality (measured via the gini coefficients of fathers in 1880). County borders are from Manson et al. (2023) and based on 1880 boundaries.

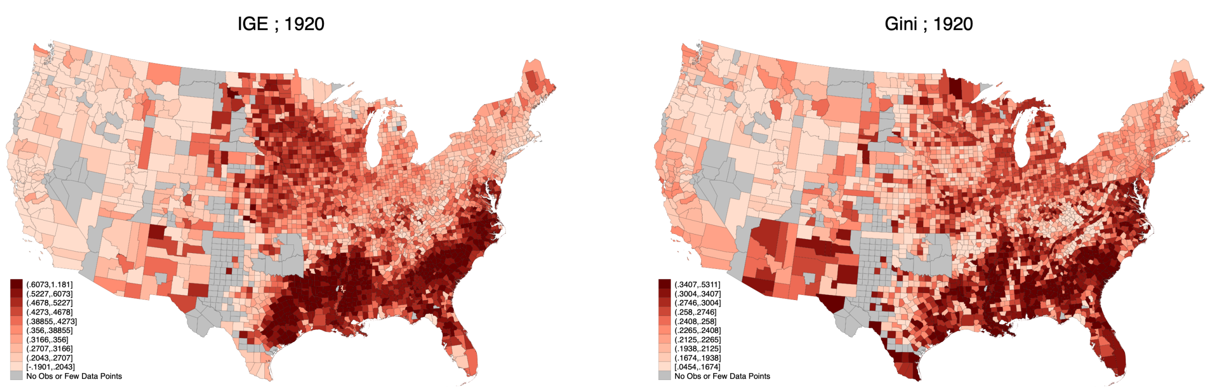


Figure 2: Geographical distribution of social mobility (measured via the IGE between fathers in 1900 and sons in 1920) inequality (measured via the gini coefficients of fathers in 1900). County borders are from Manson et al. (2023) and based on 1900 boundaries.

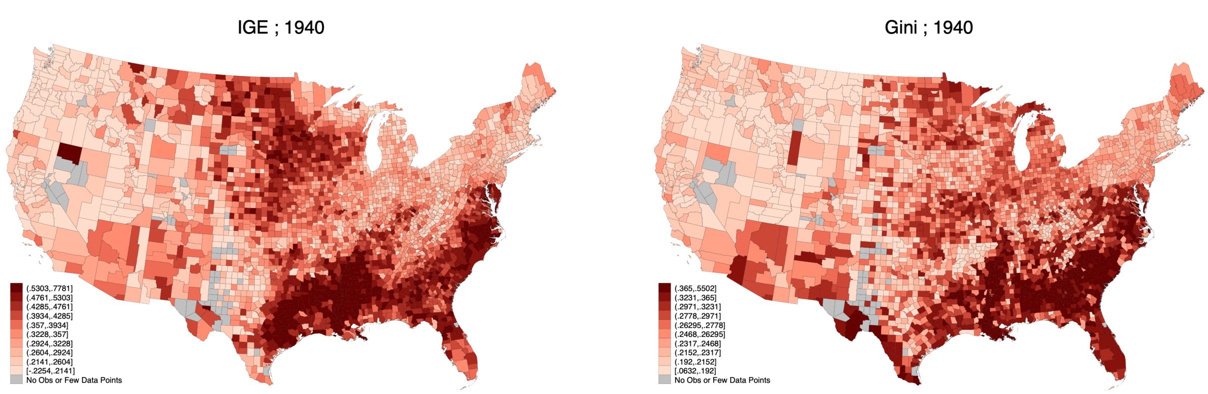


Figure 3: Geographical distribution of social mobility (measured via the IGE between fathers in 1920 and sons in 1940) and inequality (measured via the gini coefficients of fathers in 1920). County borders are from Manson et al. (2023) and based on 1920 boundaries.

in education. Additionally, we estimate the same equation using county-rank measures of persistence $rank\rho_{ct}$ and inequality $rankI_{c,t-20}$ instead of their levels. We run all these regressions separately for each interval.[17]

3.3 Dynamic GGC

To study how the relationship between inequality and socioeconomic mobility evolves over time we calculate the changes in inequality and persistence for each county at each point in time, as well as the correlation between these changes (which we call the Dynamic GGC):

We define the change in intergenerational persistence and inequality in county c as $\Delta\rho_{ct} = \rho_{ct} - \rho_{c,t-20}$ and $\Delta I_{ct} = I_{ct} - I_{c,t-20}$ respectively; and we run:

$$\Delta\rho_{ct} = \alpha_t + \delta_t \Delta I_{c,t-20} + \epsilon_{ct} \tag{3}$$

where the variable of interest is δ_t, capturing the dynamic relationship between inequality and intergenerational persistence. Figures 4 and 5 show the geographic distribution of 20-year changes in inequality and mobility. It is apparent that the distributions of *changes* of both variables have noticeably smaller geographical variation than their levels counterparts, presented above.

Notice that 3 does not allow us to measure the correlation between changes in inequality and changes in persistence if we have different measures of inequality and persistence for the two periods under consideration. This is a problem for our long-run analysis, in which we want to combine our measures for the 1900-1940 period with modern measures of inequality and mobility provided by Chetty et al. (2014b): While the data by Chetty et al. (2014b) contain actual income from tax returns, the wage predictions for the period 1900-1940 are only based on occupation, age, race, and state of residence and thus disregard any income variation within these cells. We therefore employ an alternative methodology to study the long-run relationship between changes in inequality and changes in intergenerational mobility that makes use of our novel county-rank-based measures of inequality and mobility.

This methodology is described formally below:

[17]For some counties, we only have few observations to estimate county-level measures of intergenerational persistence and inequality, leading to imprecise and sometimes extremes values. We therefore drop the lowest 5% of counties in terms of the number of observations used to construct these variables. For income, this removes counties with fewer than 74 observations. For education, the cut-off at the 5th percentile is 9 observations.

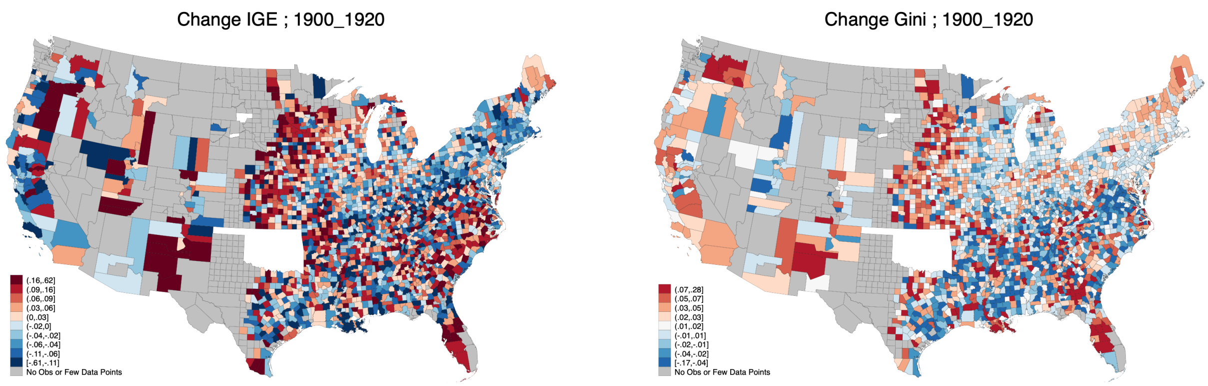


Figure 4: Geographical distribution of changes in social mobility between 1900 and 1920 and changes in inequality among fathers 1880 and 1900. County borders are from Manson et al. (2023) and based on 1880 boundaries.

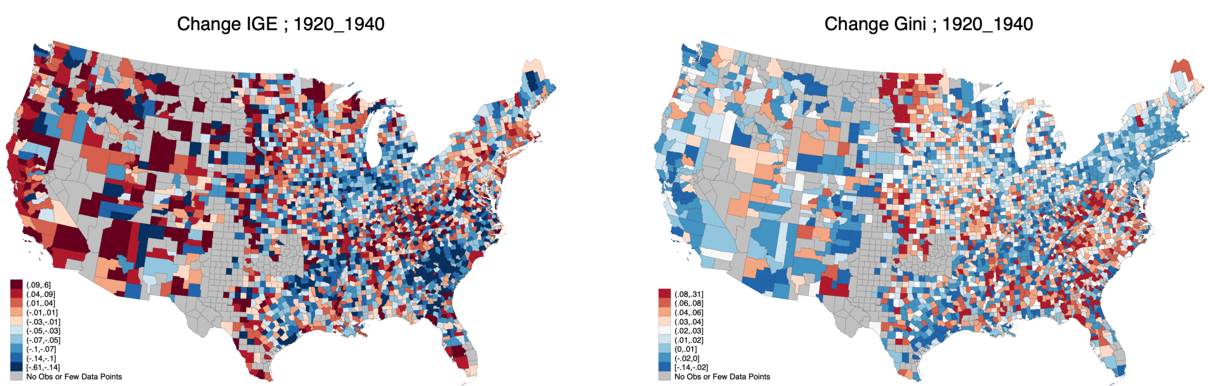


Figure 5: Geographical distribution of changes in social mobility between 1920 and 1940 and changes in inequality among fathers 1900 and 1920. County borders are from Manson et al. (2023) and based on 1920 boundaries.

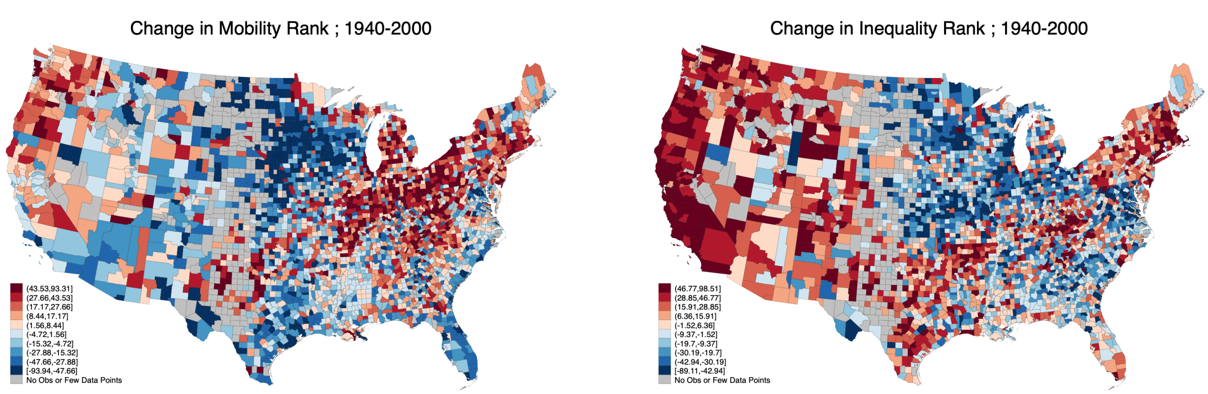


Figure 6: Geographical distribution of changes in counties' mobility and inequality ranks between 1940 and 2000. County borders are from Manson et al. (2023) and based on 1920 boundaries.

$$\Delta rank\rho_{ct}^{s} = rank\rho_{ct} - rank\rho_{cs}; \qquad \Delta rankI_{ct}^{s} = rankI_{c,t-20} - rankI_{c,s-20}$$

$$\Delta rank\rho_{ct}^{s} = \alpha_{t}^{s} + \delta_{t}^{s}\Delta rankI_{ct}^{s} + \epsilon_{ct} \tag{4}$$

where t and $s > t$ are two periods over which we evaluate the change in persistence and inequality in each county by computing the change in the respective county ranks ($\Delta rank\rho_{ct}^{s}$ and $\Delta rankI_{ct}^{s}$ respectively for each county c). In this, δ_{t}^{s} is the coefficient that captures the slope of the dynamic "Great Gatsby Curve" over the period.

To get an intuitive sense of how this methodology allows us to get around the issue of the comparability of measures over time, consider a case in which the available measures of mobility at county level differ across time (for example if our measure of mobility at time t is the IGE while our measure of mobility for time $s > t$ is the rank-rank correlation employed by Chetty et al. (2014b)). While these measures are not directly comparable, insofar as they both reflect the same underlying concept of social mobility, we expect that county ranks constructed on the basis of each measure result in similar rankings when derived from data resulting from the same data generating process.[18]

In other words, we expect that, were the high-quality tax data used by Chetty et al. (2014b) already available for the early 20th century, we would obtain county rank measures similar to the ones that we calculate based on the census income data. Using this logic, changes in the county level rankings, even if based on different underlying measures of persistence at different points in time, should reflect the relative change in the position of a county's mobility in the overall distribution of US counties. A similar argument holds for our county-rank measures of inequality, which suggests that correlating the changes of county ranks of intergenerational persistence with changes in the county ranks of inequality is likely to be a valid way of testing for the presence of a long-run dynamic GGC.

Figure 6 plots the geography of rank changes in inequality and mobility between 1940 and 2000.

[18] In the Appendix, we show that the county rank measure strongly correlates with the underlying measure of persistence in 1900, 1920, and 1940. It thus captures the same variation as the underlying measurement, but allows us to generate measures that are comparable over time even when the underyling measures are not.

	(1) IGE	(2) IGE	(3) IGE	(4) r-r	(5) r-r	(6) r-r	(7) r-r	(8) Edu	(9) Edu
County Level	1.06***	1.08***	0.92***	1.08***	0.97***	0.79***	0.24***	0.90***	0.83***
	(0.04)	(0.04)	(0.03)	(0.04)	(0.04)	(0.03)	(0.02)	(0.08)	(0.03)
County Rank	0.52***	0.46***	0.50***	0.53***	0.46***	0.44***	0.33***	0.22***	0.51***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Num. Counties	2,272	2,661	3,008	2,272	2,661	3,008	2,769	2,421	3,054
Year	1900	1920	1940	1900	1920	1940	2010	1920	1940

Robust std errors in parethenses.

Table 2: Static Great Gatsby Curves

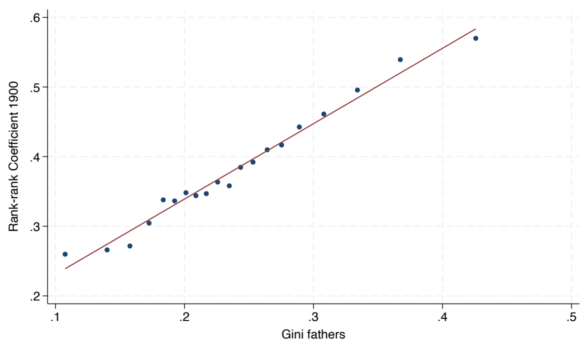
Each coefficient comes from a separate regression. The first row correlates the county persistence and the county inequality levels. Inequality is always measured as the Gini index of the income of the parents (i.e., measured in the census 20 years prior to the measurement of the son's income). Data for 1900-1940 are based on our income imputations, data for 2011 are from Chetty et al. (2014b) and refer to parents' income measured in 1996-2002 and children's in 2011/12. Persistence is measured in each county either by the intergenerational correlation of earnings (columns 1, 2, 3 marked *IGE*), the correlation of the earnings rank of the father with the rank of the son (4, 5, 6, 7, marked *r-r*), or the correlation of years of education of fathers and sons (8,9, marked *Edu*).
The second row correlates the rank of the county in the persistence distribution with the county rank in the inequality distribution. The measures of persistence and inequality that are used to create the underlying distribution are the same as in the previous row.
In the Appendix we show binned scatter plots and scatter plots with the row data corresponding to each entry in the table.

4 Results

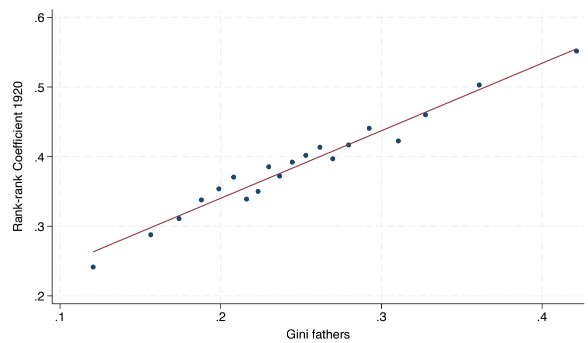
In this section, we outline our main results. Here we refer only to the baseline sample and definitions, but we want to point out that in the Appendix we reproduce the same qualitative results in a multitude of robustness checks with alternative definitions, and methodologies.

Result 1 *The intergenerational persistence of both income and education is positively correlated with inequality across US counties during the period 1900-1940, as it is nowadays.*

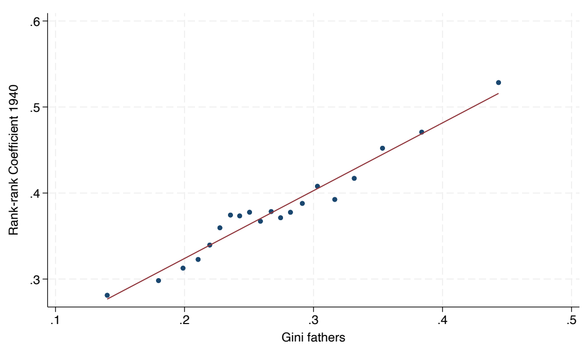
Table 2 and Figure 7 outline our findings concerning the cross-sectional relationship between intergenerational socieconomic persistence and income inequality at the level of US counties and at different points in time. The first row of Table 2 employs standard measures of socioeconomic mobility (the IGE and the rank-rank coefficient for income mobility, the intergenerational persistence of educational attainment for education) and inequality (the income Gini coefficient), while the second row employs our novel measures of socioeconomic persistence (the county ranks of persistence coefficients and of Gini indices). The first seven columns outline our results concerning the relationship between income inequality and the intergenerational persistence of income, while the last two columns present our findings regarding the relationship between intergenerational educational persistence and inequality.



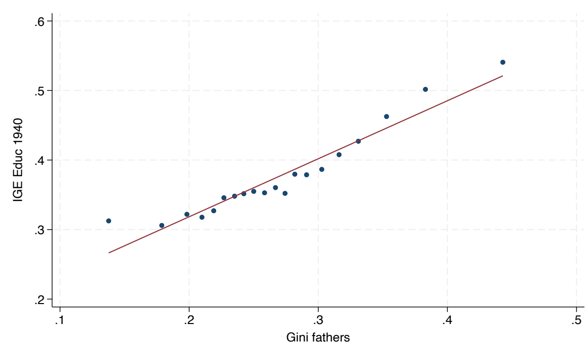
(a) Levels. r-r vs Gini, 1900



(b) Levels. r-r vs Gini, 1920



(c) Levels. r-r vs Gini, 1940



(d) Levels. Education vs Gini, 1940

Figure 7: Static Great Gatsby Curve 1900-1940

Binned scattered plots. In each, we divide the counties in vintiles of the level of the Gini Index and plot the average measure of intergenerational persistence of the counties in the vintile.

Across all specifications, we recover the positive association between intergenerational socioeconomic persistence and inequality that has been documented elsewhere for more recent time periods. As it is the case nowadays, one hundred years ago more unequal US counties tended to display more intergenerational persistence in terms of both income and education, irrespective of the measures of intergenerational persistence we use. Indeed, the strength of the association seems if anything stronger for the first half of the twentieth century than for the more recent past[19], though caution is advised when interpreting coefficient magnitudes given the limitations of our historical income measures. The Great Gatsby Curve is also apparent when looking at Figures 1 - 3. Across all three years, counties with a high inequality also tend to have a high IGE, i.e. low mobility. Especially the South and, in later years, the Midwest combine high inequality with low mobility. The West and Northeast, on the other hand, tend to have lower inequality and greater mobility.

We believe that this is the first documentation for the GGC in an historical setting, and indicates that the relationship is extremely robust to the passage of time. Thus, the hypothesis that upward mobility correlates with inequality is not only rejected today, this relationship was already not holding during the Great Gatsby era.

Result 2 *The static relationship between inequality and socioeconomic mobility is qualitatively similar when employing our novel measures of inequality and mobility using county ranks.*

Reassuringly, our results concerning the Great Gatsby Curve are qualitatively similar when we employ our novel methodology based on county ranks (see second row of Table 2). Both in the early twentieth century and closer to the present, counties that ranked highly in terms of inequality also tended to rank highly in terms of intergenerational socioeconomic persistence, irrespective of the underlying measures of persistence used to construct the ranking. The positive association between inequality and intergenerational persistence identified using the new measures applies for both income and education. As in the analysis with more established measures, it seems to be stronger in the first half of the twentieth century than in the more recent past. Overall, we interpret these results as evidence supporting the validity of our novel measures for the analysis of the relationship between inequality and socioeconomic mobility.

Result 3 *For the first half of the twentieth century, the correlation between changes in inequality and changes in the intergenerational persistence of income across US counties is*

[19]This can be seen by comparing coefficient magnitudes in columns 4 to 6 in Table 2 to those in column 7.

	(1) ΔIGE	(2) Δr-r	(3) ΔIGE	(4) Δr-r	(5) Δr-r	(6) Δr-r	(7) ΔEducation
Δ County Levels	-0.33***	-0.25*	-0.04	0.13			0.45***
	(0.07)	(0.14)	(0.06)	(0.09)			(0.14)
Δ County Rank	-0.08***	-0.06*	-0.00	0.06**	0.18***	0.25***	0.26***
	(0.03)	(0.03)	(0.03)	(0.03)	(0.02)	(0.02)	(0.04)
Observations	2,655	2,655	2,268	2,268	2,689	2,449	2,418
Year	1940/1920	1940/1920	1920/1900	1920/1900	2010/1940	2010/1920	1940/1920

Robust std errors

Table 3: Dynamic Great Gatsby Curves.

Each coefficient comes from a separate regression. The first row correlates changes in a county's persistence with changes in a county's inequality. Inequality is always measured as the Gini index of the income of the parents (i.e., measured in the census 20 years prior to the measurement of the son's income). Data for 1900-1940 are based on our income imputations, data for 2011 are from Chetty et al. (2014b) and refer to parents' income measured in 1996-2002 and children's in 2011/12. Persistence is measured in each county either by the intergenerational correlation of earnings (columns 1, 3), the correlation of the earnings rank of the father with the rank of the son (2, 4, 5, 6), or the correlation of years of education of fathers and sons (7).
The second row correlates the rank of the county in the persistence distribution with the county rank in the inequality distribution. The measures of persistence and inequality that are used to create the underlying distribution are the same as in the previous row.
In the Appendix we show binned scatter plots and scatter plots with the row data corresponding to each entry in the table.

not always positive (i.e. the "Dynamic" GGC is unstable over this period). By contrast, the correlation between changes in inequality and changes in the intergenerational persistence of education remains positive.

Table 3 outlines our results regarding the relationship between *changes* in inequality and *changes* in intergenerational socioeconomic persistence (which we call the "Dynamic" GGC). Similarly to our discussion of the "Static" GGC, the first row of Table 3 presents our results employing established measures of income inequality (i.e. the Gini Coefficient) and socieconomic mobility (the IGE and the rank-rank correlations between fathers and sons for the intergenerational persistence of income, and the father-son correlation in educational attainment for the intergenerational persistence of education), while the second row of the table presents results employing our novel measures of inequality and intergenerational socioeconomic mobility using county ranks. Moreover, columns 1 to 6 of Table 3 present our findings concerning the dynamic relationship between inequality and the intergenerational persistence of income, while column 7 documents our findings for the relationship between inequality and the intergenerational persistence of education.

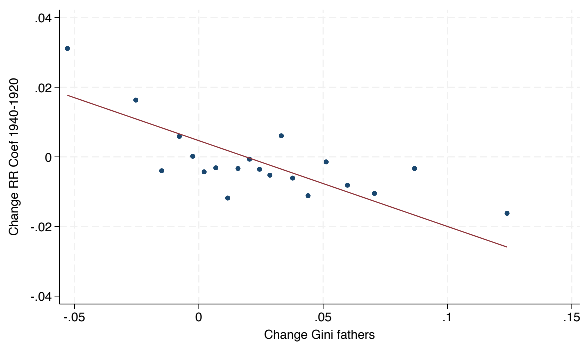
Perhaps our most striking finding is that the Dynamic Great Gatsby Curve for income is unstable across periods lasting two decades, as can be seen in columns 1 to 4 and in figures 8a, 8b. Over the period 1900 to 1920, changes in inequality at the level of US counties are not correlated significantly with changes in intergenerational income persistence. This pattern holds whether the intergenerational income persistence is measured by the IGE or by father-son rank-rank correlations. By contrast, during the period 1920-1940, we even find a negative relationship between changes in inequality and changes in the intergenerational persistence of income across US counties. Overall, thus, the dynamic GGC in the short run turns out much more noisy than the static GGC.

For the relationship between changes in inequality and changes in the intergenerational persistence of education, data limitations restrict our analysis to the period 1920 to 1940. For this period we find that changes in inequality correlate positively with changes in the intergenerational persistence of educational attainment. In other words, the Dynamic GGC for education mimics the Static GGC and is robust even during time periods where the positive relationship between changes in inequality and changes in the intergenerational persistence of income is absent in the data. In addition to Table 3 this can be seen in Figure 8c

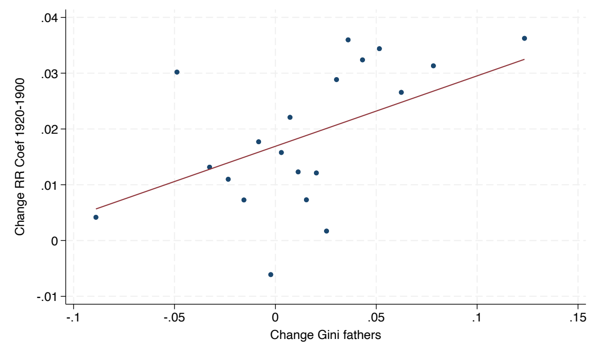
Result 4 *Evaluating the correlation between changes in inequality and changes in socioeconomic persistence using our novel measures based on county ranks produces the same results.*

The results in the second row of Table 3 (that can be visualized comparing figures 8a and A6a) provide further reassurance regarding the reliability of our novel measures in inequality and socioeconomic mobility based on county ranks. Our findings using these measures closely track our previous results using more established measures of inequality and mobility. We confirm the instability of the Dynamic GGC for income during the first half of the twentieth century. If anything, the county ranks specifications produces point estimates closer to zero than the results in row 1. Moreover, we also confirm an upward sloping Dynamic GGC for education over the period 1920 to 1940, in line with our previous findings. Overall, we interpret this pattern of findings as further validation of our novel measures of inequality and intergenerational socioeconomic mobility, as they are able to capture the same patterns in the data as more established measures even during time periods of instability in the empirical relationship between our moments of interest.

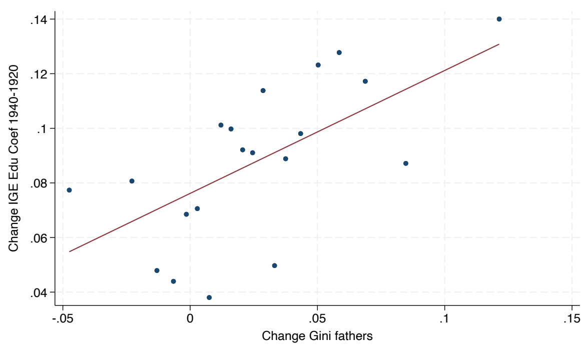
Result 5 *Changes in county ranks of intergenerational income persistence correlate positively with changes in the county ranks of inequality over the periods 1920-2011 and 1940-2011*



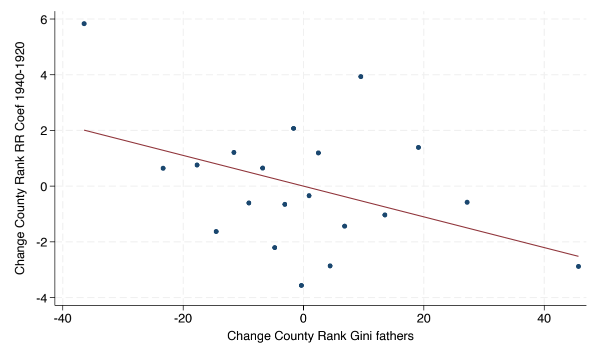
(a) Levels. Δr-r vs ΔGini, 1920-1940



(b) Levels. Δr-r vs ΔGini, 1900-1920



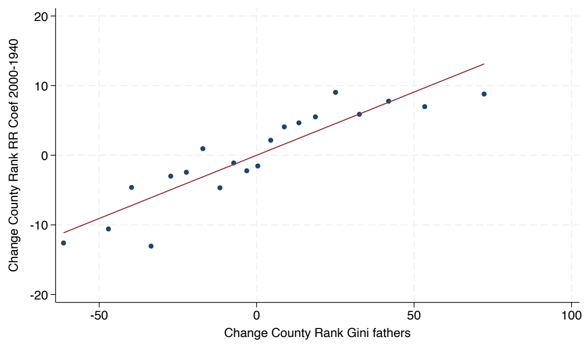
(c) Levels. Δ Education vs ΔGini, 1920-1940



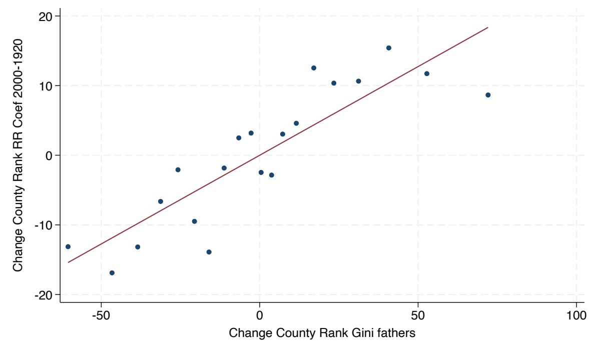
(d) County Ranks. Δr-r vs ΔGini, 1920-1940

Figure 8: Dynamic GGC.

Binned scattered plots. In each, we divide the counties in vintiles of the growth of the county rank of income inequality and plot the average growth of the county rank of persistence of the counties in the vintile.



(a) County Ranks. Δr-r vs ΔGini, 1940-2011



(b) County Ranks. Δr-r vs ΔGini, 1920-2011

Figure 9: Dynamic GGC, r-r County Ranks.

Binned scattered plots. In each, we divide the counties in vintiles of the growth of the county rank of income inequality and plot the average growth of the county rank of persistence of the counties in the vintile.

Lastly, we use our novel measures of inequality and socieconomic mobility to study the long-run association between changes in inequality and changes in the intergenerational persistence of income (we deem this relationship the "Long-run Dynamic GGC"). Our results covering the periods 1920 to 2011 and 1940 to 2011, respectively, are presented in columns 5 and 6 of table 3 and Figure 9. For both columns our underlying measure of the intergenerational persistence of income is the father-son rank-rank correlation.

For both periods of interest we find that changes in a county's rank in terms of inequality correlate positively with changes in the county's rank in terms of the intergenerational persistence of income. Quantitatively, the association seems a bit stronger over the longer period 1920 to 2011, where the slope of the Dynamic GGC is about two thirds that of the Static GGC identified with the same measures of inequality and mobility.

All in all, over this long time periods we recover the familiar upward sloping GGC that has been documented in a variety of cross-sectional settings. Again, this result is also clearly visible in Figure 6: Over the long run, especially the Northwest and Northeast have become more unequal, and also less mobile.

This finding suggests a complex relationship between inequality and intergenerational persistence: the relationship seems to be robustly positive over long time periods (indeed we can also think of the Static GGC as a long-run or "steady-state" type relationship) but can break down over shorter time periods on the order of a couple of decades.

5 Discussion

Our results reflect a subtle and potentially troubling picture of the relationship between inequality and intergenerational mobility. Several implications are particularly worth emphasizing.

Firstly, we should not be surprised by the apparent contradiction between the Great Gatsby Curve and the fact that the surge in US inequality observed over the past four decades has to date not been accompanied by a commensurate increase in the intergenerational persistence of income. Indeed, the non-existence of a relationship between *changes* in inequality and *changes* in socioeconomic mobility over several decades is fully consistent with the historical record. Unstable dynamic GGCs have coexisted with robust static GGCs, in the past, for instance during the first half of the twentieth century.

However, once we “zoom out” to analyzing longer periods of almost a century, the negative association between inequality and socioeconomic mobility revealed by the static GGC re-emerges. Taken together, we interpret the overall historical record as suggesting that a future decrease in socioeconomic mobility in response to the increase in inequality observed in the US over the last few decades is still very much a possibility, insofar as the trend of inequality is not reversed. There are, thus, reasons to worry

Finally, our findings suggest that human capital accumulation may play a significant role in the mechanism relating inequality to intergenerational income persistence. This is because changes in inequality *do correlate* in the short run with changes in the intergenerational persistence of education. The fact that changes in the persistence of income fail to do so reflects the idiosyncrasy of individual income processes and their greater unpredictability, but in the long run, the role of education in income generation could end up manifesting itself in the form of the Great Gatsby Curve.

6 Conclusion

In spite of 50 years of unprecedented increase of inequality in the US, intergenerational mobility does not seem to have decreased. This seems to contradict the apparently universal fact that inequality negatively correlates with mobility. After all, when Alan Krueger first coined the name “Great Gatsby Curve”, he was motivated by its troublesome implications, as it seems to herald not only a more unequal America, but also a more stratified and sclerotic one... that has failed to appear.

The explanation of the contradiction, as Becker et al. (2018) suggested, lies in that the correlation of *levels* of mobility and inequality does not necessarily imply a correlation of *changes*. The problem lies (or lied until now) in the impossibility to check whether changes of inequality correlate with changes in mobility. In other words, we had ample evidence of the existence and near universality of a static Great Gatsby Curve, but we had no empirical evidence whatsoever on the existence of a Dynamic one.

Our contribution is to provide such evidence. Having recovered measures of intergenerational mobility and inequality for all US counties for a period expanding over 120 years we show that while the correlation in levels is an extremely robust relationship (it was there 100 years ago as it is now) the correlation in changes is much more subtle.

During the course of the last century, changes in inequality did not correlate with changes in *income* mobility 20 to 40 years later. Thus, the fact that the increase in inequality has not preceded a decrease in mobility in our current experience is perfectly consistent with the historical record, as Becker et al. (2018) suggested.

This should not be a great relief, though, as the same record suggests two disturbing facts, perfectly consistent with the GGC: (1) changes in inequality do correlate negatively with educational mobility, and (2) in the very long run, changes in inequality do correlate negatively also with changes in income mobility.

Ironically, while Becker et al. (2018) seem to have been right, Krueger had good reasons to be worried by the Great Gatsby Curve, as its long run dynamics imply that if the inequality increase observed in the US were to become persistent, it will eventually translate into lower intergenerational income mobility.

Moreover, our results suggest that the process of human capital accumulation may bridge the gap between the short and long run dynamics of the Great Gatsby Curve. This is so because in the historical record an increase of inequality among parents did increase the predictive power of parental background on the education, albeit not the income, of their children. A mechanism describing how the increase in the inheritability of education may ends up manifesting in the inheritability of income would be able to explain both the short and long run dynamics of the Great Gabby Curve. We believe that exploring potential mechanisms that account for the joint process linking inequality, educational mobility and income mobility in a way that accounts for the empirical regularities documented in the present paper may be a productive avenue for future research.

References

Aaronson, D. and Mazumder, B. (2008). Intergenerational economic mobility in the united states, 1940 to 2000. *Journal of Human Resources*, 43(1):139–172.

Abramitzky, R., Boustan, L. P., Eriksson, K., Pérez, S., and Rashid, M. (2020). Census linking project: Version 2.0 [dataset]. https://censuslinkingproject.org.

Abramitzky, R., Boustan, L. P., Jácome, E., and Pérez, S. (2021). Intergenerational Mobility of Immigrants in the US over Two Centuries. *The American Economic Review*, 111(2):580–608.

Acemoglu, D. and Autor, D. H. (2011). Skills, Tasks and Technologies: Implications for Employment and Earnings. In Card, D. and Ashenfelter, O., editors, *Handbook of Labor Economics*, volume 4B, pages 1043–1171. Elsevier.

Andrews, D. and Leigh, A. (2009). More Inequality, less Social Mobility. *The Review of Economic Studies*, 16(15).

Autor, D. H., Katz, L. F., and Kearney, M. (2008). Trends in U.S. Wage Inequality: Revising the Revisionists. *Review of Economics and Statistics*, 90(2):300–323.

Becker, G. S., Kominers, S. D., Murphy, K. M., and Spenkuch, J. L. (2018). A Theory of Intergenerational Mobility. *Journal of Political Economy*, 126(S1):S7–S25. Publisher: The University of Chicago Press.

Berger, T., Engzell, P., Eriksson, B., and Molinder, J. (2023). Social Mobility in Sweden before the Welfare State. *Journal of Economic History*, 83(2):431–63.

Bjorklund, A. and Jäntti, M. (2012). Intergenerational Income Mobility and the Role of Family Background. *Oxford Handbook of Economic Inequality*.

Blanden, J. (2013). Cross-Country Rankings in Intergenerational Mobility: A Comparison of Approaches from Economics and Sociology. *Journal of Economic Surveys*, 27(1):38–73.

Buckles, K., Price, J., Ward, Z., and Wilbert, H. E. B. (2023). Family Trees and Falling Apples: Historical Intergenerational Mobility Estimates for Women and Men. Technical Report w31918, National Bureau of Economic Research.

Chetty, R., Grusky, D., Hell, M., Hendren, N., Manduca, R., and Narang, J. (2017). The fading american dream: Trends in absolute income mobility since 1940. *Science*, 356(6336):398–406.

Chetty, R., Hendren, N., Kline, P., and Saez, E. (2014a). Is the United States Still a Land of Opportunity? Recent Trends in Intergenerational Mobility. *American Economic Review: Papers and Proceedings*, 104(5):141–147.

Chetty, R., Hendren, N., Kline, P., and Saez, E. (2014b). Where is the land of Opportunity? The Geography of Intergenerational Mobility in the United States. *The Quarterly Journal of Economics*, 129(4):1553–1623.

Collins, W. J. and Wanamaker, M. H. (2022). African American Intergenerational Economic Mobility Since 1880. *American Economic Journal: Applied Economics*, 14(3):84–117.

Corak, M. (2006). Do Poor Children Become Poor Adults? Lessons from a Cross-Country Comparison of Generational Earnings Mobility. In Creedy, J. and Kalb, G., editors, *Dynamics of Inequality and Poverty*, volume 13 of *Research on Economic Inequality*, pages 143–188. Emerald Group Publishing Limited.

Corak, M. (2013). Income Inequality, Equality of Opportunity, and Intergenerational Mobility. *Journal of Economic Perspectives*, 27(3):79–102.

Council of Economic Advisers (2012). *Economic Report of the President*. Government Printing Office.

DiPrete, T. A. (2020). The impact of inequality on intergenerational mobility. *Annual Review of Sociology*, 46(1):379–398.

Dodin, M., Findeisen, S., Henkel, L., Sachs, D., and Schüle, P. (2024). Social Mobility in Germany. *Journal of Public Economics*, forthcoming.

Durlauf, S. N., Kourtellos, A., and Tan, C. M. (2022). The Great Gatsby Curve. *Annual Review of Economics*, 14(1):571–605.

Durlauf, S. N. and Seshadri, A. (2018). Understanding the Great Gatsby Curve. *NBER Macroeconomics Annual*, 32:333–393.

Ermisch, J., Jäntti, M., and Smeeding, T., editors (2012). *From Parents to Children: The Intergenerational Transmission of Advantage*. Russell Sage Foundation.

Fan, Y., Yi, J., and Zhang, J. (2021). Rising Intergenerational Income Persistence in China. *American Economic Journal: Economic Policy*, 13(1):202–230.

Feigenbaum, J. J. (2015). Intergenerational Mobility during the Great Depression. *Working Paper*.

Goldin, C. and Katz, L. (2010). The 1915 iowa state census project. inter-university consortium for political and social research [distributor].

Guvenen, F., Kaplan, G., Song, J., and Weidner, J. (2022). Lifetime earnings in the united states over six decades. *American Economic Journal: Applied Economics*, 14(4):446–79.

Güell, M., Pellizzari, M., Pica, G., and Rodríguez Mora, J. V. (2018). Correlating Social Mobility and Economic Outcomes. *The Economic Journal*, 128(612):F353–F403.

Hassler, J., Mora, J. V. R., and Zeira, J. (2007). Inequality and Mobility. *Journal of Economic Growth*, 12(3):235–259.

Helgertz, J., Ruggles, S., Warren, J. R., Fitch, C. A., Hacker, J. D., Nelson, M. A., Price, J. P., Roberts, E., and Sobek, M. (2023). IPUMS Multigenerational Longitudinal Panel: Version 1.1 [dataset].

Jácome, E., Kuziemko, I., and Naidu, S. (2022). Mobility for All: Representative Intergenerational Mobility Estimates over the 20th Century. Technical Report w29289, National Bureau of Economic Research.

Krueger, A. B. (2012). The rise and consequences of inequality in the united states. *Council on Foreign Relations*.

Lee, C.-I. and Solon, G. (2009). Trends in intergenerational income mobility. *Review of Economics and Statistics*, 91(4):766–772.

Manson, S., Schroeder, J., Van Riper, D., Knowles, K., Kugler, T., Roberts, F., and Ruggles, S. (2023). IPUMS National Historical Geographic Information System: Version 18.0 [dataset].

Nybom, M. and Stuhler, J. (2024). Interpreting trends in intergenerational mobility. *Journal of Political Economy*, forthcoming.

Piketty, T. and Saez, E. (2003). Income Inequality in the United States, 1913-1998. *The Quarterly Journal of Economics*, 118(1):1–39.

Ruggles, S., Fitch, C. A., Goeken, R., Hacker, J. D., Nelson, M. A., Roberts, E., Schouweiler, M., and Sobek, M. (2021). IPUMS Ancestry Full Count Data: Version 3.0 [dataset].

Solon, G. (1992). Intergenerational Income Mobility in the United States. *The American Economic Review*, 82(3):393–408.

Tan, H. R. (2023). A different land of opportunity: The geography of intergenerational mobility in the early twentieth-century united states. *Journal of Labor Economics*, 41(1):77–102.

Ward, Z. (2023). Intergenerational Mobility in American History: Accounting for Race and Measurement Error. *American Economic Review*, 113(2):3213–48.

Appendix

A Robustness

Table A1 shows that our novel approach of ranking counties based on their persistence measures is highly correlated to the actual persistence measure in 1900, 1920, and 1940. This illustrates that county ranks capture much of the same variation as the underlying persistence measures. However, they have the advantage of being unitless and allowing us to calculate changes in persistence over periods with different underyling measures of persistence.

In our main analysis, we have estimated the long-run dynamic GGC only with rank-rank-coefficients. The reason for this is that this is the key measure used in the modern data by Chetty et al. (2014b) and we wanted to keep our analysis as comparable as possible. However, since we have usually also shown static or dynamic GGCs with the intergenerational elasticity of earnings as the measure of persistence, table A2 also shows the long-run dynamic GGC when using the IGE for 1920 and 1940. To be precise, we create the difference in the county rank based on the 2011 rank-rank correlation and the county rank based on the 1940 (1920) IGE and regress this on the change in the county rank based on the gini coefficient between 2011 and 1940 (1920). Results are very similar to our main regressions and show the existence of a long-run dynamic GGC. This approach also further highlights the advantage of using county ranks: Even though we are comparing two different quantities (rank-rank correlations and IGEs), creating the county ranks first creates easily comparable variables.

Throughout the paper, we have measured a county's income inequality by the Gini coefficient of predicted incomes. This is the most wide-spread measure of inequality used in other studies of the GGC (see the review in Durlauf et al. (2022)). However, Durlauf et al. (2022) caution that "standard inequality measures such as the Gini coefficient versus the variance of log income are not monotonic transformations" (p. 577). To test the robustness of our findings to using alternative measures of income inequality, in table A3 we use the difference between the natural logarithm of the 90th percentile and the natural logarithm of the 10th percentile as our measure of inequality. As outcome measure, we use the intergenerational income elasticity. The results confirm our three key findings: The static GGC emerges in 1900, 1920, and 1940 (columns 1-3), the dynamic GGC is not present, both with regular changes and when using county ranks (columns 4-7), and the long-run GGC for 1940 to 2011 exists (Column 8). Table A4 repeats the analysis, but this time using the variance of log-income as measure of inequality. Again, our three key results hold. We conclude that our results are not sensitive to the measure of income inequality that we use.

Our measure of historical incomes is based on predictions that include age, state of residence, and occupation, following Collins and Wanamaker (2022). In table A5, we show results when we additionally also include industry in our wage prediction. This will address the fact that different types of jobs in different industries might have gotten paid very differently. Using the IGE as measure of income inequality and the gini coefficient as our measure of inequality, our results hold again: We find a static GGC for 1900-1940, no dynamic GGC in the short run, but the reemergence of the GGC in the long-run. The same is true in table A6, where we use IGE estimates that comtrol for the age of the father and son. Collins and Wanamaker (2022) further include farm ownership (measured as home ownership for farmrs) in their income prediction. We do not do this in our main results, as home ownership is not available for 1880. However, in table A7, we show results for 1900-1940 that include farm ownership in the income prediction. Specifically, we include a dummy for home ownership in the wage prediction for farmers in 1940, and allow the farmer-farm laborer total income ratio in 1960 to depend on the farmer owning his home. We find a positive static GGC for 1920 and 1940, no dynamic GGC between 1920 and 1940 either in levels or county ranks, and a positive long-run dynamic GGC between 1940 and 2010. Ward (2023) has pointed out that historical estimates of intergenerational mobility are severely affected by measurement error in fathers' occupations. He suggests to use occupation measures from different years as instruments. While this approach works well in the national sample, the inefficiency of instrumental variables makes it less suitable in our study, as the sample sizes per county are quite low, leading to very imprecise estimates. Instead, in table A8, we follow Solon (1992) and regress the son's predicted (log) income on the average of log predicted income of two observations for the fathers. For sons in 1900, we take fathers' occupations from 1880 and 1870, for sons in 1920, we use 1900 and 1910, and for sons in 1940, we use 1920 and 1930. As can be seen, we find a similar pattern as for our main results: Robust static GGCs for all three years, a noisy dynamic GGC in the short run, and the re-emergence of the GGC result in long differences. Ward (2023) also shows biases due to not accounting for race. In table A9, we therefore restrict the results to whites, only. We again find static GGCs, unstable dynamic GGCs in the short run, and the re-emergence of the GGC in the long run.

We assess the robustness of the GGC with educational mobility in tables A10 to A13. Table A10 shows that our results hold when we control for father's and son's ages in the regressions that calculate the intergenerational elasticity in education: We find static GGCs both for 1920 and 1940, and a short-run dynamic one both when using changes and when using changes in county ranks. Tables A11 and A12 show that this also holds when replacing the measure of income inequality by the variance of log incomes or the log difference between the 90th and 10th percentile. It is particularly noteworthy how robust the county-ranked regressions are, further highlighting the appeal of this approach. Finally, table A13 shows results when using the gini coefficient in education, rather than predicted income, to measure inequality in the father's generation. This also produces static GGCs for 1920 and 1940, but no dynamic GGCs.

B Additional Figures

B.1 Binned Scatter Plots

In each figure, we divide the counties in vintiles of an inequality measure (either in levels or in growth) and plot the average of a certain measure of intergenerational persistence (either in levels or in growth) of the counties in the vintile.

- IGE versus Gini, Levels and County Ranks. Fig A1
- r-r versus Gini, County Ranks. Fig A2
- 2011. r-r versus Gini, Levels and County Ranks. Fig A3
- Education versus Gini, Levels and County Ranks. Fig A4
- Dynamic GGC, IGE. Levels and County Ranks. Fig A5
- Dynamic GGC, r-r. Levels. Fig A6
- Dynamic GGC, Education. Levels and County Ranks. Fig A7

B.2 Raw Data Scatter Plots

In each figure, we plot for each county the value of an inequality measure (either in levels or in growth) and plot it against certain measure of intergenerational persistence (either in levels or in growth) for this county.

- IGE versus Gini, Levels and County Ranks. Fig A8

- r-r versus Gini, Levels and County Ranks. Fig A9
- 2011. r-r versus Gini, Levels and County Ranks. Fig A10
- Education versus Gini, Levels and County Ranks. Fig A11
- Dynamic GGC, IGE. Levels and County Ranks. Fig A12
- Dynamic GGC, r-r. Levels and County Ranks. Fig A13
- Long Run Dynamic GGC, r-r. Levels and County Ranks. Fig A14
- Dynamic GGC, Education. Levels and County Ranks. Fig A15

	Correlation coefficient for year		
	1900	1920	1940
Rank-Rank	0.938	0.912	0.964
IGE	0.961	0.974	0.977

Table A1: Correlation between measures of persistence in levels and county ranks

	(1)	(2)
Persistence measure	IGE/r-r	IGE/r-r
County Rank	0.22***	0.23***
	(0.02)	(0.02)
Observations	2,689	2,449
Year	2010-1940	2010-1920

Robust std errors

Table A2: Gatsby Long Run. County IGE rank in 1920 and 1940, versus County r-r rank in 2011.
Correlating changes in the rank of the county in the persistence distribution with changes in the county rank in the inequality distribution. Inequality is always measured as the Gini index of the income of the parents (i.e., measured in the census 20 years prior to the measurement of the son's income). Data for 1900-1940 are based on our income imputations, data for 2011 are from Chetty et al. (2014b). Persistence is measured in each county either by the IGE in 1920 and 1940 and by the rank-rank correlation between fathers and sons for 2011.

VARIABLES	(1) IGE	(2) IGE	(3) IGE	(4) Δ IGE	(5) Δ County Rank	(6) Δ IGE	(7) Δ County Rank	(8) Δ County Rank
log(p90)-log(p10)	0.15***	0.11***	0.10***					
	(0.01)	(0.01)	(0.01)					
Δ(log(p90)-log(p10))				0.01		-0.04***		
				(0.01)		(0.01)		
County rank changes					0.02		-0.06***	0.20***
					(0.02)		(0.02)	(0.02)
Observations	2,272	2,661	3,008	2,268	2,268	2,655	2,655	2,689
Year	1900	1920	1940	1900/1920	1900/1920	1920/1940	1920/1940	1940/2010

Robust std errors

Table A3: Robustness to using the log difference between the 90th and 10th percentile as measure of inequality
Inequality is measured as differences between the log of the 90th percentile of the parental income distribution and the lof of the 10th percentile of this distribution. Persistence is measured by the IGE. Rows 1-3 correlate the county persistence and the county inequality levels. Rows 4 and 6 correlate changes in persistence with changes in inequality, rows 5, 7, and 8 do the same, but based on the rank of the county in the persistence distribution and the county rank in the inequality distribution.

VARIABLES	(1) IGE	(2) IGE	(3) IGE	(4) Δ IGE	(5) Δ County Rank	(6) Δ IGE	(7) Δ County Rank	(8) Δ County Rank
Var(LogIncome)	0.81***	0.77***	0.54***					
	(0.03)	(0.03)	(0.02)					
Δ(Var(LogIncome))				-0.07		-0.30***		
				(0.05)		(0.04)		
Change in County Rank					0.00		-0.10***	0.26***
					(0.03)		(0.03)	(0.02)
Observations	2,272	2,661	3,008	2,268	2,268	2,655	2,655	2,689
Year	1900	1920	1940	1900/1920	1900/1920	1920/1940	1920/1940	1940/2010

Robust std errors

Table A4: Robustness to using the variance of log income as measure of inequality
Inequality is measured as the variance of log income among fathers. Persistence is measured by the IGE. Rows 1-3 correlate the county persistence and the county inequality levels. Rows 4 and 6 correlate changes in persistence with changes in inequality, rows 5, 7, and 8 do the same, but based on the rank of the county in the persistence distribution and the county rank in the inequality distribution.

VARIABLES	(1) IGE	(2) IGE	(3) IGE	(4) Δ IGE	(5) Δ County Rank	(6) Δ IGE	(7) Δ County Rank	(8) Δ County Rank
Gini Fathers	1.23***	1.12***	0.85***					
	(0.05)	(0.04)	(0.03)					
Δ(Gini Fathers)				-0.01		-0.27***		
				(0.08)		(0.09)		
Change in county rank					0.01		-0.09***	0.18***
					(0.03)		(0.03)	(0.02)
Observations	2,272	2,661	3,008	2,268	2,268	2,655	2,655	2,689
Year	1900	1920	1940	1900/1920	1900/1920	1920/1940	1920/1940	1940/2010

Robust std errors

Table A5: Robustness to including industry in imputing income
In predicting income, industry is used as an additional predictor. Inequality is measured as the gini coefficient in income among fathers. Persistence is measured by the IGE. Rows 1-3 correlate the county persistence and the county inequality levels. Rows 4 and 6 correlate changes in persistence with changes in inequality, rows 5, 7, and 8 do the same, but based on the rank of the county in the persistence distribution and the county rank in the inequality distribution.

VARIABLES	(1) IGE	(2) IGE	(3) IGE	(4) Δ IGE	(5) Δ County Rank	(6) Δ IGE	(7) Δ County Rank	(8) Δ County Rank
Gini fathers	1.08***	1.08***	0.93***					
	(0.04)	(0.04)	(0.03)					
Δ(Gini fathers)				-0.04		-0.30***		
				(0.07)		(0.07)		
Change in County Ranks					-0.00		-0.07**	0.23***
					(0.03)		(0.03)	(0.02)
Observations	2,272	2,661	3,008	2,268	2,268	2,655	2,655	2,689
Year	1900	1920	1940	1900/1920	1900/1920	1920/1940	1920/1940	1940/2010

Robust std errors

Table A6: Robustness to controlling for Age in IGE regressions
IGE regressions additionally control for father's and son's age. Inequality is measured as the gini coefficient in income among fathers. Persistence is measured by the IGE. Rows 1-3 correlate the county persistence and the county inequality levels. Rows 4 and 6 correlate changes in persistence with changes in inequality, rows 5, 7, and 8 do the same, but based on the rank of the county in the persistence distribution and the county rank in the inequality distribution.

VARIABLES	(1) IGE	(2) Change in IGE	(3) Change in County Rank	(4)	(5)
Gini Fathers	1.11***	0.90***			
	(0.04)	(0.03)			
Δ(Gini Fathers)			-0.16**		
			(0.08)		
Change in county rank				-0.01	0.24***
				(0.03)	(0.02)
Observations	2,661	3,008	2,655	2,655	2,689
Year	1920	1940	1920/1940	1920/1940	1940/2010

Robust std errors

Table A7: Robustness to including home ownership in imputing income for farmers
In predicting income, home ownership is used as an additional predictor for farmers to account for income differences between farmers owning their farm and tenant farmers/sharecroppers. Inequality is measured as the gini coefficient in income among fathers. Persistence is measured by the IGE. Rows 1-2 correlate the county persistence and the county inequality levels. Row 3 correlates changes in persistence with changes in inequality, rows 4 and 5 do the same, but based on the rank of the county in the persistence distribution and the county rank in the inequality distribution.

VARIABLES	(1) IGE	(2) IGE	(3) IGE	(4) Δ IGE	(5) Δ County Rank	(6) Δ IGE	(7) Δ County Rank	(8) Δ County Rank
Gini fathers	1.39***	1.01***	0.86***					
	(0.05)	(0.04)	(0.03)					
Δ(Gini fathers)				0.28***		-0.30***		
				(0.10)		(0.07)		
Change in County Ranks					0.09**		-0.05*	0.21***
					(0.03)		(0.03)	(0.02)
Observations	2,272	2,661	3,008	2,268	2,268	2,655	2,655	2,689
Year	1900	1920	1940	1900/1920	1900/1920	1920/1940	1920/1940	1940/2010

Robust std errors

Table A8: Robustness to adjusting IGE estimates for measurement error in father's occupations
IGE is based on regressing the log income of the son on the average of two predicted log income observations of the father. For sons in 1900, the father's observations are from 1880 and 1870. For sons in 1920, the father's observations are from 1900 and 1910. For sons in 1920, the father's observations are from 1920 and 1930. Inequality is measured as the gini coefficient in income among fathers. Persistence is measured by the IGE. Rows 1-3 correlate the county persistence and the county inequality levels. Rows 4 and 6 correlate changes in persistence with changes in inequality, rows 5, 7, and 8 do the same, but based on the rank of the county in the persistence distribution and the county rank in the inequality distribution.

VARIABLES	(1) IGE	(2) IGE	(3) IGE	(4) Δ IGE	(5) Δ County Rank	(6) Δ IGE	(7) Δ County Rank	(8) Δ County Rank
Gini fathers	0.47***	0.32***	0.33***					
	(0.05)	(0.05)	(0.03)					
Δ(Gini fathers)				0.16**		-0.12		
				(0.08)		(0.09)		
Change in County Ranks					0.05		-0.03	0.25***
					(0.03)		(0.03)	(0.02)
Observations	2,272	2,661	3,008	2,268	2,268	2,655	2,655	2,689
Year	1900	1920	1940	1900/1920	1900/1920	1920/1940	1920/1940	1940/2010

Robust std errors

Table A9: Robustness to restricting the data to whites
Inequality is measured as the gini coefficient in income among fathers. Persistence is measured by the IGE. Rows 1-3 correlate the county persistence and the county inequality levels. Rows 4 and 6 correlate changes in persistence with changes in inequality, rows 5, 7, and 8 do the same, but based on the rank of the county in the persistence distribution and the county rank in the inequality distribution.

VARIABLES	(1) IGE Education	(2)	(3) Change in IGE Education	(4) Change in County Rank
Gini	0.88***	0.83***		
	(0.08)	(0.03)		
Change in gini			0.43***	
			(0.14)	
Change in county rank				0.26***
				(0.04)
Observations	2,421	3,054	2,418	2,418
Year	1920	1940	1920/1940	1920/1940

Robust std errors

Table A10: Robustness to controlling for Age in IGE regressions for education
IGE regressions control for father's and son's age. Inequality is measured as the gini coefficient in income among fathers. Persistence is measured by the intergenerational correlation in education. Rows 1 and 2 correlate the county persistence and the county inequality levels. Row 3 correlates changes in persistence with changes in inequality, Row 4 does the same, but based on the rank of the county in the persistence distribution and the county rank in the inequality distribution.

	(1)	(2)	(3)	(4)
VARIABLES	IGE Education		Change in IGE Education	Change in County Rank
Var(LogIncome)	0.55***	0.47***		
	(0.05)	(0.02)		
Δ(Var(LogIncome))			0.19**	
			(0.10)	
Change in County Rank				0.26***
				(0.05)
Observations	2,421	3,054	2,418	2,418
Year	1920	1940	1920/1940	1920/1940

Robust std errors

Table A11: Robustness to using the variance of log income as measure of inequality
Inequality is measured as the variance of log income among fathers. Persistence is measured by the intergenerational correlation in education. Rows 1 and 2 correlate the county persistence and the county inequality levels. Row 3 correlates changes in persistence with changes in inequality, Row 4 does the same, but based on the rank of the county in the persistence distribution and the county rank in the inequality distribution.

VARIABLES	(1)	(2)	(3)	(4)
	IGE Education		Change in IGE Education	Change in County Rank
log(p90)-log(p10)	0.10***	0.10***		
	(0.01)	(0.01)		
Δ(log(p90)-log(p10))			0.05***	
			(0.02)	
Change in county rank				0.21***
				(0.03)
Observations	2,421	3,054	2,418	2,418
Year	1920	1940	1920/1940	1920/1940

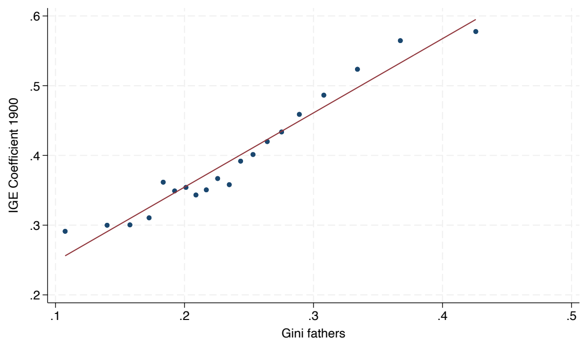
Robust std errors

Table A12: Robustness to using the log difference between the 90th and 10th percentile as measure of inequality
Inequality is measured as differences between the log of the 90th percentile of the parental income distribution and the lof of the 10th percentile of this distribution. Persistence is measured by the intergenerational correlation in education. Rows 1 and 2 correlate the county persistence and the county inequality levels. Row 3 correlates changes in persistence with changes in inequality, Row 4 does the same, but based on the rank of the county in the persistence distribution and the county rank in the inequality distribution.

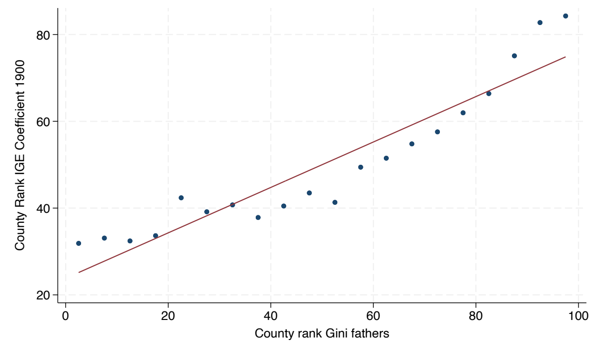
	(1)	(2)	(3)	(4)
VARIABLES	IGE Education		Change in IGE Education	Change in County Rank
Edu gini fathers	0.64***	1.05***		
	(0.09)	(0.04)		
Change in edu gini fathers			-0.11	
			(0.15)	
Change in county rank				-0.01
				(0.04)
Observations	2,421	3,054	2,418	2,418
Year	1920	1940	1920/1940	1920/1940

Robust std errors

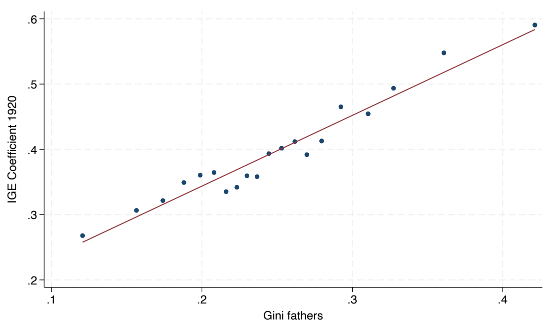
Table A13: Robustness to using educational inequality
IGE regressions control for father's and son's age. Inequality is measured as the gini coefficient in education among fathers. Persistence is measured by the intergenerational correlation in education. Rows 1 and 2 correlate the county persistence and the county inequality levels. Row 3 correlates changes in persistence with changes in inequality, Row 4 does the same, but based on the rank of the county in the persistence distribution and the county rank in the inequality distribution.



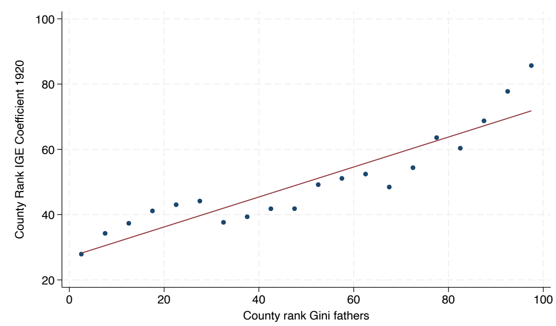
(a) Levels. IGE vs Gini, 1900



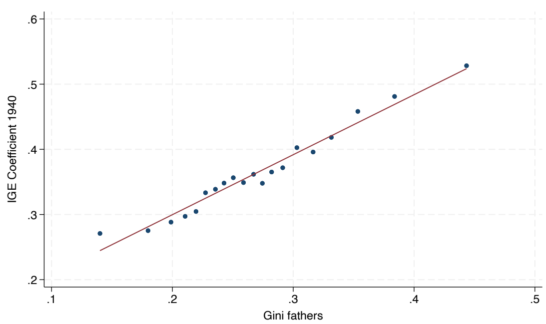
(b) County Ranks. IGE vs Gini, 1900



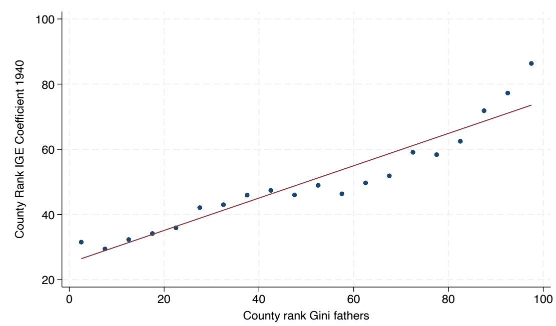
(c) Levels. IGE vs Gini, 1920



(d) County Ranks. IGE vs Gini, 1920



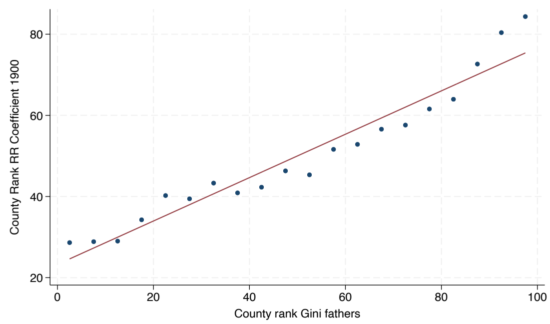
(e) Levels. IGE vs Gini, 1940



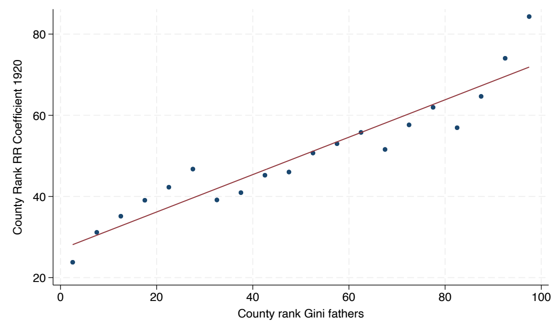
(f) County Ranks. IGE vs Gini, 1940

Binned scattered plots. In each, we divide the counties in vintiles of an inequality measure and plot the average measure of a measure of intergenerational persistence of the counties in the vintile.
In the graphs in the left, we use the level of the gini index versus the county's intergenerational elasticity in different years.
In the figures in the right we plot the county rank of the gini against the county rank of the IGE. The point of the figure is to validate the county rank as a measure of both inequality and intergenerational persistence.

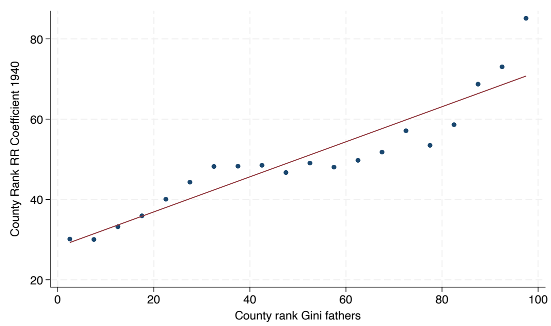
Figure A1: IGE versus Gini, Levels and County Ranks.



(a) County Ranks. r-r vs Gini, 1900



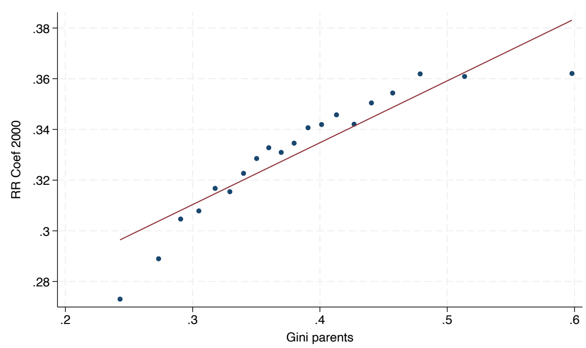
(b) County Ranks. r-r vs Gini, 1920



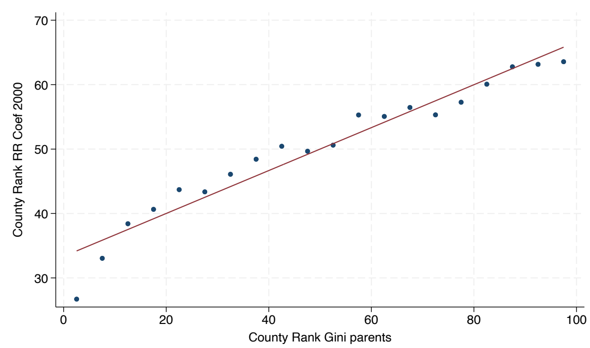
(c) County Ranks. r-r vs Gini, 1940

Binned scattered plots. In each, we divide the counties in vintiles of an inequality measure and plot the average measure of a measure of intergenerational persistence of the counties in the vintile.
We plot county rank of the Gini Index against county rank of the rank-rank correlation, as an alternative measure of persistence.
The point is to show that the GGC looks the same than if we were using IGE instead.

Figure A2: r-r versus Gini, County Ranks.



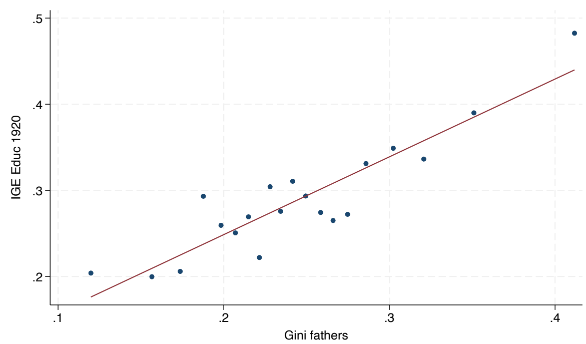
(a) Levels. r-r vs Gini, 2011



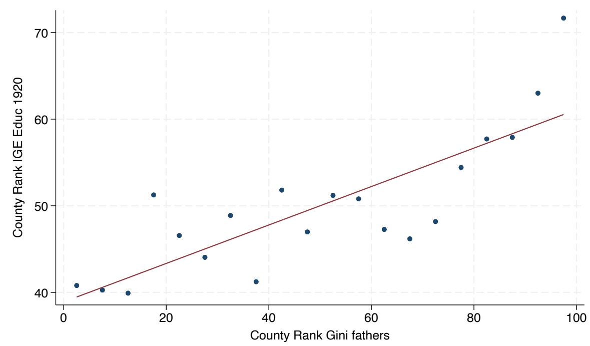
(b) County Ranks. r-r vs Gini, 2011

Binned scattered plots. In each, we divide the counties in vintiles of an inequality measure and plot the average measure of a measure of intergenerational persistence of the counties in the vintile.
Here we use the data from Chetty et al. (2014b). In the left panel, we plot the levels of the Gini Index against the rank-rank correlation for the year 2011, showing the GGC.
On the right panel, we show that the same qualitative result appears in modern data when we use the county rank as a measure.

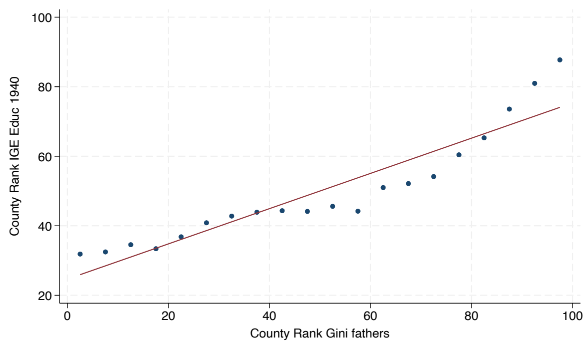
Figure A3: 2011. r-r versus Gini, Levels and County Ranks.



(a) Levels. Education vs Gini, 1920



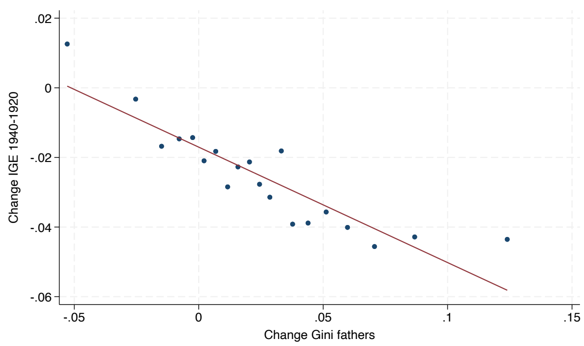
(b) County Ranks. Education vs Gini, 1920



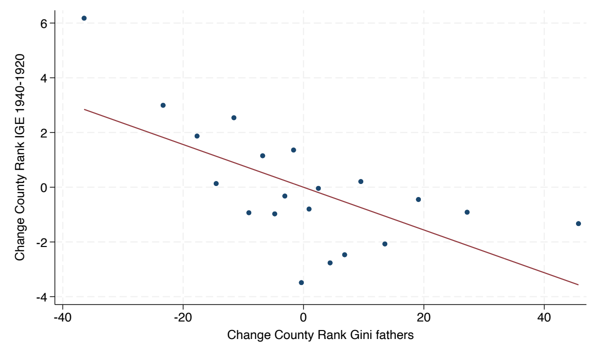
(c) County Ranks. Education vs Gini, 1940

Binned scattered plots. In each, we divide the counties in vintiles of an inequality measure and plot the average measure of a measure of intergenerational persistence of the counties in the vintile.
Here we use the correlation of educational achievement and its county-rank version, showing the GGC in education.

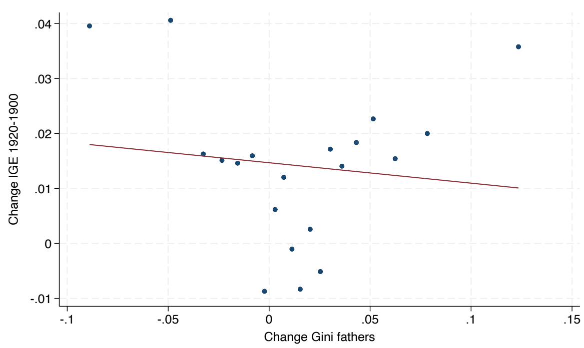
Figure A4: Education versus Gini, Levels and County Ranks.



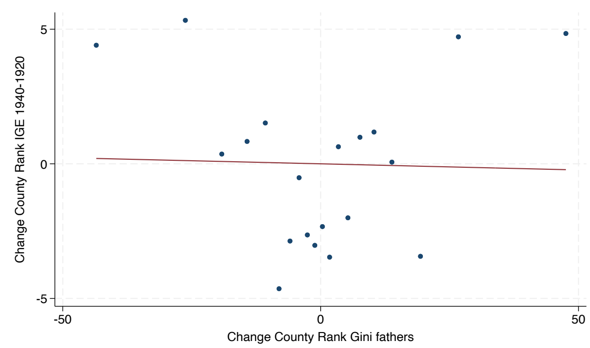
(a) Levels. ΔIGE vs ΔGini, 1920-1940



(b) County Ranks. ΔIGE vs ΔGini, 1920-1940



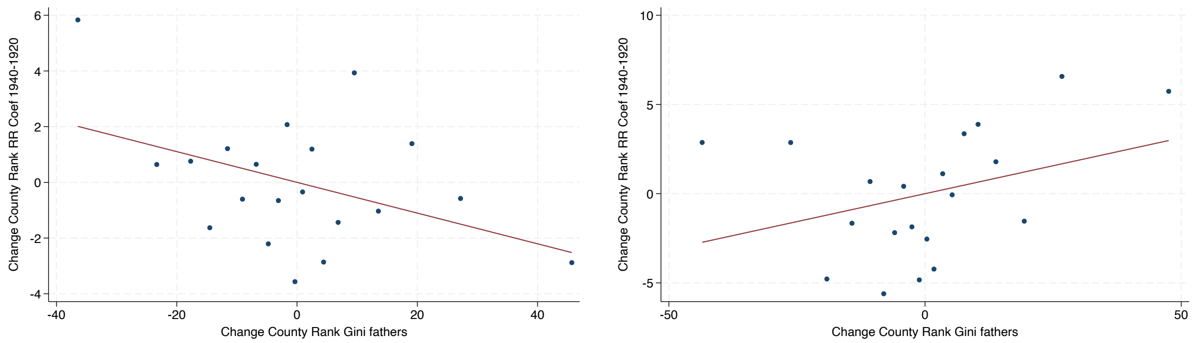
(c) Levels. ΔIGE vs ΔGini, 1900-1920



(d) County Ranks. ΔIGE vs ΔGini, 1900-1920

Binned scattered plots. In each, we divide the counties in vintiles of an inequality measure and plot the average measure of a measure of intergenerational persistence of the counties in the vintile.
Here we show that the dynamic version of the GGC does not always generate positive correlations. In the left we plot change in Gini index versus change of IGE, in the right the county-rank version of both. In the top line for 1920-1940, in the bottom for 1900-1920

Figure A5: Dynamic GGC, IGE. Levels and County Ranks.

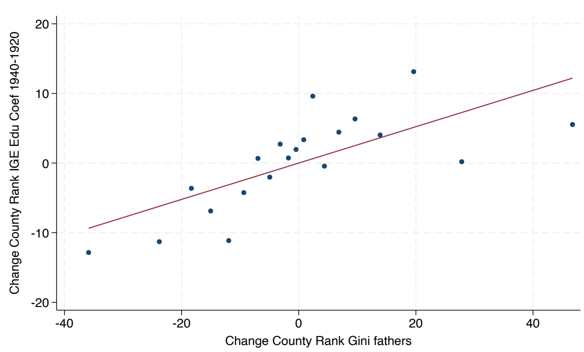


(a) County Ranks. Δr-r vs ΔGini, 1920-1940 **(b)** County Ranks. Δr-r vs ΔGini, 1900-1920

Binned scattered plots. In each, we divide the counties in vintiles of an inequality measure and plot the average measure of a measure of intergenerational persistence of the counties in the vintile.

Here we plot the change in the county rank of the Gini index versus the change in the county rank of the father-son rank-rank correlation. The left panel for 1920-1940, the right for 1900-1920. The point is to show that we get similar results as those in the main text with county ranks.

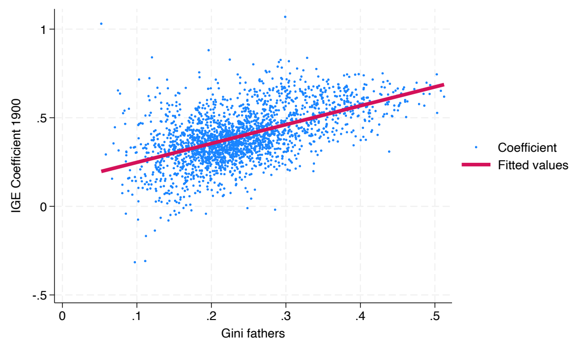
Figure A6: Dynamic GGC, r-r. County Ranks.



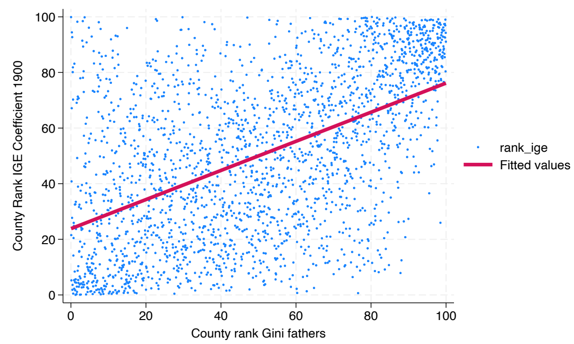
Binned scattered plot. We divide the counties in vintiles of an inequality measure and plot the average measure of a measure of intergenerational persistence of the counties in the vintile.

We plot the change in the Gini index versus the change in the father-son correlation of educational attainment for 1920-1940 both in county-ranks, showing that the results with county ranks are again similar to those in levels.

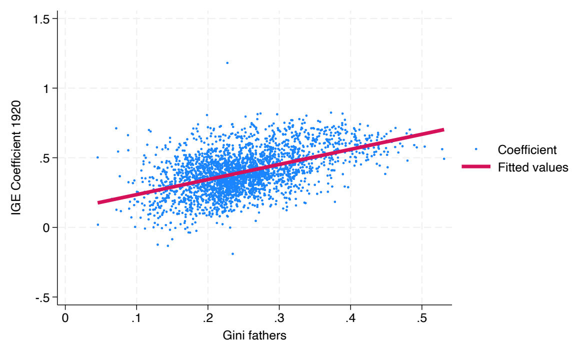
Figure A7: County Ranks. ΔEducation vs ΔGini, 1920-1940



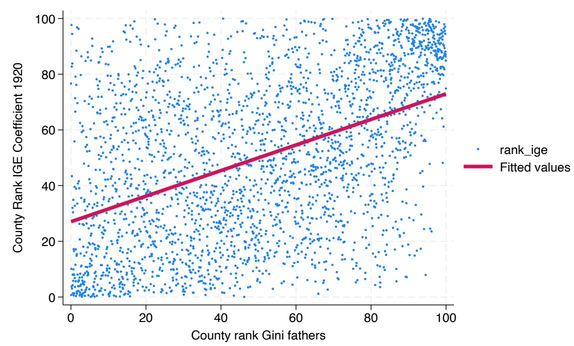
(a) Levels. IGE vs Gini, 1900



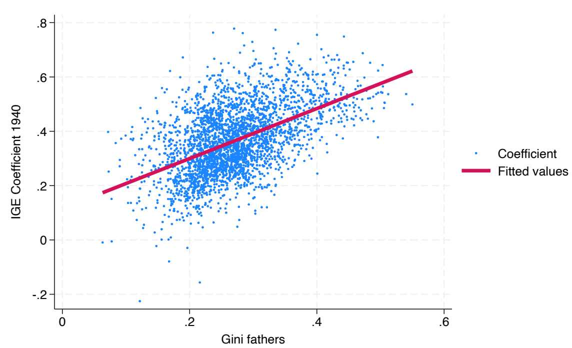
(b) County Ranks. IGE vs Gini, 1900



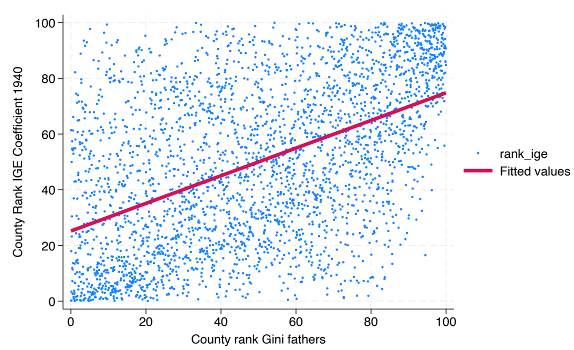
(c) Levels. IGE vs Gini, 1920



(d) County Ranks. IGE vs Gini, 1920

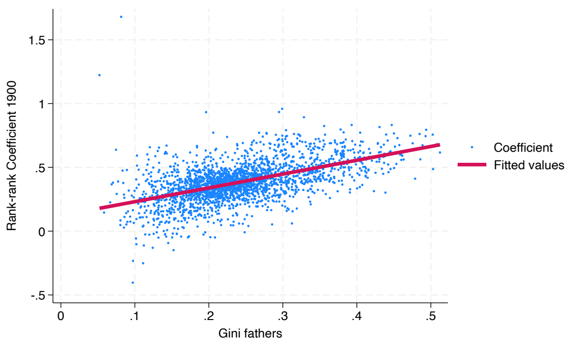


(e) Levels. IGE vs Gini, 1940

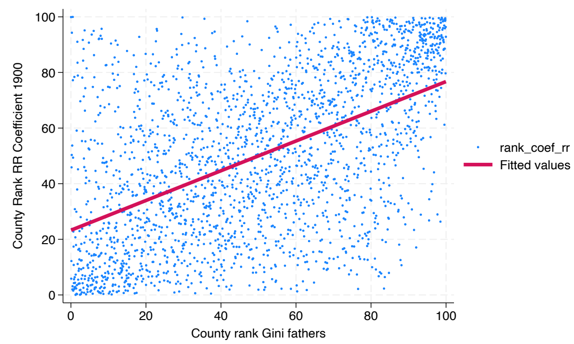


(f) County Ranks. IGE vs Gini, 1940

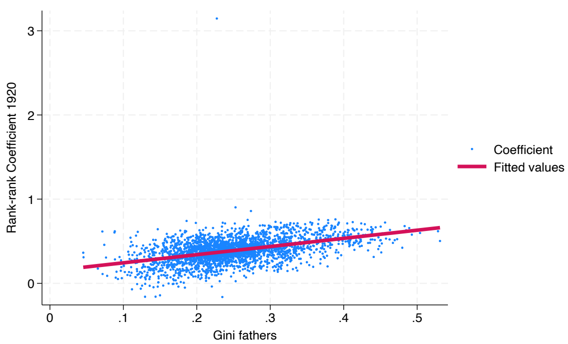
Figure A8: IGE versus Gini, Levels and County Ranks.



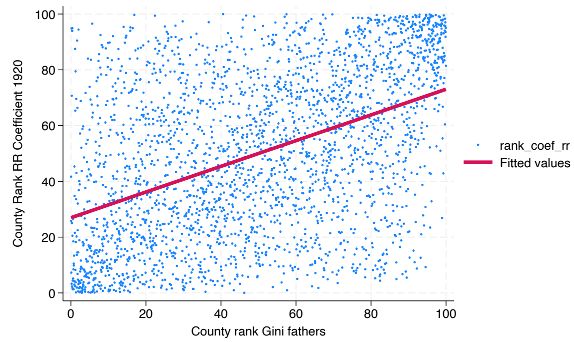
(a) Levels. r-r vs Gini, 1900



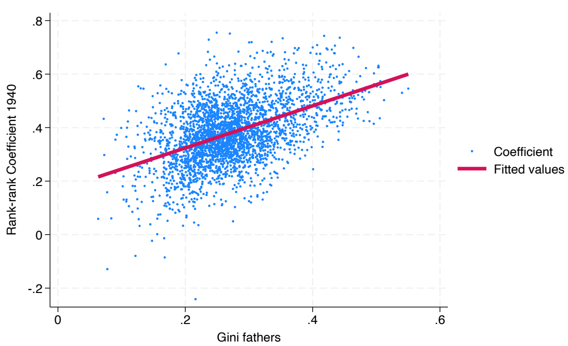
(b) County Ranks. r-r vs Gini, 1900



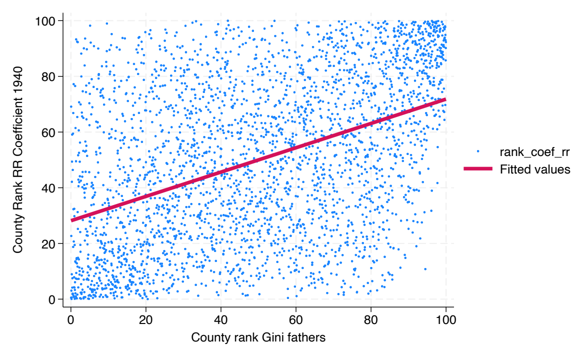
(c) Levels. r-r vs Gini, 1920



(d) County Ranks. r-r vs Gini, 1920

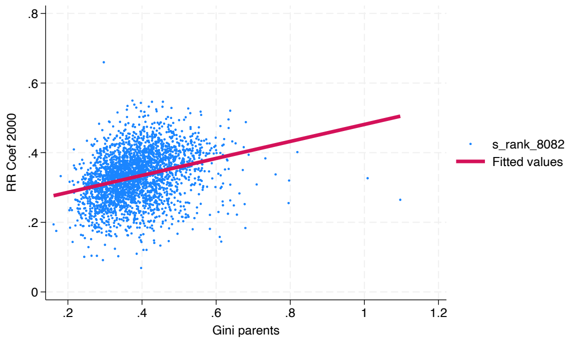


(e) Levels. r-r vs Gini, 1940

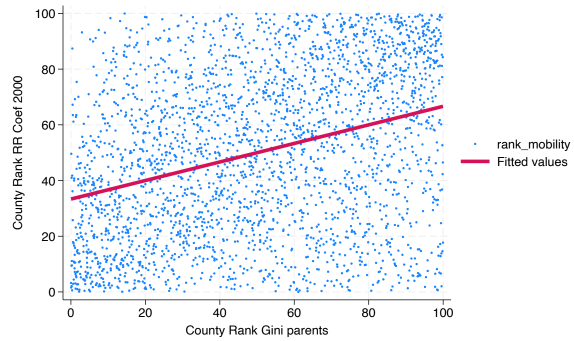


(f) County Ranks. r-r vs Gini, 1940

Figure A9: r-r versus Gini, Levels and County Ranks.

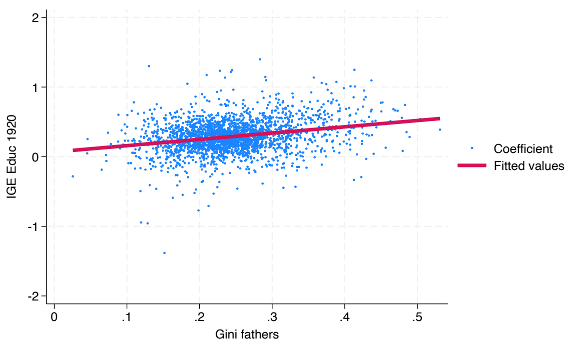


(a) Levels. r-r vs Gini, 2011

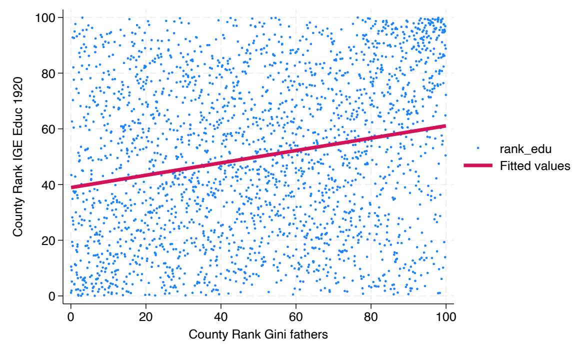


(b) County Ranks. r-r vs Gini, 2011

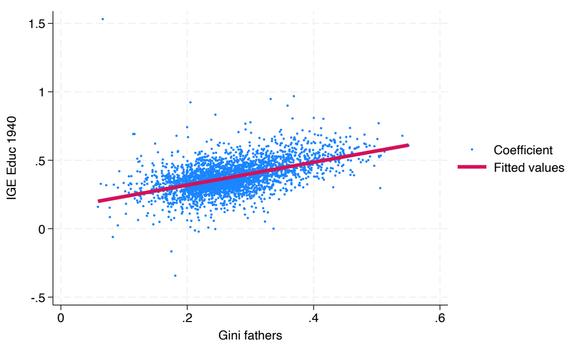
Figure A10: 2011. r-r versus Gini, Levels and County Ranks.



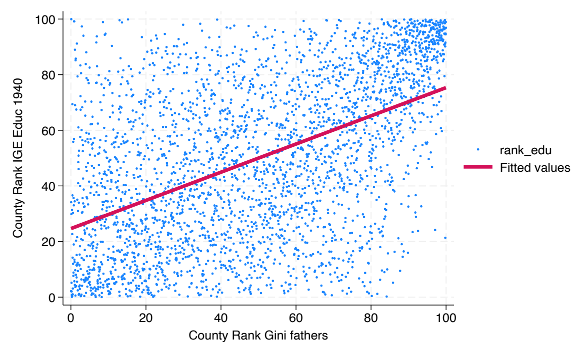
(a) Levels. Education vs Gini, 1920



(b) County Ranks. Education vs Gini, 1920

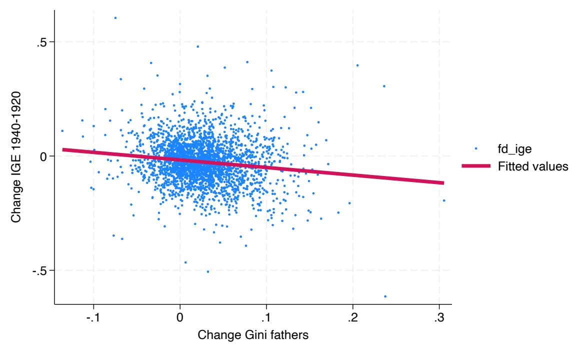


(c) Levels. Education vs Gini, 1920

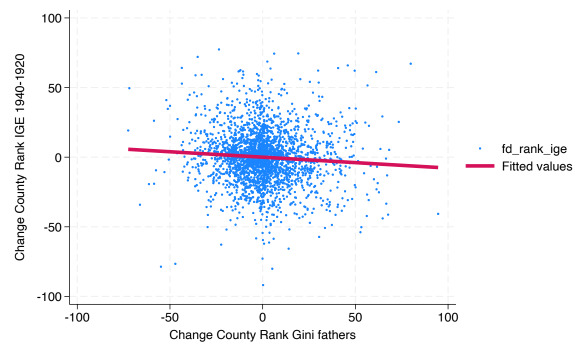


(d) County Ranks. Education vs Gini, 1940

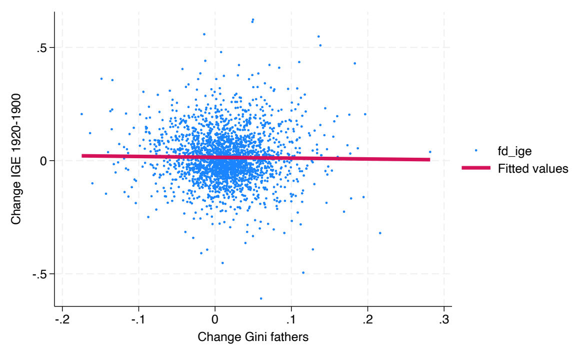
Figure A11: Education versus Gini, Levels and County Ranks.



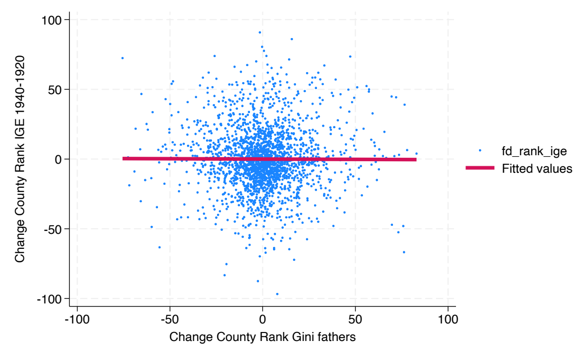
(a) Levels. ΔIGE vs ΔGini, 1920-1940



(b) County Ranks. ΔIGE vs ΔGini, 1920-1940

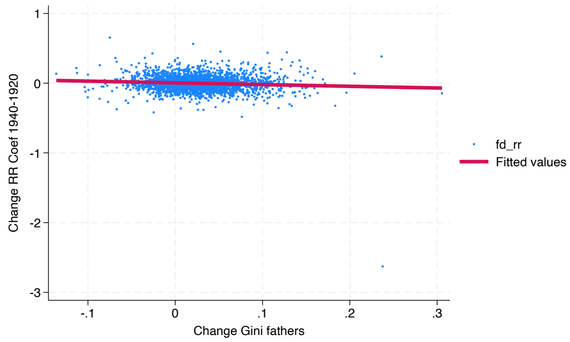


(c) Levels. ΔIGE vs ΔGini, 1900-1920

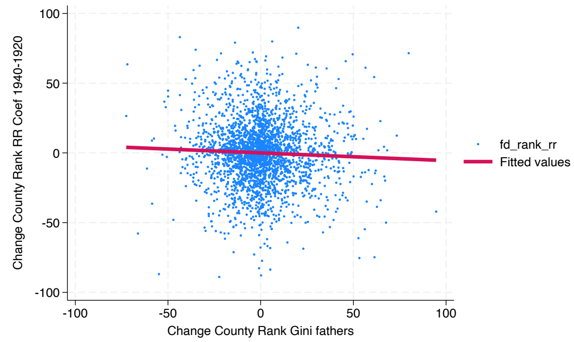


(d) County Ranks. ΔIGE vs ΔGini, 1900-1920

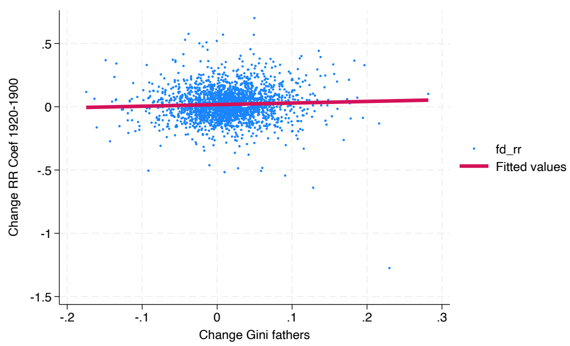
Figure A12: Dynamic GGC, IGE. Levels and County Ranks.



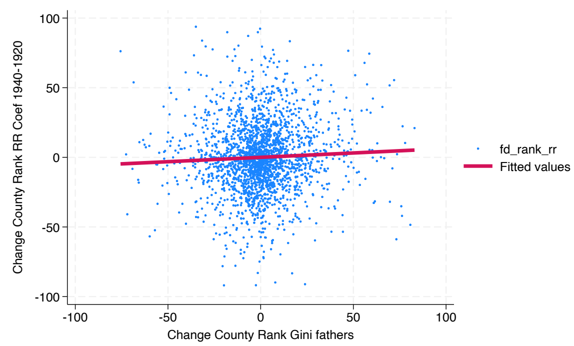
(a) Levels. Δr-r vs ΔGini, 1920-1940



(b) County Ranks. Δr-r vs ΔGini, 1920-1940

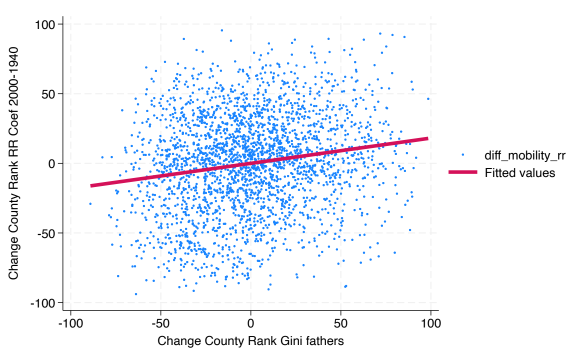


(c) Levels. Δr-r vs ΔGini, 1900-1920

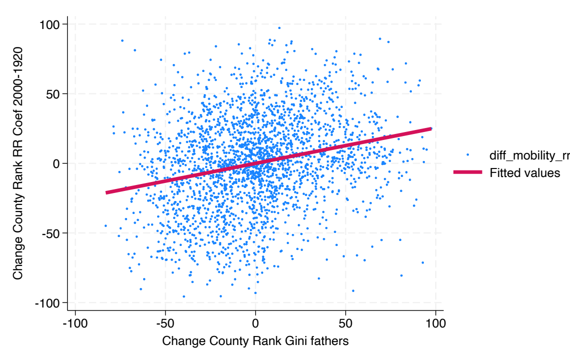


(d) County Ranks. Δr-r vs ΔGini, 1900-1920

Figure A13: Dynamic GGC, r-r. Levels and County Ranks.

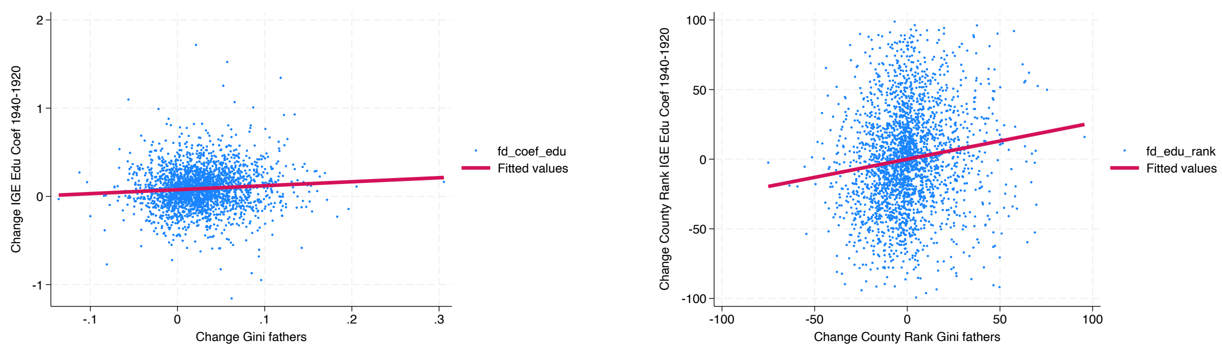


(a) County Ranks. Δr-r vs ΔGini, 1940-2011



(b) County Ranks. Δr-r vs ΔGini, 1920-2011

Figure A14: Long Run Dynamic GGC, r-r. Levels and County Ranks.



(a) Levels. ΔEducation vs ΔGini, 1920-1940

(b) County Ranks. ΔEducation vs ΔGini, 1920-1940

Figure A15: Dynamic GGC, Education. Levels and County Ranks.